ANGLIA RUSKIN UNIVERSITY

ESTIMATING THE ROLE OF SCARCITY, PRICES AND POLITICAL FRAGILITY IN FOOD AND FUEL RIOTS: A QUANTITATIVE AND AGENT-BASED MODELLING APPROACH

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A thesis in partial fulfilment of the requirements of Anglia Ruskin University for the degree of Doctor of Philosophy.

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On a more personal note, I think it is important to highlight that the studies presented in this thesis constitute only a small part of the research that I carried out as part of my PhD. This research was part of a larger modelling project called GRO, which involved several other researchers. When I joined, the project had just started and, although there was a general direction, as for all the projects it took almost a year to define roles and focus of the research. I believe that the value in a PhD is not only the findings produced, but also the personal growth involved in the process. During the past three years I transitioned from the figure of student to that of researcher, by

learning, exploring, failing and repeating. During my PhD I taught myself econometrics and how to develop an ABM from scratch, calibrate it and validate it. This experience enriched me as a person and as a researcher and will prove invaluable to start my academic career.

ANGLIA RUSKIN UNIVERSITY
ABSTRACT

FACULTY OF SCIENCE & TECHNOLOGY

DOCTOR OF PHILOSPHY

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Climate and environmental changes are argued to increase the occurrence of conflict. In particular, two types of conflict seem to be driven by underlying environmental processes: food and fuel riots. Although research focussed on understanding the dynamics that cause food riots exists, the evidence is mixed and a solid quantitative analysis on the factors that cause these type of events is missing. Research on fuel riots is currently non-existent. The aim of this research was hence to identify, quantify and simulate the interconnections between scarcity of natural resources, international prices, political fragility and the occurrence of food and fuel riots. The approach implemented was mainly quantitative, with use of statistics, econometrics and Agent-Based Modelling (ABM). These methods allowed a parameterisation of these relationships and inclusion of the results in three different version of an ABM: Food, Fuel and Food and Fuel ABMs. The findings show that national availability of resources does not significantly impact the occurrence of food and fuel riots, while international prices and national political fragility do. Thresholds above which riots are more likely to happen were identified for both the price of food and fuel. For food, volatility was found to have a bigger impact than absolute prices, while for fuel the evidence was mixed and more research is required. In addition, food and fuel riots increase the likelihood of one another. Although the introduction of these parameters in the ABMs did not add to the predictive power of the underlying statistical models, the ABMs form the basis for further developments, in particular as regards the evolution of shocks to the production of resources and consequences in terms of food and fuel riots. This is evidenced by the scenarios developed and implemented in this thesis.

Keywords: food riots; fuel riots; environmental security; environmental conflict; agent-based model; scenarios

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1. Introduction

1.1. The Global Observatory Project

This PhD was part of the Global Resource Observatory (GRO) Project at the Global Sustainability Institute (GSI), Anglia Ruskin University. GRO is a multi-model modelling project that brings together findings from different fields (economy, social, environmental and finance) to investigate and provide short-term forecasts for how scarcity of natural resources impact different dynamics and sectors of society, mainly conflict, economy and the finance sector. The team working on GRO involved two more PhD students (i.e. Roberto Pasqualino and Efundem Agboraw), one post-doc, one principal investigator, one project manager, one research assistant and several collaborators and the work presented here constitutes my original contribution. Figure 1.1 represents the main societal structures whose dynamics were studied and modelled in the GRO Project, i.e. economy, political and finance. These structures were analysed within the framework of the natural environment.

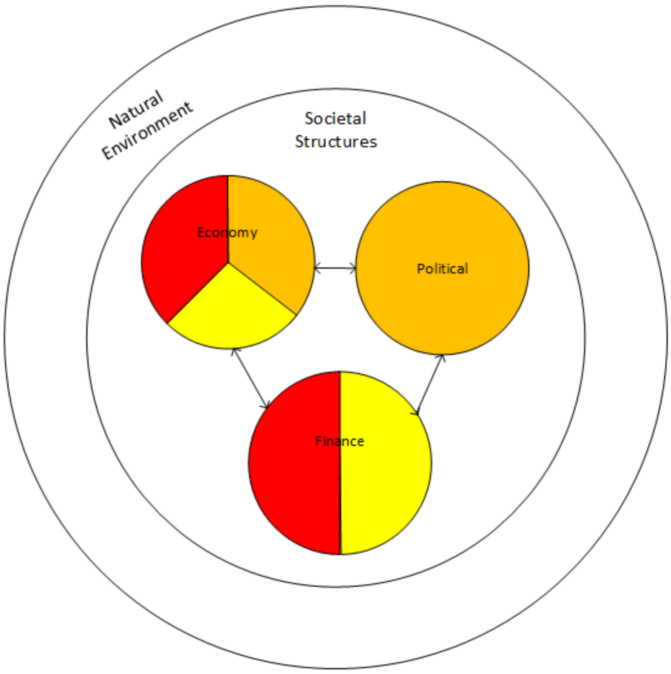

Figure 1.1 – The societal structures studied and modelled in the GRO Project, within the framework of the natural environment. The three different colours identify the topics studied within each PhD connected to the GRO project. The colour orange

relates to my PhD presented in this thesis, red relates to the work of Roberto Pasqualino and yellow to the work of Efundem Agboraw (own elaboration).

The project's main aim is to provide policy-makers and the wider public with clear and understandable findings related to this subject. The project established a set of principles the research team had to abide to:

1. *Short-term timeframe* (5 years). Most of the models developed in this area of research provide long-term forecasts (e.g. Meadows, et al., 1972; Barney, 2002; Barker, et al., 2006), whereas policy and decision makers usually work with very short political mandates, i.e. 5-7 years. The decision to develop models with short timeframes was aimed at bridging this time gap between research and policy and provide politicians with actionable and timely information relevant to their political mandate, also highlighting the longer term risks connected to these topics
2. Fully *data driven*. Chapter 3 explains that models can either be abstract or empirically grounded. Abstract models are usually easier to build, but their outcomes tend to be disconnected from reality and hence hard to interpret. To provide policy makers with actionable information, the models were based on empirical data, a principle that partly shaped how the models have been built
3. *Forecasts free* to the public. Information about possible political fragilities and scarcity of natural resources are in the hands of those few that can afford to pay expensive assessments that are carried out by consultancies expert in the field. GRO's mission was also to make the results freely available to the wider public to initiate a public dialogue on the matter and to popularise relevant information. For this reason the data collection focussed solely on free databases, still checking for their comprehensiveness and consistency
4. *Transparency*, no black-box models. The majority of models developed to provide forecasts are black-box or similarly difficult to interpret. In order for GRO's models to provide accessible information, the models had to be accessible and transparent as well. The principle coined was to 'keep it sophisticatedly simple', but not simplistic.

All these principles have shaped the research being presented here and provided the starting point for some key methodological choices. In particular, the part of the project related to my PhD aimed at exploring and quantifying the interconnections between scarcity of natural resources, their international prices, national political fragility and the occurrence of food and fuel riots, as shown by the orange-coloured spheres in Figure 1.1. The ultimate objective was to develop a fully data-led computer model that captured these dynamics and could provide short-term forecasts for these relationships.

1.2. Rationale and scope of the research

Climate and environmental changes are argued to affect different parts of society and different social structures. One of the possible consequences attributed to these environmental dynamics is an increased occurrence of conflict. In particular, two types of conflict seem to be driven by underlying environmental processes: food and fuel riots.

The period 2008 – 2011 saw a large increase in the occurrence of these events, particularly in North Africa and the Middle-East. This period can largely be attributed to the Arab Spring, which started as a series of demonstrations against the high food prices and the lack of food, and subsequently turned violent. The demonstrations then escalated in a more generalised discontent with the current establishment in the region. However, this type of events was not confined to this region, as riots were reported in different parts of the globe. The pressing nature of the problem and the interconnectedness of the system makes this topic worth studying with a systemic and quantitative approach.

Climate and environmental pressures are forecast to increase in the future, hence raising concerns for a potential increase in the occurrence of food and fuel riots. Although research focussed on the understanding of the dynamics that cause food riots, the evidence is mixed and a solid quantitative analysis on the factors that cause this type of events is currently missing. To the best of my knowledge, research on fuel riots is currently non-existent.

This thesis will hence address these gaps in literature by using these events as a basis for the study. In particular, this thesis constitutes a first attempt to identify and quantify the interconnections between different parts of the food and energy systems and, in particular, the dynamics that lead from scarcity of resources to the occurrence of two specific environmental conflicts (food and fuel riots) and their mutual relationships.

The approach implemented was mainly quantitative, with extensive use of statistics and econometrics and computer modelling, in particular Agent-Based Modelling (ABM). I applied quantitative methods to the investigation of the links between scarcity of natural resources, international prices, political fragility and the occurrence of food and fuel riots. These methods allowed a parameterisation of these relationships and inclusion of the results in three different version of an ABM, i.e. the Food ABM, the Fuel ABM and the Food and Fuel ABM. All three models include all the countries of the world as agents and an international trade network. Their names specify whether they include the dynamics that lead to the occurrence of food (Food ABM), fuel (Fuel ABM) or both types of riots (Food and Fuel ABM).

The research being presented here will answer the following research questions that will be further specified in Chapters 2 and 3:

- Is there a linked environmental causal factor in the triggering of civil unrest in different countries around the world?
    - Do international prices have an impact on the occurrence of food and fuel riots? What has the biggest effect, absolute prices or volatility? Is there a threshold for prices over which food and fuel riots are more likely to happen?
    - How does availability of food and oil impact the occurrence of riots?
    - Does national political fragility have an impact on the occurrence of food and fuel riots?
    - Are food and fuel riots characterised by the same dynamics? Do they have an impact on the occurrence of one another?
    - What is the probability of food and fuel riots to occur according to these variables?
- Which is the optimal method that can be used as a policy tool that can simulate these dynamics using a data-led approach?
    - Does adopting a fully data-led approach in developing an ABM generate a ‘good’ model?

    - Does the introduction of stochasticity and interaction between the agents and the feedback between food and fuel riots result in more accurate predictions than the underlying statistical extrapolation?

- Can these models be used to predict future riots?

1.3. Thesis overview

This chapter summarised the main principles of the project that this PhD was part of, also outlining the scope and rationale for the research presented in the next chapters. Chapter 2 will introduce the current literature on the different topics involved in this research, that can largely be referred to the academic area of environmental and climate security. Chapter 3 will introduce the different modelling methods that can be applied to this subject. A justification for the choice of different statistical models and ABM as methods will be provided, alongside the modelling journey that I went through to complete my PhD. Chapter 4 will present different studies undertaken to parameterise some of the dynamics that lead to food and fuel riots, briefly discussing the results of the models. Chapter 5 will present the ABMs that were developed as part of this research alongside their calibration, validation and simple forecasts for future occurrences of food and fuel riots. Chapter 6 will introduce the possible next steps that could be taken to improve this research, particularly presenting further studies on prices that could not be implemented in the models due to their initial stage of development and different scenarios that show the forecasting potential of the models. Finally, Chapter 7 will bring together the findings from this research with the main literature, answering the research questions set out above and highlighting the policy relevance of this research.

2. The environmental, economic and political dynamics that drive conflict and riots

This chapter will draw on existing literature to describe what is currently established and emerging knowledge about the different dynamics that lead to environmental conflict and, more specifically, to the occurrence of food and fuel riots. For the sake of clarity and organisation of the text, the link between the environment and conflict has been broken down in specific dynamics treated as pieces of a jigsaw that each section will describe singularly. This is obviously a simplification of the system that is the subject of this thesis, as will be described later in the text. This system is highly complex and the dynamics are interrelated and present feedback loops across multiple sectors and scales of analysis, with underlying trends and the presence of shocks and stressors.

In particular, the first section will focus on the basic dynamics that drive human-induced scarcity of natural resources and climate change. The second and third sections will report findings from literature about the connections between scarcity and abundance of natural resources and conflict. The fourth section will focus on the dynamics that lead from climate change and variability to conflict, whereas the fifth section will report literature on food and energy security and conflict. The sixth section will narrow the discussion to food and fuel riots, with the following section addressing the topic of food and fuel price formation. The eighth section will provide literature on systemic risk and, finally, in the conclusion section the gap in the literature that this research aims to address will be clearly identified and stated.

2.1. Human drivers of scarcity of natural resources and climate change

First and foremost it is important to distinguish between two main types of natural resources: renewable and non-renewable. The former are characterised by a continuous supply stream, which usually occurs naturally. The natural resources that are normally classified as renewable are water, sun, wind, biomass, soil and food. Non-renewable are instead extracted from natural reservoirs. These are mainly fossil fuels (e.g. coal, oil and natural gas) and mined materials (e.g. phosphates and rare earth elements). Groundwater is also widely considered a non-renewable natural resource due to the long time it takes for the deposits to replenish.

The concept of scarcity differs greatly according to which category of natural resources we refer to. Renewable resources are considered to be scarce (or their use unsustainable) when the exploitation rate is greater than the rate of natural replenishment or renewal. In the case of non-renewable resources, these are limited, scarce resources as their natural replenishment occurs at rates that are not compatible with human time scales (i.e. they replenish on a geological time scale). This chapter will account the dynamics that generally involve renewable and non-renewable resources, and the experimental part of this thesis will mainly focus on fossil fuels and food.

The idea that we live in a finite world with limited availability of natural resources is not a recent discovery. Indeed, the highly contested report on the 'Limits to Growth' published in Meadows, et al. (1972) concluded that 'If the present growth trends in world population, industrialisation, pollution, food production, and resource depletion continue unchanged, the limits to growth on this planet will be reached sometime within the next one hundred years. The most probable result will be a rather sudden and uncontrollable decline in both population and industrial capacity' (Meadows, et al., 1972, p. 23). Their report was based on a computer model that simulated the interactions between human and natural systems and that could shed light on what different futures may look like under different scenarios. Due to the limited technology and the scarce knowledge and data available on these dynamics at the time, their findings were contested by different academic fields. The report and the underlying model underwent several updates, the latest in Meadows, et al. (2004), reaching similar results. Despite the critiques aimed at this piece of work (e.g. Turner, 2012; Castro, 2012) recent research found that the original predictions were indeed quite accurate and that global trends have so far closely followed the most unsustainable path identified by the researchers, which would eventually lead the world to collapse or 'overshoot' (Turner, 2008; Jones, et al., 2013; Pasqualino, et al., 2015). Pasqualino, et al. (2015) recreated and calibrated the latest version of the original model whilst updating the data used to compare the results. The main difference between the standard scenario in Meadows, et al. (1972) and reality is the extraordinarily positive technological change, complemented by a high dematerialisation of human economy and its crystallisation in the services sector, which were underestimated in the original model (Pasqualino, et al., 2015).

Another milestone in the academic field of sustainability was the study on 'Planetary Boundaries', first published in Rockstrom, et al. (2009) and later updated in Steffen, et al. (2011). The researchers reinforce the idea that humanity has a limited, safe operating space characterised by complex dynamics that present thresholds. The final list contains nine planetary boundaries: i) climate change, ii) novel entities, iii) stratospheric ozone depletion, iv) atmospheric aerosol loading, v) ocean acidification, vi) biogeochemical flows, vii) freshwater use, viii) land-system change and ix) biosphere integrity. Their findings show that four of these have already been crossed, in particular i, vi, viii and ix. Similarly to Meadows, et al. (1972), the researchers also warn that the crossing of any of these thresholds could result in a regime shift with potential catastrophic consequences for humanity.

Climate change is one of the most worrying dynamics. This is defined as 'a change in the state of the climate that can be identified (e.g. using statistical tests) by changes in the mean and/or the variability of its properties, and that persists for an extended period, typically decades or longer. It refers to any change in climate over time, whether due to natural variability or as a result of human activity' (IPCC, 2007, p. 30). The main consequences of climate change are sea level rise, scarcity of natural resources such as food and water, increased losses of biodiversity and ecosystem services and increased occurrence of extreme events such as droughts and floods (IPCC, 2007). This dynamic is partly driven by human activities, which emit increasing levels of greenhouse gases (GHGs) and alter the concentration of these gases in the Earth's atmosphere, causing the warming of the planet (IPCC, 2007).

Indeed, the interactions between the environment and human activities and structures, commonly referred to as socio-ecological systems (SES) in social sciences, present all the characteristics of complex adaptive systems. Some of these are the presence of thresholds, non-linear behaviours and interconnectivity amongst different components of the system, or in this case between different SESs (Homer-Dixon, 1991; Ostrom, 2009). These characteristics will be listed and explained in detail in the following chapter.

Literature has widely explored the dynamics that characterise SESs and in particular the effects of human activities on the environment and their feedbacks on human activities. The fundamental drivers of scarcity of natural resources and human-made climate change have been identified as being population growth and economic development (Sterman, 2012; Schäfer, 2014). The first driver can be associated with the Malthusian school of thought (Malthus, 1926), which was the first theory concluding that the world's population would increase indefinitely alongside its use of natural resources – in particular food – ultimately resulting in famine and starvation. Although this theory has contemporary followers (Ehrlich, 1970; Ehrlich and Ehrlich, 2009) and is still at the centre of the debate (e.g. Neomalthusian model over scarcity of resources that leads to conflict), it was highly contested for being overly pessimistic (e.g. from the Cornucopian school of thought, see for example Boserup and Schultz, 1990). Since then, humanity and technology (e.g. agricultural revolution) have progressed alongside the social structures that we have put in place to thrive and regulate our development as a species, and the 'Malthusian Catastrophe' has not materialised yet (at the global level). The creation of human economy and economic development that benefited the now developed countries first and currently characterises the developing world played a relevant role in the increase of income per capita, which was vital in lifting whole populations from poverty. However, this process, coupled with exponential population growth, translated in an increase in consumption of fundamental natural resources used to create goods and consumables (Wackernagel and Rees, 1996), increasing urbanisation (due to shift from agricultural-based systems to industry, which led to the migration of rural population to the cities), ultimately driving human-made climate change via changes in land use, increase in the use of energy by burning fossil fuels, increasing pollution and emissions of GHGs (IPCC, 2014). This is another important driver of how human activities affect the natural environment.

Although these dynamics have been active for centuries, particularly since the first industrial revolution in the 19^{th} Century, the size of world's population and economy have not stopped growing. The United Nations (UN) most recent forecast for the world population is 9,725 millions by 2050 and 11,213 millions by 2100 (UN, 2013). In addition, the Intergovernmental Panel for Climate Change (IPCC) predicts a likely warming of the planet between 1.5 and 4 degrees by 2100 according to different GHG concentration levels (IPCC, 2014). The consequences of this scenario in terms of changes to the climate and its feedbacks on human activities would possibly be devastating. In particular, food security, the delivery of ecosystem services, sea-level rise and the occurrence of extreme events would likely be worsened (on average) by the increase in global temperatures. Some of these dynamics are already occurring (King, et al., 2015).

However, development and economic theories argue that economic growth will contribute to the slow down of population growth by positively affecting women's education, which in turn decreases the birth rate of countries (e.g. Becker, 1960). In addition, economic theories such as the Economic Kuznets Curve (Kuznets, 1955) argue that economic growth also has a positive impact on populations' environmental concerns and these dynamics should ultimately reduce the impact of human activities on the natural environment. In general, empirical research seems to agree on the inverse relationship between economic growth and population growth, whereas the link between economic growth and environmental impact remains an open debate (e.g. Meadows, et al., 1972; Meadows, et al., 2004; Randers, 2012). In particular, it is not known whether the limited availability of natural resources and the negative feedbacks from the natural environment on human activities will allow this process to complete. For instance, findings from Schäfer (2014) support the idea that technological advances and economic development contribute to a decline in depletion of natural resources. However, Barbier and Homer-Dixon (1999) argue that scarcity of natural resources hinders the potential for economic development of poor countries that are heavily resource-dependent by directly constraining growth, but also by indirectly affecting the potential of these countries to innovate. Another opinion is provided by Bagliani, et al. (2008) who empirically tested the environmental Kuznets curve hypothesis using data for the ecological footprint of 141 countries, finding no evidence for the decoupling between economic growth and environmental impact.

As mentioned above, climate change can result in negative consequences for economic growth. For instance, Burke, et al. (2015) explored the consequences of climate change in terms of productivity, finding that variations in temperature have a non-linear impact on economic activities by reducing productivity in both agricultural and non-agricultural sectors and both rich and poor countries. Their findings reveal that productivity peaks at an annual average temperature of 13 degrees. Since productivity in all regions and countries is coupled to global climate, warming of the planet can cause a 23% reduction in global incomes by 2100 and increase income inequalities due to areas affected differently from climate change.

2.2. Food, energy and water security

The effects of the dynamics presented in the previous section can be better understood and represented by analysing each broad category of resources: food, energy and water. In general, the availability of these resources is affected by long-term social trends such as an increasing global population, global economic growth, environmental and climatic changes and international conflict, which are expected to increase in the future, hence worsening the conditions of security for these resources (IPCC, 2007). During the last few decades, research has increasingly focussed on the issue of security related to natural resources, which is notably different from their scarcity as security involves the notion of access.

2.2.1. Definition and drivers of food security

FAO (2006) defined global food security as: i) sufficient availability of quality food, either grown or imported, ii) access to food resources, iii) provision of adequate diet, clean water, sanitation and health care to meet the needs of populations and iv) a stable supply of food through time. A fundamental factor in the food security equation is the demand for food. Mitchell, et al. (2015) highlights the difference between simple demand and effective demand, especially valid in the case of food. Simple demand equates to the caloric intake needed by populations, whereas effective demand corresponds to the real access to food. The latter concept is the one truly important in the definition of food security and involves households' income and price of food. On the same lines, Pinstrup-Andersen (2009) argues that, at the household level, food security does not necessarily equate to nutritional security. This is due to the intra-household food distribution, which is seldom based on the nutritional needs of the members, and to access to food with good nutritional quality.

The specific drivers of food insecurity can be identified as i) decreasing availability of high-quality land, ii) decreasing marginal returns from agriculture intensification, iii) increasing climate change and water scarcity and iv) increasing demand for food (Homer-Dixon, et al., 2015). The first driver is mainly attributable to the fact that the land required to grow crops is in itself a limited resource, which is becoming increasingly scarce due to competing demand from different sectors (e.g. biofuels and food production), and its quality is degrading due to short-term oriented intensification practices. The second driver derives from the fundamental economic law of 'diminishing returns', which postulates that the increase in one factor of production whilst maintaining the other factors unvaried will result in a marginal increase in output, which decreases with time. In this case, doubling the input of technology (e.g. the use of fertilisers or the addition of machinery to cultivate the land) without increasing the land cultivated will first result in an initial doubling of the output. Subsequent increases in technology will result in decreasing marginal increases that tend to zero with time. As for the third driver, climate change affects the production of food through increase in temperatures, change in precipitation patterns (impacting the availability of water), rising sea levels (causing the salinisation of agricultural lands), increased extreme events (e.g. droughts and floods) and increased pollution (e.g. ocean acidification). Although research has found that an increase in temperatures and higher CO_2 concentrations due to climate change will initially benefit cultivations in particular regions of the globe, the overall effect is forecast to be negative, thus reducing global food production (Parry, et al., 2004; Wheeler and von Braun, 2013). Finally, the fourth driver can be brought back to the main general drivers listed before of increase in population and economic growth, which has an indirect effect on people's diets. Indeed, higher-income households tend to consume more and in particular more processed food and red meat, which is a highly water-, land- and food-intensive product (Godfray, et al., 2010).

2.2.2. Definition and drivers of energy security

As for energy security, the International Energy Agency defines this concept as "the uninterrupted availability of energy sources at an affordable price" (IEA, 2014, p. 4). The specific drivers of energy insecurity can be identified as: i) increasing demand for fuels, ii) decreasing oil production and iii) decreasing Energy Return On Investments (EROI)[1] for fossil fuels (Homer-Dixon, et al., 2015). The first driver of energy insecurity can once again be brought back to the one of the general drivers listed before, i.e. economic and population growth. As economy grows incessantly, increasing amounts of high-quality energy is required to sustain the complex system

[1] Note that in current literature the terms Energy Returns on Investments (EROI) and Energy Returns on Energy Invested (EROEI) are used interchangeably (e.g. Bardi, 2009). Seldom a definition is provided and when it is provided the definitions match (see for example Hammerschlag, 2006), where the definition for EROI is the same as that more commonly used EROEI). In this thesis the two terms will be used as reported by the original author being referenced, assuming them as synonyms.

that typify our social structures, which also are composed of an increasing number of people. (Different forms of) energy is used as a fundamental input in the production of every good we consume, and the larger an economy, the larger its production and the larger its energy requirements (Bardi, 2014). The second driver can be explained by introducing the theory of 'peak-oil': this theory argues that the production of non-renewable resources – and more particularly oil – initially grows, then reaches a peak and then starts its descent towards zero. This relationship was first introduced by Hubbert (1956), and takes the form of a bell-shaped curve. According to this, the peak corresponds to the moment in time when half of the endowments for the resource have been extracted (Bardi, 2009; Bardi, 2014). Jevons was the first scientist to try to model resource depletion in 1895 (Bardi, 2014). This author focussed his theories on coal, arguing that the easy coal is extracted first, which is cheap and easy to locate and extract. Its production becomes increasingly more difficult and expensive with time, ultimately making the resource economically not viable (Bardi, 2014). In addition, Lasky's law postulates an inverse relationship between the quality of the ore and its abundancy, i.e. lower-grade ores are more plentiful in the Earth's crust than higher-grade ones (Bardi, 2014). These two concepts cause the bell shape of the curve theorised by Hubbert and can be described by the Energy Returned on Energy Invested (EROEI), which is the ratio between the energy produced by the resource extracted and the energy required to extract that resource (through a Life Cycle Assessment) (Bardi, 2009; Bardi, et al., 2011; Bardi, 2014). Resources with EROEI ≤ 1 are not economically profitable and not worth being extracted as the same amount of energy resulting from the extractive process is required as an input, although it is easy to imagine pathological cases where resources are extracted although their EROEI < 1 (e.g. when its production is being subsidised). For resources to be economically viable, their EROEI should be ≥ 3. Currently, only renewable resources, and in particular wind power and solar photovoltaic have a viable EROI of around 30 (Cleveland, et al., 2006) and 10 (Bardi, 2009), respectively (Bardi, 2009). In other words, as the quality of the resources discovered decreases due to Lasky's law, the investments (energy) required to extract increases, increasing the price of the final resource, until the resource becomes too expensive[2] to extract and its production is

[2] This is an over-simplification of the relationship between availability of resources and their prices. As it will be introduced later in this chapter, multiple factors influence the price of the resources, which

slowly abandoned, i.e. peak-oil. Research has found that some regions have already experienced peak-oil (e.g. USA in the 70s and USSR in the 90s), sometimes with catastrophic consequences for countries (Bardi, 2014). Global peak-oil has been forecast for the first half of the 2000s, whereas peak-oil discovery has already occurred around 1977 (Bardi, 2009). However, the theory of peak-resources is still currently highly debated.

2.2.3. Definition and drivers of water security

The United Nations (UN) defines water security as ‘the capacity of a population to safeguard sustainable access to adequate quantities of acceptable quality water for sustaining livelihoods, human well-being, and socio-economic development, for ensuring protection against water-borne pollution and water-related disasters, and for preserving ecosystems in a climate of peace and political stability” (UN, 2013, p. 7). Water is likely the most important resource for humanity, as it is central for the survival of our species, for the environment and for human activities (UN, 2013). The drivers that lead to water insecurity can once again be generally brought back to population increase and economic growth, which impact the availability of water both directly through water abstraction for personal use, agriculture and industry, but also indirectly through climate change, which can result in droughts and the salinisation of fresh water reservoirs (Mitchell, et al., 2015), and via international trade, through the concept of ‘virtual water’, i.e. the amount of water embodied in the traded goods and services. Water quality is another important factor, as domestic, industrial and agricultural practices can increase water pollution, with negative consequences for populations and ecosystems (UN, 2013).

2.3. Scarcity of natural resources and conflict

The literature that explored connections between the socio-environmental dynamics presented in the previous section and the emergence of conflict is large and highly interdisciplinary, and comprises studies undertaken with different approaches, which inevitably led to conflicting results.

Once again, the neo-Malthusian and Cornucopian schools of thought are the two main opposing theories that underlie the debate on the link between scarcity and conflict. In

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makes them difficult to predict.

particular, in the 1960s and 1970s a new wave of concerns over the potential mismatch between population and availability of natural resources, commonly referred to as neo-Malthusians, emerged (Urdal, 2005; Bernauer, et al., 2012). These authors believed that population would soon outgrow the resource base of countries, triggering environmental degradation and scarcity of natural resources such as arable land, water, forests and fisheries and this would result in widespread hunger and violent conflict (Hardin, 1968; Ehrlich, 1970; Norman, 1993; Ehrlich and Ehrlich, 1996; Renner, 2002; Ehrlich and Ehrlich, 2009).

One of the most cited authors whose research can be associated to the neo-Malthusian school is Homer-Dixon. In Homer-Dixon (1991), for instance, the author identified seven, possibly interrelated, environmental issues that can lead developing countries to inter- and intra-state conflict: climate change[3], stratospheric ozone layer depletion, acid deposition, deforestation, degradation of cultivated land, water scarcity and pollution and dwindling fisheries. The author argues that these environmental dynamics can be grouped under the term ‘global change’ and act on different spatial (e.g. global, regional, local) and temporal (e.g. millennia, years) scales. In addition, these dynamics have reached different levels of maturity (e.g. climate change and stratospheric ozone layer depletion).

Homer-Dixon (1994) coined the term ‘environmental scarcity’, which includes three drivers of scarcity of renewable resources: environmental change, population growth and unequal resource distribution. The author hypothesised three dynamics that can lead to different types of violent conflict: i) decreasing availability of resources such as water and land can lead to “simple-scarcity” conflicts or resource wars; ii) migration caused by environmental stresses can result in “group-identity” clashes and iii) environmental scarcity leads to economic crisis and stress for institutions, which can result in “deprivation” conflicts. These dynamics often interact and give life to two patterns, resource capture and ecological marginalisation. The former results from the combination of scarcity and population growth, which translates in an unequal distribution of the resources in favour of elites. The latter results from the

[3] The author originally wrote ‘greenhouse warming’. This term and ‘global warming’ were introduced in the 90s, but it was believed to be misleading, as not the whole globe would become warmer due to GHG emissions. This process is now more commonly defined ‘climate change’ due to its more objective connotation. In this thesis I will use this last term as a synonym to greenhouse warming to allow for consistency throughout the text.

combination of unequal distribution of resources and population growth that can lead to migration of the poorest sectors of the population to high-risk areas (e.g. sides of mountains and close to the sea). The author suggests two strategies that societies can implement to avoid environmental-scarcity-led conflict: i) by promoting policies to disincentivise the use of that resource and incentivise substitutes or ii) by decoupling their economies from the use of these resources and importing them from abroad. However, the author does not elaborate on the possible negative economic consequences of abandoning the production of the resource and of increasing imports, which can also lead to increased exposure to systemic risk. Both strategies require two types of ingenuity: social ingenuity to act as a buffer for the most vulnerable parts of society and to provide incentives for the development of new technologies and technical ingenuity to develop these new technologies to substitute for the environmental loss. The former is a precursor of the latter and the implementation of both requires strategic thinking by decision-makers in terms of when and where the need is the greatest.

Cornucopians are once again opposed to the neo-Malthusian view that population pressure and resource scarcity can lead to conflict (Urdal, 2005; Bernauer, et al., 2012). Although they acknowledge that environmental issues can sometimes constitute a risk for human wellbeing, their thought is structured around three main counter-theories: firstly, the natural resources whose availability is commonly thought to be low, are plentiful at the global level and will remain so even if global population continues to rise (e.g. Lomborg, 2001); secondly, humanity will adapt to these scarcities through market mechanisms and technological innovation (e.g. Simon, 1996), with one author arguing that this dynamic of scarcity is necessary for agricultural innovation (Boserup and Schultz, 1990). Indeed, Cornucopians criticise neo-Malthusian arguments for being overly deterministic and ignorant of economic and socio-political factors (e.g. Gleditsch, 1998; de Soysa, 2002a; de Soysa, 2002b; Barnett and Adger, 2007; Salehyan, 2008; Koubi, et al., 2012); finally, Cornucopians believe that conflict is more likely to be triggered from abundance of natural resources, rather than scarcity, due to the wealth that these represent. This theory is commonly referred to as ‘Resource curse’.

Empirical literature on the link between scarcity of natural resources and conflict seems to agree that environmental stresses contribute to the occurrence of conflict in specific cases (Homer-Dixon, 1994; Bernauer, et al., 2012), although the evidence in both the qualitative and quantitative literature is mixed for larger studies (Böhmelt, et al., 2014; Bretthauer, 2014). For instance, Homer-Dixon (1999) qualitatively reviewed several case studies demonstrating that many of these support a model where climate leads to resource shortages, which in turn promote conflict. Ide (2015) undertook a qualitative analysis to establish the conditions necessary for conflicts over scarcity of resources to turn violent using a series of case studies from the global south. The author found that a mix of structural conditions – negative othering, i.e. the negative contrast between different collective identities and low power differences between competing political parties – and one triggering condition, i.e. recent political change, are sufficient for a violent escalation of conflicts over renewable natural resources and that there is no single sufficient condition. Other conditions generally regarded as necessary, i.e. high power differences between political parties and resource appropriation, or the exclusion of local groups from the use of scarce renewable resources, were not found to be significant. Bretthauer (2014) focuses her analysis on the impact of scarcity of arable land and water on conflict using a case-studies qualitative approach. Her findings show that the combination of agricultural dependence, poverty and low levels of tertiary education leads to the emergence of conflict in case of scarcity of natural resources and that low levels of tertiary education is a necessary condition for conflict. Conversely, she found that the non-dependence on agriculture is a necessary condition for non-conflict and that high levels of tertiary education help avoid conflict. The author recognises the limitations of the method used, i.e. fuzzy set qualitative comparative analysis, as this does not prove a link between scarcity and conflict, but rather compares the conditions of different case studies analysed.

Now exploring the quantitative literature on the link between scarcity and conflict, Urdal (2005) specifically tested the neo-Malthusian and Cornucopian theories by analysing global time-series for a series of social, political and conflict variables between 1950 and 2000. His results do not provide evidence for either theory. In particular, the author found that high population growth, urbanisation and large refugee communities do not significantly impact the risk of conflict within countries. However, land scarcity combined with high population growth increases the risk of armed conflict. The main bulk of research on scarcity of natural resources and conflict focussed on water scarcity, with a few other examples. Studies from Hauge and Ellingsen (1998) and Gleick (1993) provide evidence that water scarcity can lead to armed conflict. Raleigh and Urdal (2007) also found a connection between water scarcity and land degradation and conflict and Lecoutere, et al. (2010) and Tir and Stinnett (2012) found similar conclusions. Other systematic empirical analyses agree that shared water resources can involve low-level conflicts, although the idea of 'water wars' does not find support in these empirical studies (Toset, Gleditsch and Hegre, 2000; Gleditsch, et al., 2006; Hensel, et al., 2006; Brochmann and Hensel, 2009; Dinar, 2009; Dinar, et al., 2011). Interestingly, other authors such as Kalbhenn (2012), Dinar, et al. (2007), Wolf (2002), and Yoffe, et al. (2003) found that cooperation is more likely than conflict between countries with shared water resources. Esty, et al. (1998) found no connection between environmental scarcity indicators for soil degradation and deforestation and state failure, whereas Bohmelt, et al. (2014) found a connection between population pressure, agricultural productivity, and economic development and risk of water conflict.

In conclusion, the literature on scarcity and conflict is abundant and the findings mixed. Qualitative studies seem to agree on environmental roots for some conflicts, in particular the author Homer-Dixon, whose views I share due to his objective and exhaustive accounts of case studies. Findings from quantitative studies provide evidence both for and against this connection.

2.4. Resource curse and conflict

The term resource curse refers to the situation where countries with large endowments of natural resources fail to achieve a sustained economic growth (Barbier, 2005). This is due to the disproportionate investments in the extraction of those resources, whilst neglecting to promote investments in other sectors of the economy such as education and social security. Once the endowments of the country are depleted or no longer economically viable, the country is left in a state of deep poverty, since the whole economy was based on the extractive industry. The wealth generated during the extractive years, is usually appropriated by the elites, since these countries are usually characterised by high levels of corruption. These countries tend to be located in the southern hemisphere, where natural resources are still plentiful (Lopez, 2010).

Conflict in these countries tends to be aimed at resource appropriation or related to rent-seeking behaviours (Carbonnier, et al., 2011).

Research has been focussing on searching for evidence for the resource curse and on identifying the factors that distinguish resource-wealthy countries that achieved economic growth with low conflict (e.g. Canada) and those that struggle to achieve the same (e.g. Nigeria). Van del Ploeg (2006) and Frankel (2010) provide two comprehensive literature reviews of the resource curse. In particular, Frankel (2010) highlights five channels that can generate the resource curse and that find some support in the literature: i) when the price volatility of commodities is high, which can be detrimental to the country's economy; ii) specialisation of a country in the extraction and production of natural resources can concentrate wealth and labour in this sector, neglecting the manufacturing sector, which carries positive externalities; iii) abundance of mineral resources can lead to civil war, which in turn can hinder economic development; iv) abundance of mineral resources and some crops can lead to corruption, social inequality, class structure, chronic power struggles, absence of rule of law and property rights and finally it can hinder democracy; v) 'The Dutch Disease', which is due to a country's specialisation in the export of natural resources, resulting in an increased monetary flow in the extractive sector, increased public spending and debt, the appreciation of the national currency. Consequently, the country's exports become relatively more expensive, which benefits the extractive sector and is detrimental to the other sectors of the economy. When the prices of national commodities decrease, the legacy of this process will be an economy relying mainly on the export of natural resources, with under-sized other sectors of the economy, in particular manufacturing. Collier and Goderis (2008) add 'lack of education' as a potential further cause of the resource curse and Carbonnier, et al. (2011) highlight four critical variables related to a country's institutions: i) constraints to the executive power, ii) level and type of corruption present in the country, iii) the country's type of regime and iv) the presence of armed violence and conflict.

Authors that found evidence of the resource curse are Sachs and Warner (1995; 2001), Gylfason and Zoega (2006), Sala-i-Martin and Subramanian (2003), Kaldor, et al. (2007), Ross (2001) and Smith (2004). For instance, Collier and Goderis (2008) use an econometric approach to explore global data between 1963 and 2003, finding strong evidence for the resource curse hypothesis. In particular, the authors found that commodity booms, i.e. price spikes in commodities, have positive effects on output in the short-term that translate in negative long-term effects, particularly for mineral resources. The authors also found that good institutions (i.e. countries that have a high score for the International Country Risk Guide) are sufficient to avoid the resource curse and that the resource curse process is explained by real exchange rate appreciation, public and private consumption and, less importantly, from external debt, manufacturing and services. These findings support literature on the importance of the Dutch disease in countries with large endowments of natural resources and also the literature that identifies scarce redistribution as the root of the curse.

Carbonnier, et al. (2011) reached similar conclusions by analysing a panel dataset to evaluate the relationships between extraction of natural resource, governance and development in developing countries. In particular, the authors found an inverse relationship between resource extraction and Adjusted Net Savings (ANS), which is a measure of a country's wealth that takes into account the depletion of natural resources (Barbier, 2005). However, they also highlight that this negative effect can be avoided by nurturing government and institutions.

Other authors focussed on specific countries, finding evidence of the resource curse in Democratic Republic of the Congo, Equatorial Guinea, and Nigeria and highlighting as the main causes the Dutch disease, the government's focus on producing revenues through the extraction of natural resources and armed violence (Mehlum, et al., 2006; Collier and Goderis, 2008; Carbonnier, 2011). Further on this, the civil wars in Angola, the Democratic Republic of the Congo and Sierra Leone support the argument that countries with large endowments of natural resources are more likely to experience conflict (Le Billon, 2003; Collier and Hoeffler, 2004; Le Billon, 2005; Rosser, 2006). Other authors focussed on specific types of regime, for instance Andersen and Aslaksen (2008) found that the resource curse is more likely to involve presidential rather than parliamentarian democracies.

Authors who found a positive relationship between endowments of natural resources and economic growth are, amongst others, Alexeev and Conrad (2009) and Brunnschweiler and Bulte (2008), even in Africa (Deaton and Miller, 1995) and low-income countries (Raddatz, 2007).

Other countries like Nigeria experienced both economic growth and conflict due to the resource curse (Sala-i-Martin and Subramanian, 2003). Sala-i-Martin and Subramanian (2003) note that most of the income generated from the country's oil endowments was appropriated by the establishment, without increasing the living standards in the country.

Other authors such as Van der Ploeg (2011), Heinrich (2011), Di John (2011), Delacroix (1977), Davis, et al. (2003) and Herb (2005) argue against the existence of a resource curse.

2.5. Climate change and variability and conflict

The review of the literature on climate change and variability and conflict presents a complex landscape, with authors that found a direct or indirect connection between these two phenomena (Homer-Dixon, 1991; Miguel, et al., 2004; Barnett and Adger, 2007; Hendrix and Glaser, 2007; Nel and Righarts, 2008; Burke, et al., 2009a; Hendrix and Salehyan, 2012; Hsiang, et al., 2013b; Salehyan, 2014; Maystadt and Ecker, 2014; Raleigh, et al., 2015; Hsiang, et al., 2015; Chen, et al., 2016; Carleton, et al., 2016), authors that reject a connection between the two (Besley and Persson, 2011; Gartzke, 2012; Slettebak, 2012; Bergholt and Lujala, 2012) and finally authors that report findings that back this relationship only in specific circumstances (Bernauer, et al., 2012; Bretthauer, 2014), or that found little evidence (Buhaug, 2010; Benjaminsen, et al., 2012; Theisen, et al., 2013; Forsyth and Schomerus, 2013). Salehyan (2014), attributes the mixed findings in the literature as subjective bias of the researchers, whereas Scheffran, et al. (2012) argues that the main difference in findings is related to the temporal scale used in the studies and the methodology implemented where long-term, historic studies find a link between climate variability and conflict and more recent, data-based studies find mixed results.

Importantly, Seter (2016) distinguishes between 'climate change' and 'climate variability'. The first term refers to the long-term (i.e. persistent) change in climate temperatures and dynamics driven by natural and human impacts, whereas the second refers to short-term variability in climate conditions (e.g. occurrence of extremes). The author argues that these two terms are often confused or used as synonyms, leading to confounding results and literature, since arguing that climate variability is a cause for conflict is different from arguing that climate change is a cause of conflict.

Seter (2016) argues that climate variability affects the occurrence of conflict by inducing both favourable and unfavourable economic conditions and migration driven by economic factors.

Other authors argue that climate change affects conflict through increased migration (Findley, 1994; McLeman and Smit, 2006; Barnett and Adger, 2007; Nordås and Gleditsch, 2007; Raleigh and Urdal, 2007; Raleigh, et al., 2015; Burrows and Kinney, 2016). In particular, Mitchell, et al. (2015) state that climate change promotes the migration of populations, forcing them to move to areas that are either more at risk (e.g. hills and sea front) or that already experience environmental stress, which puts further pressure on the local environment and availability of resources such as food and water. This can erode the legitimacy of governments, resulting in intra- and inter-state tensions and conflict. In addition, Burrows and Kinney (2016) argue that, in general, literature agrees on the importance of climate and migration for conflict, however different authors disagree on the relative importance of these variables as compared to other causes of conflict.

Several studies found large associations between climate and conflict at the local (Miguel, 2005; Fjelde and von Uexkull, 2012; O'Loughlin, et al., 2012; Hsiang, et al., 2013a; Harari and La Ferrara, 2013), national (Levy, et al., 2005; Burke, et al., 2009a; Hendrix and Salehyan, 2012), continental (Hsiang, et al., 2011) and global (Hsiang, et al., 2013b) scales. Hsiang, et al. (2013b), is one of the large quantitative studies and one of the most robust and comprehensive in the field. The authors found that deviations from precipitation patterns and changes in temperature cause a systematic increase in the risk of different types of conflict, with changes in rainfall having a larger effect than the changes in temperature. The effect on large scale conflict is larger than that on interpersonal conflict. In addition, the authors found that these relationships are non-linear and hold for different sets of spatial and temporal scales. The authors list six theories explored in literature that explain the connection between climate change and conflict and that are, in their opinion, empirically supported: i) when climate change causes an economic decline, society's trade-off between engaging in conflict and operating normally is reduced; ii) economic decline caused by climate change erodes the strength of governmental institutions, which lose legitimacy and the ability to control and repress rebellions; iii) when climate change increases inequalities, societies will protest to restore the balance; iv) when climate change causes migration or urbanisation, conflict can emerge over geographically stationary resources that were not scarce before; v) climate change can alter the way conflicts are exacerbated by, for instance, changing the landscape and vi) climate change can result in conflict by altering people's cognitive abilities or attribution (e.g. heat wave).

Theisen, et al. (2011) empirically tested the link between climate variability and conflict by analysing data on postcolonial Africa. The authors found little evidence of the drought-conflict connection, arguing that socio-political and geographic factors such as politically marginalized population, high infant mortality, proximity to international borders, and high local population density are better descriptors of risk of civil war in Africa. Hsiang, et al. (2015) discredited these results arguing that the approach used by Theisen, et al. (2011) was fundamentally flawed and showed that the approach used was 'statistically underpowered in this context' (Hsiang, et al., 2015, p. 3).

Carleton, et al. (2016) constitutes the most up to date review of the relationship between climate and conflict. The authors argue that although initial studies concluded that the link between climate and conflict was inconclusive, the availability of new and more reliable data improved both the techniques implemented and the findings from research, essentially proving a link between these two topics. In this paper, the authors re-analyse and summarise the findings from 56 empirical studies on the link between climate and conflict. The aggregated results show that, generally, intergroup conflicts (e.g. wars) are significantly affected by both positive temperature and negative precipitation shocks, whereas interpersonal conflict (e.g. homicides) reports a smaller significant effect for temperature. The authors identify two pathways that lead from climate shocks to conflict that gained wide support in the empirical literature: i) the decrease in productivity due to the climate shock decreases the opportunity cost for conflict. This thesis is supported by Chassang and Padro-i-Miguel (2009) and Miguel, et al. (2004); ii) physio-psychological causes, i.e. warmer temperatures influence the bodily production of hormones, neurotransmitters and neuromoderators, resulting in a more aggressive behaviour. This thesis is supported by Ranson (2014), Card and Dahl (2011) and Jacob, et al. (2007). Other authors that focussed on the connections between temperature and conflict are Burke, et al. (2009a), who found that warmer temperatures promote civil wars in Africa, and

Gartzke (2012) who conversely did not find a causal relationship between temperatures and interstate conflict.

Barnett and Adger (2007) argue that climate change threatens human security by impacting the availability of natural resources, which in turn can affect conflict in certain circumstances. This view is also shared by Bächler (1999), Homer-Dixon (1999) and Kahl (2006). The case studies that support this connection are Rwanda (André and Platteau, 1998), Kenya (Kahl, 2006), the Philippines (Homer-Dixon, 1994; Kahl, 2006), and Bangladesh (Swain, 1996), but other case studies identified different factors leading to conflict such as corruption or group marginalisation (e.g. Turner, 2004; Benjaminsen, 2008; Benjaminsen, et al., 2012). However, even for the case studies where support for this link was found, the literature found contrasting results, Rwanda being an example (Percival and Homer-Dixon, 1995).

A series of authors focussed instead on rainfall patterns (proxy for climate change) and conflict. Miguel, et al. (2004) focussed on rainfall patterns and civil war in Africa finding a significant, inverse relationship, between rainfall and conflict, findings which are shared by Hendrix and Glaser (2007). Ciccone (2011) criticises these conclusions by arguing that the authors' approach in accounting for rainfall patterns may be flawed, but Miguel and Satyanath (2011) illustrate that Ciccone's (2011) critique lacks theoretical support. Hendrix and Salehyan (2012) found that extreme rainfall patterns (e.g. droughts and floods) increase the probability of conflict and Maystadt and Ecker (2014) found similar results for droughts and conflict in Somalia.

Other studies used natural disasters as proxy for climate change and its relationship with conflict. Nel and Righarts (2008) found a positive relationship between natural disasters and conflict, especially in low- and middle-income countries. These findings are contrasted by Slettebak (2012), who found that natural disasters decrease the likelihood of civil war.

Notwithstanding the conflicting findings presented by the literature, most authors agree on considering climate and environmental change and scarcity of resources as a stressor or catalyst for conflict (e.g. Gaub, 2012; Bleischwitz, et al., 2014). Whether countries and population will react violently to these pressures, will likely depend on social and political variables such as regime type and the perceived legitimacy of the government. For instance, Schleussner, et al. (2016) is a large quantitative study that implements event coincidence analysis and tested the relationship between climate-related disasters and conflict in countries with ethnic divisions. The study found no direct connection between climate calamities and conflict, however these events exacerbate the conflict potential in ethnically fractioned countries.

2.6. Food and energy security, prices and conflict

Previous research explored the interconnections between food security and conflict, with some authors arguing about the existence of a vicious cycle between food security, food prices and conflict (Devereux and Maxwell, 2001; Auyero and Moran, 2007; Brinkman and Hendrix, 2011; Raleigh, et al., 2015). Indeed, research has highlighted a positive relationship between global scarcity of food and increases in international food prices (Godfray, et al., 2010; Raleigh, et al., 2015; Puma, et al., 2015), with some authors arguing that this relationship is a self-reinforcing feedback in itself (Brinkman and Hendrix, 2011). However, price spikes are not the only consequence of food insecurity: research has shown the existence of a positive relationship also between global scarcity of food and increased probability of conflict (Brinkman and Hendrix, 2011; Raleigh, et al., 2015). Indeed, Brinkman and Hendrix (2011) argue that food insecurity increases the chances of a democratic breakdown in politically fragile countries and that the feedback between food insecurity and conflict is self-reinforcing. At the same time, high international food prices can impact food security (Brinkman and Hendrix, 2011; Berazneva and Lee, 2013; Hendrix and Brinkman, 2013; Bellemare, 2014; Smith, 2014; Raleigh, et al., 2015) and the political stability of countries (Seddon and Walton, 1994; Arezki and Bruckner, 2011; Bates, 2011; Berazneva and Lee, 2013), also causing political changes at the national level (Brinkman and Hendrix, 2011).

Raleigh, et al. (2015) explored these interconnections by analysing data for African countries and found that climate variability indirectly affects the occurrence of conflict through food prices. Indeed, the authors found that low levels of rainfall can cause an increase in the prices of food, which can give life to a self-reinforcing feedback between price of food and violent conflict. The authors add that, due to the high levels of financial aid present in conflict-affected regions, food price volatility is more likely than price increases in these instances. Finally, the authors argue that climate variability and prices affect countries differently. This adds to the theory that political and economic characteristics of countries are critical in whether states experience conflict, a view that is shared by other authors (Nordås and Gleditsch, 2007; Raleigh and Urdal, 2007; Theisen, 2008; Barnett, 2010).

Similarly, Brinkman and Hendrix (2011) argue that food insecurity is neither a sufficient nor necessary condition for conflict and that countries are more likely to experience conflict if already politically fragile, an opinion which I share. However, Mitchell, et al. (2015) argue that fragile countries tend to be those most at risk of food insecurity. Indeed, Brinkman and Hendrix (2011) argue that fragile states are usually characterised by high imports of food, which exposes them to high international food prices and price fluctuations. Finally, authors such as Reenock, et al. (2007) and Østby (2008) observe that in the conflict equation, the critical variable is not absolute food insecurity, but rather how this is distributed within and between groups.

Interestingly, some authors disagree on the hypothesis that positive shocks in world prices (i.e. increase in prices) are a trigger for conflict, arguing that whether this results in higher levels of conflict depends on the social group taken into account. Positive price shocks have positive effects on farmers and food producers, whilst negatively impact the income of consuming households. Negative price shocks mirror these effects. The findings from McGuirk and Burke (2016) endorse this hypothesis: the authors evaluated the effect of shocks in world prices on the occurrence of civil conflict in Africa distinguishing between food producers and consumers and found that positive price shocks reduce conflict in areas that produce food and increase the likelihood of violence from net food consuming areas. The authors use their findings to distinguish between two types of conflict related to food price shocks: factor and output conflict. The first type involves struggles to control territories, whereas the second refers to conflict over the appropriation of surplus. In case of a positive price shock, the first type of conflict is discouraged in food producing areas, whereas the second type increases. In net food consuming areas, both types of conflict increase. The authors also warn that food price projections to 2050 suggest an increase in both types of conflict.

Weezel (2016) is also critical of the connection between international food prices and violence. The author undertakes a quantitative analysis on African countries between 1990 and 2011 and finds a significant relationship between high food prices and increase in violence, using a country-specific food price index based on a country's food-import pattern. However, the effect of food prices is relatively small, consisting in an additional violent event in a country in a month for two standard deviation increase in the food price index. In addition, when trying to use his model for predictions, the addition of the food price index as independent variable does not improve the model's prediction greatly, immediately questioning the validity of the relationship between international food prices and violence. This is a clear example of the subjective bias mentioned by Salehyan (2014) in the authors' interpretation of their own results, as the presentation of the author's results suggests that he expected to find the opposite result, i.e. a non-significant relationship between food prices and conflict. Similarly to Weezel (2016), Weinberg and Barker (2014) evaluated the relationship between national food prices and social unrest coming to similar, although less critical, conclusions: the authors find a positive, significant relationship between the two variables, recommending the inclusion of food prices in any study on conflict.

As for the connection between energy resources, energy prices and conflict, these dynamics are underexplored in the current literature. In fact, specific literature mainly focussed on oil resources. For instance, Le Billon and Cervantes (2009) found a positive relationship between oil scarcity, oil prices and the occurrence of conflict. Their findings agree with the larger literature on scarcity of resources and conflict that supports a positive connection between the two topics. However, the authors argue that this literature fails to account for oil prices, tensions between countries over oil reserves and international geopolitics, which need to be included in future studies to capture the full picture. Similarly, Cotet and Tsui (2013) quantitatively analysed oil availability and connections with conflict. By analysing data on world oil explorations and discoveries, they evaluate how oil availability affects the incidence of violent conflict. Their results show no trace of this connection, rather, oil-abundant nondemocratic countries have larger defence expenditures, which the authors explain as the increasing cost of these countries to defend their natural endowments from external appropriation. The authors admit the presence of a large amount of noise in their data. Elaborating further on their findings, these perfectly fit with the resource curse hypothesis and the idea of conflict over the abundance of natural resources, which, in the cases analysed by the authors, were possibly prevented by the large expenditures in defence.

Bruckner, et al. (2012) focussed their analysis on oil prices and democracy. By analysing the effects of oil price shocks on democracy between 1960 and 2006, the authors found that increases in international oil prices result in higher levels of Gross Domestic Product (GDP) for countries that are net oil exporters, which in turn results in more democratic institutions in these countries. However, the effects are rather small. Ebel and Menon (2000) through a careful analysis of the power relationships in the Caspian area with its natural endowments of energy resources such as natural gas and oil, warn that revenues from sales of energy resources is the critical factor that could destabilise the region, sparking conflict. Particularly, the authors point out that the misuse of these revenues could increase tensions and conflict between and within countries located in this area, where borders are highly disputed, both for the appropriation of resources, but also for discontent in populations when the revenues are employed to cause shifts in the balance of power rather than being invested in social support. However, their analysis is solely theoretical and descriptive.

Literature that explores the impact of the price of commodities more generally also applies to energy resources. For instance, Besley and Persson (2008) found that increases in the prices of exported and imported commodities can result in a higher incidence of conflict within countries. However, the authors acknowledge the limitations of the data and method they use. Conversely, in their study on Sub-Saharan Africa between 1981 and 2006 Brückner and Ciccone (2010) found that a drop in the price of commodities exported to OECD countries increases the risk of civil war in African countries. Dube and Vargas (2013) tested two theories on how commodity price shocks affect the occurrence of conflict: i) the 'opportunity cost effect', i.e. positive price shocks can lower conflict by increasing labourers' pay, which reduces the push to appropriate resources violently and ii) the 'rapacity effect', i.e. an increase in the contestable income results in an increase in gains from appropriation, which in turn can result in increased violence. By analysing data on Colombia's exports of oil and coffee, evidence shows that a negative price spike for coffee in 1990 is consistent with the opportunity cost effect, since it decreases labourer's pay thus lowering the opportunity cost of people joining armed forces, and results in different levels of conflict as a demonstration of malcontent in the zones where coffee was cultivated. Conversely, a positive price spike for oil is consistent with the rapacity effect, with increased conflict in the oil-producing regions for appropriation of the resource. The authors add that these patterns remain valid for other agricultural and natural resources and conclude that price shocks affect the incidence of conflict in different directions according to the type of commodity.

Bazzi and Blattman (2014) argue that previous literature came to different conclusions due to differences in the timeframe covered in the studies, but also due to theoretical and methodological issues, such as the non-disaggregation of the shocks and the failure to account for the dependence of data typical of time-series. With their study the authors also found evidence of the opportunity cost effect, but challenge the rapacity effect. The authors analyse the effect of exports price shocks for different commodities in developing countries and find that price shocks have no influence on the outbreak of new conflicts, thus challenging what they call the 'state-prize theory'[4]: rather, they find that rising prices of different commodities lead to shorter and less deadly (on-going) wars. Their findings also support the 'opportunity cost effect'.

2.7. Definition and dynamics of food and fuel riots

The previous section showed different types of conflict. One of the main distinctions is between inter-state and intra-state conflicts and, as highlighted in the paragraphs, both can be environmentally driven. Recent research has found that since the dissolution of the USSR, political analysis increasingly focussed on intra-state rather than inter-state conflicts (Carment, et al., 2011; Carment and Samy, 2012), probably in response to an increasing trend in this direction (Evans, 1994; Hensel, 2002). For this reason, this research focussed on two specific types of environmentally driven, intra-state conflict: food and fuel riots.

2.7.1. Definition of food and fuel riots

Several studies have tried to understand the dynamics that lie behind the occurrence of food riots and some tentatively quantified them. However, as frequently happens in research, one of the key differences between these studies were the definitions used to classify these episodes, i.e. food riots, hence leading to databases whose length varied widely and whose analyses led to very different results. The main distinction between the different definitions is whether the events need to involve the use of violence.

[4] Referred above as the 'rapacity effect'.

Arguably, the motivation behind this choice was very much due to the desired size of the database as, fortunately, violent protests related to scarcity or price of food are uncommon. The inclusion of non-violent forms of protest allowed authors to compile larger databases, hence allowing the use of more robust quantitative analyses (e.g. Bellemare, 2014). Other differences in the definition used to collect data on food riots related to the number of people involved and the reason behind the social upheaval, i.e. scarcity of food or high food prices (e.g. Cuesta, 2014). The definition used throughout this work was coined by a recently-published report from the Food Price Watch: “a food riot here is defined as: a violent, collective unrest leading to a loss of control, bodily harm or damage to property, essentially motivated by a lack of food availability, accessibility or affordability, as reported by the international and local media, and which may include other underlying causes of discontent” (Cuesta, 2014, p. 1). I chose this definition because of its comprehensiveness and for the reputation of the organisation that published the report, i.e. World Bank (WB).

The term ‘fuel riots’ was, as frequently happens, coined by the media, and the definition of this type of events is unclear. In addition, there is no mention of fuel riots in academic literature, which makes the research provided in this thesis completely novel. Based on the newspaper articles reporting of the occurrence of fuel riots (see Appendix 2), the term fuel riot refers to a violent upheaval related to scarcity, price or policy affecting fuel subsidies, i.e. both pledge of their institution or demonstration against their removal. The term ‘fuel’ is deceptively broad, which makes it difficult to identify which energy resource is the subject of the grievance. Amongst the newspaper articles reviewed for this thesis it was found that this term was mainly used to refer to petrol and its synonyms (e.g. gasoline for American English), natural gas in one case (Russell, 2011) or simply fuel. The simplest definition of fuel cites: “any substance burned as a source of heat or power, such as coal or petrol” (Collins, 2016), which can include any type of fossil fuels, i.e. coal, oil, natural gas. Since a clear definition of fuel riots was missing, this research adapted the definition given of food riots to define fuel riots replacing the word ‘food’ with ‘fuel’. In the first instance, this research will interpret fuel riots as ‘oil riots’ because, as it will be explained in Chapter 4.2.2, oil is the only energy resource with a truly international market and prices which, as will be presented in that section, is a key variable in explaining the occurrence of fuel riots.

2.7.2. Drivers of food and fuel riots

Violent uprisings related to the price of food or scarcity thereof have been occurring for the past four centuries (Brinkman and Hendrix, 2011; Berazneva and Lee, 2013; Smith, 2014; Bellemare, 2014; Demarest, 2014). However the latest wave of food riots occurred in 2008 triggered increased research on this type of event. O'Brien (2012) compared the 2008 food riots with the other most prominent food riots occurred in Britain during the 18th Century, trying to identify key differences and similarities. The main difference noted by the author regards the target and motivations of the riots: historical riots in Britain tended to target people in charge of food management and distribution, whereas the more recent wave targeted the government establishment more generally. In particular, O'Brien (2012) argues that the 2008 food riots may have initially been motivated by issues around lack of access to food, to then transform in a generalised dissent and discontent with the current establishment.

Since 2008 research has thus been focussing on the drivers of food riots, which notably are food insecurity (Lagi, et al., 2011; Crawley, et al., 2012) and high international food prices (Hendrix, et al., 2009; Lagi, et al., 2011; Gaub, 2012; Crawley, et al., 2012; Bellemare, 2014; Smith, 2014; Bleischwitz, et al., 2014).

Starting from the connection between food availability and the occurrence of food riots, several authors argue that countries are more likely to experience food riots in case of food production shocks (e.g. King, et al., 2015) or if a country is a net food importer (e.g. Lagi, et al., 2011). However, these arguments are challenged by part of the literature. For instance, Buhaug, et al. (2015) analysed the indirect effects of food production shocks on the occurrence of food riots in Sub-Saharan Africa. The authors found no evidence of a link between reduced agricultural output and an increase in the incidence of food riots. This opinion is shared by several other authors who believe that scarcity of food is not a direct cause of food riots, but rather a catalyst (e.g. Sneyd, et al., 2013).

A different perspective is provided by Legwegoh, et al. (2015) who focus on diets and hence food security. The authors note that most of the countries struck by food riots in 2008 did not experience food shortages and by implementing a mixed method study on Cameroon, they found that people's propensity to riot is conditional to their diets, i.e. when the price of a staple that they consider essential increases making it unaffordable, this may exacerbate the households' willingness to riot. However, different willingness to riot was associated to different food groups. The authors thus echo Demarest (2014) and Hossain and Kalita (2014) in arguing that to achieve a better understanding of the reasons why some countries rioted, future research needs to take into account people's diets (what staples are central for a certain culture) and/or society and local political, economic and social factors as to what are the most important responsibilities that populations attribute to the government. Finally, the authors do not find any significant relationship between food riots and demographic variables such as age and unemployment, at least for this case study.

As for the relationship between international food prices and food riots, previous studies such as Hendrix, et al. (2009) and Berazneva and Lee (2013) found a significant positive relationship between these two variables. In particular, Hendrix, et al. (2009) found that this relationship is non-linear, with the distribution of these events skewed towards the extremes of the price distribution, and bidirectional, with both price increases and decreases causing these events.

Lagi, et al. (2011) is one of the most widely cited pieces of literature on food prices and food riots. The authors compiled a database of food riots for North Africa and Middle East covering the period of the Arab Spring and calculated a threshold for the international price of food over which food riots are more likely to occur. This threshold is set at 210 of the nominal Food and Agriculture Organisation Food Price Index (FAO FPI). Notwithstanding the merits of this paper, a careful review of the methodology implemented by the authors posed questions about the robustness of their findings. In particular, the authors fail to provide a definition of food riot used to compile their database, which also included entries (newspaper articles) that regarded generalised Arab Spring protests against the government rather than food riots. Finally, the method implemented by the authors to calculate the threshold for the FAO FPI is unclear and the paper was never published in a peer-reviewed journal, which leads to question the robustness of their results.

Bellemare (2014) investigates both food price increases and food price volatility as possible causes of food riots, offering a more in-depth perspective. The author uses monthly data at the global level for the period 1990 – 2011, econometrically testing the relationship between these two price variables and the occurrence of food riots.

His results show no significant connection between food price volatility and the occurrence of food riots, whereas food price increases significantly affect this type of event, also providing causal evidence between the first two dynamics. In fact, the author's findings show a decrease in the likelihood of food riots when the volatility in the international price of food is high, which he justifies as an increased revenue for the rural, food producing areas, which are usually the most fragile and the most likely to take the streets. However, an in-depth review of the article raised concerns on the author's database on food riots, in particular, this could not be reproduced as it was collected through newspaper search engines that require an academic subscription, and, in addition, these databases add and remove entire newspapers at their own discretion, making the reproduction of the author's database (and hence results) difficult.

Berazneva and Lee (2013) specifically analysed the 2007 – 2008 food riots in African countries and compared the economic, social and political characteristics of countries that experienced food riots against those that did not. The authors found that the African countries that did experience food riots were characterised by higher levels of poverty, larger populations, lower food production, were heavily impacted by a negative food production shock, fewer political rights, lower levels of civil liberties, less foreign aid and located on the coast.

Some authors argued that international prices for food rarely translate perfectly into national prices for the same commodities (Brinkman and Hendrix, 2011; Smith, 2014; Raleigh, et al., 2015). Indeed, this depends on structural factors such as the country's level of dependency on imported food and the competitiveness on the market (WFP, 2009), but also, as will be presented later in the text, governments use different instruments to shield domestic markets from international prices, such as trade barriers, taxes and subsidies, and government interventions (WFP, 2009). Notwithstanding these factors, Smith (2014) still found a positive relationship between a sudden increase in domestic food prices and urban unrest.

Hendrix, et al. (2009) highlight the importance of the type of regime: in their study on data between 1961 and 2006 for 55 African cities, the authors found that autocracies experience fewer food riots than democracies, although hybrid regimes experience more food riots than democracies. The explanation provided by the authors is that autocracies are more successful at repressing protests, which are tolerated in democracies, whereas hybrid systems usually show weak accountability processes, which leads their populations to protest. Indeed, several authors have found that food riots are more likely to occur in countries with low income (Von Braun, et al., 2008; Arezki and Bruckner, 2011; Lagi, et al., 2011) and with low government effectiveness (von Braun, 2008; Lagi, et al., 2011). In a more recent paper with a longer time-frame (1961 – 2010), Hendrix and Haggard (2015) confirm their preliminary results on the difference between democracies and autocracies, with the former experiencing more food riots than the latter. The authors also add to their previous arguments for why democracies see more food riots than autocracies the different set of policies implemented by these two types of regimes: democracies are more likely to implement policies that favour rural areas, which are often detrimental to the urban populations (Hendrix and Haggard, 2015). This last argument is supported by Carter and Bates (2011): in their research the authors found an initial connection between food prices and the occurrence of food riots, which however disappears once accounting for countries' agricultural policies. According to their models, countries that implement policies that favour the urban population in case of a food price shock are less likely to experience food riots. Crawley, et al. (2012) challenge the evidence that sees democracies more prone to food riots than autocracies. In their research they found that democratisation reduces the likelihood of food riots. In addition, these authors found that poverty and income inequality directly and positively affect the occurrence of food riots.

Some authors argue that another main cause of food riots, particularly during the 2008 global food crisis, was the effective or prospected removal of food subsidies (Brinkman and Hendrix, 2011). Government price subsidies are defined as 'policy interventions engendering a deviation of consumer or producer prices from appropriate benchmark levels' (IMF, 2008, p. 5). Developed, developing and low-income countries normally subsidise the prices of food and energy resources to ensure their affordability, especially when the prices increase (IMF, 2008; Hendrix, et al., 2009). However, these constitute an onerous expenditure when the price of imported goods spikes, especially for poor countries[5]. As will be presented in Chapter 4, the

[5] See IMF (2008) for an in-depth explanation of food and energy subsidies and a review of subsidies currently in place.

newspaper articles gathered to compile the databases of food and fuel riots used in this research often mentioned as one of the causes of the violent protests either the effective or threatened removal of food or fuel subsidies.

Other authors focussed instead on the consequences of food riots. Food riots are widely believed to negatively affect the political stability of countries (Crawley, et al., 2012) and that the political instability and unrest created can spread to neighbouring countries (Lagi, et al., 2011) and through networks (Puma, et al., 2015). Goldstone (2011), for instance, argued that these events can trigger larger grievances such as civil wars, like in the case for the French Revolution and the Arab Spring. According to the author, these events usually take place in urban areas that experience fast urbanisation, where underlying pressures and malcontents are exacerbated by rising food prices, which are simply a demonstration of the population’s disapproval of an inept government. The idea that food riots are simply a trigger for larger grievances is shared by other authors (e.g. O'Brien, 2012). On the same line, Gaub (2012) developed a theoretical framework based on the events of the Arab Spring. The author focuses on the importance and interplay between three main elements: (i) root causes or conditions for conflict; (ii) catalysts of conflict; and (iii) triggers of conflict. The author argues that the presence of structural conditions for instability (e.g., scarcity of natural resources, unequal income distribution or large population growth) is not sufficient to produce conflict. Indeed, the author’s main argument is that the identification and analysis of “catalysts of instability” is key to understanding conflict potential. These can be seen as sudden changes in the above-mentioned conditions (e.g., a rapid increase in the unemployment rate of a country or spikes in food prices). Once a situation has reached conflict potential by adding a catalyst to one or more root causes, there is still the need for a trigger to boost the conflict likelihood. These could be natural disasters, new elections or, as in the case of the Arab Spring, an isolated event of social distress, like the episode that is commonly known as the starting point of the Arab Spring, when Mohamed Bouazizi set himself on fire as a protest for too high prices of food. This type of analysis is becoming mainstream as other authors define climate change, resource scarcity, a rapidly increasing population and volatility in prices as “stressors” or “stress multipliers” (OECD, 2012; Bleischwitz, et al., 2014; Cuesta, 2014). Moreover, the presence of thresholds and tipping-points in the fragility spectrum has increasingly been acknowledged in the recent literature (OECD, 2012).

2.8. Formation of international prices for food and fuel

As presented in the previous section, the international price of food is a critical driver of social unrest and, in particular, of food riots. Despite the lack of literature on fuel riots and their drivers, it is credible to believe that the same dynamics that characterise and drive food riots also apply to fuel riots. For this reason, this section will also explore the drivers of fuel prices.

Literature on the drivers that led to the recent food price spikes seems to agree on a few key factors. However, different authors disagree about the importance of each factor in the lead up to the price spikes. Literature on price formation generally disaggregates drivers of food prices into long- and short-run drivers, with the former driving the underlying trend and the latter determining short-term volatility. For instance, Brinkman and Hendrix (2011) identify as demand-side long-run drivers – or what the authors call structural factors – of international food prices i) higher income levels and demand, ii) population growth and iii) demand for biofuels. The supply-side long-run drivers they identify are i) scarce investments in the agriculture sector and low levels of productivity growth and ii) low national food stocks. Amongst the short-run factors that determine international food prices, the authors note on the demand side i) low exchange rates for US$ and ii) speculation, whereas on the supply side we find i) energy prices, i.e. which influence the prices of key agricultural inputs such as fertilisers, mechanisation and transport, ii) low exchange rates for US$, iii) food production shocks due to climate variability, iv) export restrictions and v) violent conflict. Several different authors (e.g. Roache, 2010; Trostle, 2011; Tadesse, et al., 2014) generally agree on the importance of most of these factors.

Now explaining some of the less intuitive factors, one of the most widely cited drivers of the 2008 food price spike is the Australian drought occurred in the same year. Lagi, et al. (2015) debunked this common belief by correlating Australia's and global food production. Australia's food production only constitutes around 1.8% of global grain production, which is insufficient to explain the magnitude of the price shock registered. However, the authors neglect to comment on the fact that such a shock could be enough to bring an already fragile system over the edge. Similarly, Coulibaly

(2013) and King, et al. (2015) cite the unfavourable weather in Eastern Europe and Russia as one of the factors of the 2011 international food price spike. However, to the best of my knowledge, the impact of these droughts on prices have not been formally evaluated.

Changing diets is another widely cited factor that may drive food prices. In particular, developing countries such as India and China have achieved higher incomes due to economic development, which resulted in an increased demand for meat (Brown, 1995). A shift from grains- to meat-based diets could heavily affect the demand for specific grains, since livestock is fed specific crops. However, authors are sceptical on the relevance of this factor (e.g. Bobenrieth, et al., 2013). For instance, Lagi, et al. (2015) argues that this increased demand was mainly met internally by the countries, as they remained net food exporters throughout the period.

Headey (2011) fundamentally agrees with the long- and short-run drivers of international food prices listed by Brinkman and Hendrix (2011). The author provides an in-depth account of the events that led to the 2008 international food price spike. Amongst the demand-side long-run drivers of food prices, the author cites demand for biofuels, which during 2007 – 2008 absorbed 30% of US' maize production. The notion of biofuels as long-run drivers of international food prices is however highly contested. Gilbert (2010) is one of the authors that did not find this variable critical for the 2008 food price spike. Lagi, et al. (2015) is the most recent and, in my opinion, robust study on drivers of food prices. The authors successfully modelled the price trends between 2004 and 2011. The model highlights that the underlying upward trend in international food prices is due to an increasing production of biofuels, which is due to an increasing demand for this alternative fuel and to US policies promoting their production. This trend effectively reduces the share of agricultural output destined to human consumption both by redirecting the production of current crops suitable for the production of biofuels and by replacing the cultivation of crops destined to human consumption, which are not as profitable. This causes an imbalance between supply and demand of food destined for human consumption at the international level, which causes prices to increase.

The model developed by Lagi, et al. (2015) also successfully recreated the 2008 and 2011 price spikes by introducing a variable that represented speculation in the food futures markets. These markets function as insurance on crops: food producers and buyers agree a price at which future crops will be sold, in order to insure the goods against possible negative future price shocks. The scarce regulations that characterise these markets allowed the development of 'index funds' that enable investors (speculators) to place bets on future commodities price spikes (Worthy, 2011). These findings suggest that the elimination of restrictions to investments in commodity markets and governmental policies in support of biofuels (ethanol) are the two main factors that directly concurred to generate the 2008 and 2011 food price spikes. Robles and Cooke (2009) and Gilbert (2010) also found that speculation on futures markets could have contributed to the price spikes. Irwin, et al. (2009), instead, found contradictory evidence and Sanders and Irwin (2010) and Headey and Fan (2008) noted that commodities with lower speculative capital showed higher price spikes than commodities with large speculative capital.

Headey (2011) agrees with Brinkman and Hendrix (2011) that rising oil prices was a critical factor that contributed to the food price spikes. Oil prices also registered higher levels[6], which caused further pressure on food prices by rising costs of trade and transport. Lagi, et al. (2015) also elaborate on this factor, arguing that it may have played a part. However, a careful analysis of the time-series showed the peak in oil prices occurring after that in food prices, which led the authors to believe that both peaks were a result of the same dynamics, i.e. speculation on commodity markets.

On the supply side, Headey (2011) cites the mismatch between production and consumption of food during the 80s and 90s as a possible factor contributing to the food price spikes. This was due to the low real prices, which hindered investments in increasing food production, which showed slack for the following two decades. During this period, countries used their national stocks of food as a buffer, which avoided price increases, leading the author to consider low food stocks as a short-run factor of prices. Countries use these resources as a buffer to cover short-term food shortages, but also tend to use these stocks strategically by either releasing them onto the markets when the price is high to gain revenues and, simultaneously, control prices, but they can also decide to accumulate them in case of future food shortages or to push prices up. Whether food stocks have an impact on international prices is indeed a highly contended issue. Headey and Fan (2008) argue that in the run up to

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[6] See later in the text for an account of the dynamics that drive fuel prices.

the 2008 price spike, China's decision to reduce excessive food stocks at the beginning of the decade was critical. When the food price spiked, low stocks meant that there was no buffer that countries could use. Lagi, et al. (2015) provide a different perspective on food stocks: the authors found that a price model based on food stock dynamics predicts well the trend in food prices up to the year 2000, but not afterwards. The authors explain that food stocks followed different dynamics during the price spikes due to speculation rather than interaction between supply and demand. Similarly, Tadesse, et al. (2014) found the role of stocks not significant in explaining food price volatility and price spikes. Bobenrieth, et al. (2013) provide further insights: the authors argue that a food production shock is not sufficient to create a price spike, but needs to be coupled with low stocks of food as the buffer that these normally provide does not exist. Although the authors agree that stocks are endogenous and do not drive prices, they found that the Stock-to-Use Ratio (ratio between national stocks and national consumption) is a good indicator of a country's vulnerability to price shocks.

Another supply-side factor cited by Headey (2011) is the low-exchange rates for the US$. Indeed, the low-interest rates that characterised the housing and stock markets, particularly in the US could have redirected investments to futures on commodity markets and foreign currencies. This could have resulted in the depreciation of the US$, which could have in turn boosted exports, causing higher prices in the US and lower prices everywhere else. The incidence of this factor is unclear in the current literature: Mitchell (2008) found that the depreciation of the US$ concurred to the development of the price spikes by 20%, whereas Abbott, et al. (2011) argued that this figure is around 50%. Lagi, et al. (2015) found a correlation between peaks in prices and exchange rates, but their analysis suggests that this is probably due to both dynamics depending on the same factors, rather than causality.

As mentioned above, export restrictions is one of the factors that several authors cite as critical in determining the 2008 and 2011 food price spikes. Indeed, during both peaks countries implemented trade policies to protect national markets from rising international food prices. These took the form of export quotas or higher export taxes, export bans, reduction or removal of import tariffs, and higher national subsidies (Trostle, 2011), with export restrictions being the most impactful. Indeed, in the wake of the rising food prices countries such as India, Thailand and China implemented trade restrictions, which contributed to generate panic behaviours in the international market (Yang, et al., 2008; Headey, 2011; Martin and Anderson, 2011). The successfulness of these measures in shielding internal markets from high international prices is contested (see Tadesse, et al., 2014; Puma, et al., 2015 for two contrasting opinions) and most authors also point to the negative effects on the international markets: the main effect is a curtailed supply and the trigger of a chain reaction of panic behaviours, such as aggressive buying and other countries implementing export bans. These promote uncertainty and push prices even further (Tadesse, et al., 2014), developing what Puma, et al. (2015) call a 'multiplier effect'.

Now focussing on fuel prices, fossil resources are, as mentioned earlier in the text, non-renewable. The most famous system implemented in environmental economics to define prices of non-renewable resources is the 'Hotelling's Rule' (Perman, et al., 2003). The rule is derived by its inventor, Harold Hotelling, and postulates that the price of a non-renewable resource needs to increase by the same amount as the interest rate to cover for the opportunity cost of the lost revenue that would result from the extraction and sale of the resource (Hotelling, 1931). The price behaviour resulting from this rule is an exponential growth of prices, which, in its most basic form, does not find evidence in the real world. More realistic economic theories such as those presented in Section 2.1 of this chapter have tried to develop models that could explain the prices of non-renewable resources. In particular, it is common knowledge that prices of non-renewable resources should, in theory, reflect the scarcity (or abundance) of the resource. Simply put, this is due to the finite nature of these resources and to the diverse quality and accessibility of ores present in the Earth's crust. The increasing scarcity of the resource and the idea that accessible deposits are those discovered and exploited first, should result in a cost of extraction which increases linearly with time. Coupling this with basic neoclassic economics, the price should have a balancing action between supply and demand, increasing when production cannot meet supply, which results in a decrease in the demand and thus in an excess of supply, which should bring the price back down. This should bring the market to the equilibrium price, which, in case of perfect competition, should equal the cost of extraction of the resource. Obviously, this is another oversimplification of reality[7] and, as we will see shortly, the prices of non-renewable resources have not been following a clear and consistent path.

Now focussing on the empirical literature, oil is the only energy resource whose market is effectively global and for which international prices are available, which is why this thesis will focus on oil prices. Several authors have tried to empirically identify the drivers of oil prices, also attempting to develop models to predict oil price fluctuations. The common opinion shared by the literature is that oil prices are difficult to predict and seem to follow an erratic path (Hamilton, 2009). This is mainly due to the complexity of the economic relations that characterise the energy system, but also by the several organisations and institutions involved, which all work towards different self-serving agendas (e.g. OPEC, national governments, etc.). In particular, several authors (e.g. Hamilton, 2009; Kilian, 2009) attribute the 2008 oil price spike to the increased oil demand from developing countries and global peak oil.

To describe the 2008 peak, Kilian (2009) distinguishes between three types of shocks that can have different consequences for international prices: i) oil supply shocks, i.e. temporary disruption to oil supply; ii) aggregate demand shocks, i.e. shocks involving global demand for oil due to fluctuations in the global business cycle and iii) precautionary demand shocks, i.e. a change in the expectations about future availability of oil that induces countries to accumulate stocks. The author argues that the main consequence of the first type of shocks is a small and temporary increase in international oil prices during the first year, whereas the other two have a large and sustained impact on oil prices, which is immediate in the case of precautionary demand shocks and delayed in case of aggregate demand shocks. The author argues that historical and recent oil price shocks have been mainly driven by a combination of the last two types of shocks, which is contrary to what the main literature seems to indicate.

Hamilton (2009) discussed a variety of factors such as speculation on commodity prices, increasing global demand for oil, time delays and physical limitations to oil supply, OPEC's monopoly in setting global oil prices and scarcity rents (the cost of exhausting a non-renewable natural resource), arguing that all these possibly had an

[7] For a more in-depth explanation of prices of non-renewable resources and for different economic models that have been proposed see Perman (2003).

influence on the price spike. However, the author identified three of these as key factors: i) low price elasticity of demand (the change in demand due to a change in prices), ii) increasing demand for oil from developing countries and iii) the inability of global supply to increase. These caused an initial pressure on prices, which in turn triggered increased speculation. The author also argues that scarcity rents will be permanently factored in future prices, which will ramp up and remain high once global peak oil will be reached.

However, these hypotheses fail to explain the sudden crash of oil prices after the shock and the low price regime registered recently. Part of the reason for this recent lower price regime seems to have been political rather than driven by physical or social dynamics. Indeed, several journalistic pieces (e.g. Ahmed, 2015) point to Saudi Arabia as the main actor whose actions are keeping oil prices low. Speculating on the reasons behind its behaviour, the country has been engaging in a dumping action by keeping its production at record levels perhaps with the aim of driving other oil producers (e.g. Russia) who cannot sustain production with such low margins of revenue out of business. Another speculative hypothesis involves policies to tackle climate change and the increasingly affordable renewable energies. Saudi Arabia seems bound to reach peak oil in 2028 (Ebrahimi and Ghasabani, 2015) and the country may be trying to sell as much oil as possible in sight of a future ruling out of fossil fuels and the rise of renewable resources. In addition, by keeping international oil prices low, the investments in other sources of energy such as renewables and non-conventional oil (e.g. through fracking) are effectively disincentivised.

2.9. Systemic risk and cascading effects

The dynamics presented in the previous sections have important consequences for the stability and resilience of the global system, both when considered singularly and in association. These can be localised, such as conflict between tribes, or a fully-fledged global multi-system crisis such as that occurred in 2008 (see below). What emerged clearly from the previous sections is that there is not one single cause or driver for each of the dynamics presented, rather multiple drivers can be responsible for triggering a specific dynamic. In addition, different dynamics can interact due to the high connectivity of the system, giving life to an extremely complex system where single drivers of specific dynamics are hard to identify. These conditions constitute fertile ground for systemic risk and cascading effects: this term identifies the risk related to the whole system, due to the high interconnectivity between its components. For instance, a climate shock such as a prolonged drought could heavily affect the production of food of a region. As we have seen in the previous paragraph, if this region is key to the global food supply, this could start a chain reaction that could lead to high international food prices and social unrest.

The concept of systemic risk is relevant for different disciplines such as finance (e.g. May, 2013), economics (e.g. Schweitzer, et al., 2009) and socio-ecological systems more in general (e.g. Filatova and Polhill, 2012). Recent literature developed different frameworks that try to capture and analyse systemic risk (e.g. Ostrom, 2009; Liu, et al., 2013). The most relevant and recent conceptual framework is that developed by Homer-Dixon, et al. (2015). In their paper, the authors argue that the events of 2008 were part of an unprecedented set of crises, known as 'Synchronous Failures' (SF). This type of crisis originates within different singular SESs and is mainly driven by human interaction with the natural environment. The reasoning behind this conceptual framework is that the natural environment sustains humanity and its activities, which in turn affect the natural environment negatively by exhausting natural resources and driving environmental and climate change. These dynamics in turn feed back negatively on human activities. The authors identify three global trends that contribute, either in combination or isolation, to the development of SFs: i) the incessant increase in size of human activities as compared to the natural resources and processes on which they rely; ii) increasing connectivity between different components of human technological, economic and social systems and iii) rising homogenisation between different human cultures, practices and technologies. These drivers contribute to the development of SFs in three main ways: i) although these dynamics build up slowly in the system, these are potentially very powerful over time and generate simultaneous stresses for human societies; ii) these dynamics increase the likelihood of systemic risk and also help to synchronise different SESs, allowing for shocks to propagate farther and faster in the global network; iii) the higher connectivity generated results in less transparent systems and processes, whose dynamics and reactions are harder to predict. This in turn results in a lower adaptive capacity of societies. These 'deep causes' (Homer-Dixon, et al., 2015, p.3) translate into SFs through three processes: 'long fuse big bang', simultaneous stresses and ramifying cascade. The first process regards the slow accumulation of the multiple stresses in one SES, which eventually results in a sudden, non-linear shift in the system's behaviour. The second process regards the simultaneous occurrence of more than one stressor and, finally, the third process entails the shock to one of the nodes in the network, which, due to the high connectivity, generates cascading effects and propagation to neighbouring and distant countries. In SFs, these processes never appear singularly, but always as a combination of at least two or more.

In other words, once the drivers of a crisis that have been developing within an SES have reached a critical tipping point by interacting with human structures (such as the economy) by affecting key dynamics (like prices), the crisis breaks out in that system. If the same happens in more than one SES, these can interact, speeding up the failure process and resulting in a globalised, systemic crisis. This generalised crisis can then translate in widespread political instability and deadly conflict, which then feeds back negatively on the environment and other human institutions that sustain our society (our political systems, for example), locking humanity in a never-ending vicious cycle. The notion of SF is a conceptual framework that can help to identify the environmental root causes and dynamics of this type of crisis. Homer-Dixon, et al. (2015) tested the framework on the 2008 global crisis and found that, in their opinion, this crisis was an interaction between three different crises that had slowly been building in three different SESs: food, energy and financial systems. These were driven by food and energy security-related issues and closely followed the three stages proposed by the authors to eventually translate in a generalised multi-system crisis. However, this framework is only theoretical and the same authors call for more empirical research in this matter.

Another framework, which is now widely implemented in UK academia, is the 'Water, Energy, Food Nexus'. The Nexus approach simply entails the consideration of the interrelationships between the different natural resources, i.e. food, energy and water, whilst undertaking research in sustainability. As presented throughout this chapter, there exist synergies and trade-offs in the exploitation of natural resources and reinforcing feedbacks between society and the natural environment, which a nexus approach can help account for and/or study (De Laurentiis, et al., 2016).

Now moving to the empirical literature, few authors assessed the potential systemic risk connected to different sectors of society. Zhang, et al. (2011) provide some insights on the connections between past climate changes and societal crises. The authors quantitatively established that climate change was the main underlying cause of societal crises in preindustrial societies, which resulted in economic crises for the world. Indeed, their analysis highlighted that natural and social factors such as climate and environmental change, uncontrolled population and consumption growth and disparity in the distribution of resources, due to several interlinkages already highlighted in the previous paragraphs, can result in a generalised crisis.

Puma, et al. (2015) focussed instead on the global food system, implementing social network analysis to evaluate its resilience. Their findings show that the high interconnectivity of the global food system makes it vulnerable to self-propagating disruptions in case of a climate-related extreme event and that interconnectivity on the trade network is increasing, with countries relying more and more on food imported by a few large producers. These dynamics are consistent with the view that greater connectivity in networks such as international trade make the system overall more robust to shocks that impact a random node, but also more fragile when the node impacted is at the centre of the network. Similarly, Suweis, et al. (2015) found that due to the increasing reliance of countries on food imports, the global food system is becoming less resilient and simultaneously more sensitive to external perturbations (e.g. shocks).

Another example of empirical research involving systemic risk is Bleischwitz, et al. (2014), who implement a Nexus approach to map countries at risk of Nexus-driven conflict and who are central for the global supply of natural resources. The study identified 15 countries located in both Africa and Asia that are key supplier of natural resources for the global market, who also are at high risk of Nexus-related conflict. In the eventuality that any of these countries' current fragilities was exacerbated by water or food crises, this could translate in a socio-economic breakdown due to their centrality in the international trade of key resources.

2.10. Conclusions

This chapter presented theories and evidence from literature on the different topics explored with this research. In particular, there seems to be an understanding of the finiteness of natural resources available on the planet. However, whether conflict could be one of the possible consequences of scarcity of natural resources is still an open debate. Evidence of the connection between climate change and variability and conflict is overwhelmingly mixed, although the argument of subjective interpretation of the results by the researchers is compelling. However, there seems to be an agreement on a role of scarcity (Hauge and Ellingsen, 1998; Baechler, 1999; Homer-Dixon, 1999; Bocchi, et al., 2006; Kahl, 2006; Hendrix and Glaser, 2007; Urdal, 2008; Burke, et al., 2009b; OECD, 2012; Raleigh, et al., 2015), climate change (Carty, 2012; FAO, 2013; Wheeler and von Braun, 2013; Zezima, 2014) and variability and price of food (Nomura, 2010; Lagi, et al., 2011; Zhang, et al., 2011; Arezki and Bruckner, 2011; Carter and Bates, 2011; OECD, 2012; Hsiang, et al., 2013a; Barrett, 2013; Bellemare, 2014) as catalysts for conflict and increased fragility.

As for food riots, literature overwhelmingly identified food prices (whether international or domestic) as the major driver, although the different effect of volatility and absolute values of (international) prices on food riots remains unclear. Research showed that the political conditions of countries play a critical role in the exacerbation of distress in reaction to high food prices, with mixed findings for different political regimes and the urban/rural narrative. In particular, the political fragility of countries seems to be both cause and consequence of food riots. Literature on fuel riots is instead non-existent.

The challenges ahead of humanity are multiple and complex. Climate change is expected to increase global food insecurity (Rosegrant and Cline, 2003; Schmidhuber and Tubiello, 2007; Maxwell, et al., 2010; Godfray, et al., 2010; Huang, et al., 2011; Berazneva and Lee, 2013; Wheeler and von Braun, 2013) and international food price spikes are likely to become more common (Berazneva and Lee, 2013), with negative consequences for geopolitical stability through the occurrence of more frequent food riots (Smith, 2014). Currently, international trade helps feed 16% of the world population and this figure is bound to increase due to the growing world population (Fader, et al., 2013). This raises further concerns for the systemic risk related to international trade that can be exacerbated via trade restrictions and spikes in international prices, which requires further analysis (Wheeler and von Braun, 2013). In addition, the consequences for countries’ political fragility of a global peak-oil forecast for the first half of the 21st century are currently unknown.

Studies on global food security usually focussed on solutions to provide future balance between consumption and supply of food (Rosegrant and Cline, 2003; Schmidhuber and Tubiello, 2007; Godfray, et al., 2010; Anderson, 2010; Calzadilla, Rehdanz and Tol, 2011) and a comprehensive account of how shocks to the global production of food propagate through the international food system to generate political instability and food riots is missing. The same is true for energy resources. In addition, the link between food and fuel resources and prices is currently underexplored.

The study of the interconnections between scarcity of natural resources, their prices and the occurrence of riots was mainly undertaken with econometric techniques (e.g. Berazneva and Lee, 2013; Raleigh, et al., 2015), which lack the possibility of introducing and evaluating the effects of feedbacks between resource security, the international economy and the occurrence of riots. The interconnectedness of the dynamics highlighted throughout this chapter make these interactions worth exploring with a systemic approach to test the consequences of what-if scenarios and possible policy interventions to avoid a violent escalation. Several authors call for further research in the dynamics of the system and systemic risk through a modelling approach (Schweitzer, et al., 2009; Wheeler and von Braun, 2013; Raleigh, et al., 2015; Puma, et al., 2015). One effective method that can start to disentangle the several relationships that characterise the complexity of the global food and energy systems is computer modelling. Previous literature has implemented this methodology to explore specific dynamics, which will be presented in the following chapter. Although different modelling techniques have been applied, a dynamic assessment of the processes that lead from food and energy insecurity to the occurrence of food and fuel riots is currently missing. The applications of different modelling techniques along with examples from the literature will be presented in the next chapter.

The dynamics highlighted in this chapter classify this as a complex system and as such is characterised by non-linear behaviours and the presence of thresholds. The aim of this thesis is therefore to parameterise the global food and energy systems and study dynamics and interactions between scarcity of these two resources, their prices and the occurrence of food and fuel riots. Also, through the implementation of scenarios this thesis will explore the consequences of trade restrictions for prices and riots. This thesis will therefore contribute to the fields of environmental security, global food and energy security, international economics and political science by exploring and quantifying dynamics related to the occurrence of food and fuel riots and, remarkably, opening a completely novel stream of research in fuel riots.

3. Methodology and methods implemented

The literature review of the environmental security field presented in the previous chapter clearly identified a research gap: a lack of a holistic, systemic view of how the physical environment drives human conflict. In particular, this research addresses the lack of knowledge on how scarcity of natural resources affects the occurrence of food and fuel riots by interacting with human structures such as international trade of natural resources, their international prices and national political fragility.

Due to the clear interconnectedness of these different systems and dynamics, a modelling approach was the most appropriate methodology to investigate these relationships. This chapter will explain in detail why a modelling approach was suitable as a methodology to approach these issues, whilst reviewing different general modelling approaches and more specifically simulation model paradigms. In addition, the 'modelling journey' will detail the fundamental steps that I went through to design my research. In conclusion, the architecture of the models developed in the following chapter will be introduced, detailing the single methods that were implemented and the reasons why these were chosen.

3.1. Why modelling at all?

Quantitative models are usually perceived by non-experts as complex and a high level of maths skills seems to be required to understand the assumptions and dynamics on which they are based. The same concern is experienced in relation to complexity itself: people in general feel incapable of dealing with this concept (Vester, 2007). This can sometimes be true, but what people usually fail to take into account is that models surround us in our everyday life and that we thrive in a huge complex system that is the world and to which we are interrelated. People use models in their everyday lives when shopping, when making decisions or simply when compiling schedules for the day. People make their decisions and act on them based on their mental image of the world, precisely because the real world is too complex to understand (Sterman, 1991).

"A model is a simplification – smaller, less detailed, less complex, or all of these together – of some other structure or system" (Gilbert and Troitzsch, 2005, p. 2). The authors Gilbert and Troitzsch (2005) and Epstein (2008) list the possible uses of simulations and, more generally, of models: i) increase the understanding of a specific behaviour, entity or system; ii) make predictions of the future state of a system or a dynamic; iii) develop tools to substitute for human (in)capabilities; iv) guide data collection processes; v) suggest dynamics analogies; vi) formulate new questions; vii) support a methodology; viii) discover ranges of validity for specific outcomes; ix) highlight uncertainties in a system's processes; x) investigate a system's possible responses to crises; xi) highlight trade-offs and identify areas where efficiency gains can be achieved; xii) inform policy-dialogue; xiii) exogenously perturb a system to challenge the robustness of extant theories; xiv) demonstrate inconsistencies between common psychological constructs and real data; xv) reveal complexities in apparently simple systems; xvi) educate the general public; xvii) train and introduce novices to familiarise with a new subject; xviii) entertain with simulation-based videogames.

Investigating the dynamics of a complex system is a complex task in itself. Complex systems are usually too big and complicated to 'fit a human brain' and are associated with specific properties (Waldrop, 1992; Ladyman, et al., 2013):

1. *Nonlinearity* and *numerosity*. A simple system is a description of a process where its components, their interactions and outcomes are known. In a simple system a process can be tracked with accuracy from where it originates to where it ends, also being able to define how it operates. For instance, a perfectly linear relationship between two variables can be defined as a simple system, represented by a straight line. Complex systems usually consist of several components characterised by a high level of interaction, where relationships between the different variables included is non-linear and can be approximated with different types of function (e.g. power law or logistic). Often these relationships and their outcome are not fully known or understood.
2. *Feedbacks*. A complex system is usually characterised by complex interactions among its components. A feedback can be defined as the reaction from a component or variable of the system that follows an action from a different component of the same system. Feedbacks can either be negative or positive. Negative feedbacks generate a balancing effect between two variables or components of the system and represent an inverse relationship. Conversely, positive feedbacks generate a reinforcing effect and represent a positive relationship (Forrester, 1971; Sterman, 2000; Mollona, 2008).

3. *Indeterminacy of action*. Complex systems are usually characterised by “a large number of uncoordinated interactions between [their] elements” (Ladyman, et al., 2013, p. 39). The order in which these interactions occur is neither completely casual (random) nor follows a set schedule (Holland, 1995; Holland and Mallot, 1998).
4. *Robustness and lack of central control*. In complex systems, the order is said to be robust because, even if the system is perturbed by endogenous forces, it still remains stable. The exposure to internal perturbations of a centrally controlled system is higher.
5. *Emergence*. In complex systems, the presence of a large number of components interacting with each other in a spontaneous order and with a lack of central control gives life to emergent patterns. Emergent patterns are those characteristics or behaviours resulting from a complex system that could not be captured by merely studying its single components in isolation (Holland, 1995; Holland and Mallot, 1998).
6. *Rigid but flexible structure*. Complex systems are typically not decomposable – removing or changing one element may completely alter the behaviour of the system. However, a system can persist even after an alteration of its components, simply the system will undergo a reorganisation of its components and dynamics.
7. *Hierarchical organisation*. A complex system is usually formed by several different sub-systems and components all interacting one with the others. These can be nested across a range of levels and can be organised in a hierarchical structure.

The aim of this research was to investigate the interconnections between the scarcity of natural resources, their price on international markets, how they are traded internationally and how these dynamics, coupled with national political fragility, contribute to increasing the occurrence of food and fuel riots in countries. The process just described clearly fits the definition of a complex system, where the interaction between the several different components of the system, i.e. feedbacks, results in non-linear relationships and emergent patterns. The main system, i.e. the world limited by the definition of the complex system subject of this study, consists of multiple subsystems organised in a hierarchy (e.g. for countries to be able to trade natural resources they have to have produced them first), where the elements act in a spontaneous order without being controlled centrally.

Starting from the complex system 'world' and its dynamics, the complexity was reduced by defining the boundaries around the subject of this research to include only five components: i) scarcity of natural resources, ii) prices of natural resources, iii) international trade of natural resources, iv) national political fragility of countries and v) how these components interact to affect the occurrence of food and fuel riots in countries. Although these limits have reduced the complexity involved in this research, the system that it aims to analyse is still too complex to 'fit a human brain'. For this reason and because modelling allows the development of scenarios and the possibility to provide predictions for the system subject of the analysis, modelling constitutes one of the most effective approaches to undertake this research.

3.2. Critical review of modelling paradigms

As mentioned in the previous section, models are naturally embedded in our everyday lives. However, these models are usually a simple and informal representation of reality that exists in our minds. When models are subject of research and investigation, this picture of reality needs to be translated in a more formal formulation through the use of mathematical equations and/or with the help of statistics and computer modelling.

3.2.1. Broad categories of models

Independently from the type of model being developed, the quantitative formalisation of a system or its dynamics always implements mathematical statements. The most basic version of quantitative models are hence mathematical models, which can be defined as "an abstract, simplified, mathematical construct related to a part of reality and created for a particular purpose" (Bender, 2012, p. 2). These models describe the system in simple mathematical terms using a concise language. They comprise a system of (differential) equations that describes each component of the system, their change and how these are interrelated. This type of purely mathematical models is commonly used in the study of scientific subjects such as physics and biology.

Other types of models build on mathematical models by expanding them to include different characteristics. One of the most useful classifications of some of the different models used in economics is that proposed by Sterman (1991), who divides models in three broad classes: *optimisation* models, *simulation* models and *econometric* models. The main difference between these is the purpose of the model itself. The first ones are normative models, i.e. their purpose is to prescribe the best path (e.g. policy) to obtain the optimal outcome (e.g. rate of adoption for a new technology). One of their applications is in the industry sector, where their introduction helped developing methods to increase efficiency in production (e.g. The Kanban method, Price, et al., 1994). By modelling the production process through a set of equations, these models can determine the best values for various system parameters such as the number of machines required to execute a particular operation. The main limitations of this type of models are the fundamental assumption of the existence of linear relationships between the variables (Gilbert and Troitzsch, 2005), and the lack of interaction between them. Several studies have tried to overcome these limitations, hence developing a new set of modelling approaches: fuzzy models (Nelles, 2001); probabilistic non-linear models for optimization processes (Das and Dennis, 1998); optimisation and non-linear equations (Smyth, 1998) and Stochastic kernel (Quah, 1997). Although these recent methods introduced non-linearity in optimisation techniques, this brought along the characterising challenge of this type of dynamics: in non-linear systems there may be many local optima, and finding the global optimum, if it exists, can be difficult. Neoclassical economic theories generally rely on there being a single optimal state, which may not be the case in many real-world systems. More generally, optimization models are static, and what is optimal for one set of actors may not be optimal from the point of view of another set – so optimization of what and for whom is a problem.

Econometrics is a branch of statistics, which was developed and applied to economic studies and includes other techniques such as multivariate analysis. Econometric models shape and test the causal relations between one (or more) independent and one (or more) dependent variables by specifying the system with a set of equations. They do so by assigning values to the parameters using real data as input then assessing the impact of one unit change in the independent variable(s) on the dependent one(s), keeping all the rest constant. The magnitude of the impact is represented by the estimation of its associated coefficient. Every effect not explicitly formulated in and measured by the model is summarised in the error term. The accuracy and validity of the model are tested by providing a forecast for the system. The main components of an econometric model are: i) specification, this formalises the model structure by identifying the relationships between the variables and expressing them in formal equations; ii) estimation, this identifies the statistical analyses needed to inform the parameters and weights of the different components of the model; iii) testing, this tests the relationships between the dependent and the independent variables; iv) forecasting, this allows the modeller to make predictions for the system based on the model specification and estimation. Econometric modelling presents important limitations: firstly, since econometrics heavily relies on statistical techniques to estimate parameters and functions included in the model, it suffers from the same drawbacks, such as the fact that everything that the model is not able to capture is summarised by an error term included in the main equation, or that the observations are usually assumed to be normally distributed (Johnson and Wichern, 2002; Grafen and Hails, 2002; Dekking, et al., 2005; Mazzocchi, 2008; Gujarati, 2012; Coolidge, 2012). Finally, econometric models do not allow any dynamic representation of the feedbacks between the different variables and components of the system, which makes the analysis static and partial. Therefore, future predictions rely on the system being statistically stationary. During the years, efforts have been made to overcome some of these limitations, in particular focussing on clarifying the composition of the error term of the models through the development of additional tests. Despite these important limitations, econometric models are still widely used and implemented in a variety of sectors, the reason probably being their practical approach and the language they use (e.g. significance of the results), which is very common across different academic disciplines.

Simulation models partially overcome some of the most important drawbacks of econometric modelling. In particular, these allow the introduction of dynamic feedbacks between the different components of the model. The purpose of a simulation model is to represent and mimic the real system that is the subject of the study. The key specifications of simulation models are:

1. A simplified representation of reality (as all models). The structure being included in the model resembles the structure of the system in the real world (if known), but simpler, which allows a better understanding of the processes involved

2. Level of detail. This specification is of utmost importance because it can make the difference between a model that is clear, understandable and able to answer its research question and a model that is overly complex and whose results are difficult to interpret. The right level of detail depends on the research question the model is built to investigate. If the model includes too much detail, its final outcomes will be difficult to interpret because the subject of interest is lost in a large amount of data. Conversely, not enough detail could jeopardise the simulation of the system, resulting in a model that is simplistic, and not just simple
3. Simple representation of the behaviours of key actors. The same argument said for the system in general can be applied to the representation of the behaviours of the key actors in the system. The level of detail has to be 'granular' enough to allow the investigation of the subject of the model, while avoiding broadening the level of analysis beyond the scope of the research.

Some of the limitations of simulation models are somehow similar to those of econometric models. As mentioned above, simulation models are based on assumptions that simplify reality, and as Sterman (1991) states "any model is only as good as its assumption" (Sterman, 1991, p. 20). Uncertainty is another major issue in simulation and any other type of model. Since every component of the model is a simplified version of reality, each of them factors in a certain degree of uncertainty. Unless the further complexity is coupled with more constraints, uncertainty builds up as the complexity of the system increases, making the predictions of the model less certain.

All these modelling approaches are and have been used to study complex systems, either in isolation or integrated. For instance, optimisation models find their main application in the industry and engineering sectors (e.g. Price, et al., 1994), whereas econometrics and simulation are more widely used in the fields of economics and social science (e.g. Meadows, et al., 1972; Bellemare, 2014). Although classifications are useful, the difference between these types of models is less clear-cut in reality. In particular, the field of simulation is ever developing and hybrid models are becoming more common (Teose, et al., 2011; Vincenot, et al., 2011; Swinerd and McNaught, 2012; Monasterolo, et al., 2013).

The analysis of a system as complex as the one being studied here required a mix of methodologies that could represent and disentangle complexity while respecting the principles dictated by the GRO project. As detailed above, optimisation models were too simplistic for the research questions posed in this research. As for the other modelling techniques, both econometrics (e.g. Arezki and Bruckner, 2011; Bellemare, 2014) and simulation modelling (e.g. Meadows, et al., 1972; Cioffi - Revilla and Rouleau, 2010) have been used to investigate similar research questions. Due to the complementarity of these two approaches, these have both been implemented in different parts of this research.

In conclusion, notwithstanding the drawbacks that characterise simulation models, there seems to be an increasing realisation that "all models are wrong, but some are useful" (Box and Draper, 1987, p. 424), the point being that some models are a better approximation of reality and are therefore more helpful in the study of specific dynamics. The reason for modelling is not to recreate reality, but to make it simpler, pinpointing the key components of the system that is the subject of the study, including them in the model and investigating how they interact, with the aim to find out the systematic behaviours of the system and to distinguish what is important from what can be neglected for a given problem or to test and challenge assumptions.

3.2.2. Different simulation modelling paradigms

Within the field of simulation modelling we can distinguish between different modelling paradigms, which Gilbert and Troizsch (2005), Gilbert (2008) and Squazzoni (2012) classified differently. Below is a comprehensive list.

3.2.2.1. System Dynamics (SD)

This modelling paradigm finds its roots in Control Engineering, a discipline that analyses dynamic systems by summarising them as systems of difference and differential equations (Forrester and Senge, 1980). SD was originally developed as a tool to study complex systems (Forrester, 1961) through the concept of stocks, flows, feedbacks and delays, which are mathematically formalised along with parameters and relationships in a system of equations. The main advantage of using SD is its macro-level perspective in the analysis of systems because it treats the part of the real-world subject of the analysis as an undifferentiated whole (Brauer and Castillo-Chavez, 2012). The properties of the target system that can be described with an SD model are its whole state and its variations: the former is represented with state variables in the form of 'levels', whereas the latter is represented with 'rates' (Gilbert and Troitzsch, 2005).

Any given variable of the system can change since its value depends on the behaviour of the other variables. Therefore SD allows for interdependence, also including nonlinear interaction. Although this modelling paradigm allows the modelling of heterogeneous aspects of the system's behaviours, its macro-level perspective of the system does not typically focus on individual-level heterogeneity. The hypothesis on which it grounds is that "the system behaviour is the result of circular and time-delayed relationships between structural components, factors or variables" (Squazzoni, 2012) and thus requires full ex-ante knowledge and description of the system's structures (Randers, 1980; Hanneman and Patrick, 1997; Gilbert and Troitzsch, 2005; Grüne-Yanoff and Weirich, 2010). In other words, SD is not appropriate to model a system whose structure changes over time.

The main implementation of SD is as a support to policy evaluation and analysis and as a tool for improving management in both public and private sector (Forrester, 1971; Sterman, 2000; Mollona, 2008; Squazzoni, 2012). Examples of the implementation of SD in analyses of sustainability include climate dynamics (Sterman, 2013), ecology (Norling, 2007), socio-environmental issues (Meadows, et al., 1972; Meadows, et al., 2004) and consumption paradigms (Bianchi, et al., 2009).

3.2.2.2. Microsimulation

Microsimulation was developed to overcome the limits of SD in analysing the dynamics of systems. As mentioned above, SD models are used to investigate and forecast global patterns, but do not capture individual behaviours. These two approaches are complementary, since microsimulation is used to forecast the potential effects of a given policy on individuals and groups. Indeed, microsimulation operates at the level of individual units, which are given a set of rules to shape changes in their state or behaviour. Rules can either be stochastic or deterministic and will determine the outcomes of the simulation (Figari, et al., 2014).

This approach is particularly recommended when the policy being tested applies differently to different groups. Another difference between SD and microsimulation is that the former provides a deterministic approach, whereas microsimulation introduces an element of stochasticity in the model, in order to assess the overall impact upon a number of given aggregate variables. Microsimulation does not contemplate behavioural heterogeneity of the agents, but it does contemplate individual heterogeneity in the distribution of the parameters. Although this represents an improvement from its predecessor, microsimulation is of no use when trying to analyse social interaction, since it does not include interaction between units (Gilbert and Troitzsch, 2005; Squazzoni, 2012). In addition, this modelling technique is based on statistical data and therefore is limited in not being able to simulate novelty, i.e. the future is assumed to be the same as the past. Microsimulation has mainly been applied to the fields of medicine to simulate past and future trends of the spread of diseases (e.g. Draisma, et al., 2009; Edwards, et al., 2010), urban and traffic modelling (e.g. Helbing and Tilch, 1998; Blue and Adler, 2001) and is more generally used by government departments to investigate the effect of policies on specific sectors of the population.

3.2.2.3. Queuing or discrete event models

Queuing or discrete event models are a representation of a system "in terms of its entities and their attributes, sets, events, activities and delays" (Kheir, 1988, p. 98). This modelling paradigm differs from the others for its 'discrete' properties. Differential equation models (SD and microsimulation) and the other approaches that will follow, assume a continuous distribution of time. They work in time steps as queuing models, but unlike the latter they are equidistant. This means that when an event takes place in a model built with the other approaches, the variables are simultaneously updated in the same time step. In queuing models, instead, there are no set times at which the whole system is forced to update, rather events are put into a queue and may occur at arbitrary times. In addition, most of the variables are usually assumed to be constant (Gilbert and Troitzsch, 2005). However, any one event could lead to a change in the system macro-state by triggering a chain of other further events in other parts of the system. For instance, traffic model systems (e.g. Di Febbraro, et al., 2004) or resource use in computing (e.g. Buyya and Murshed, 2002) can be based on this modelling technique.

3.2.2.4. Multilevel simulation models

Multilevel simulation models analyse systems by applying different levels of analysis to different objects included in the simulation of the system. This approach best applies to situations where a homogenously distributed population of individuals is considered, with applications in a wide variety of fields such as medicine (e.g. Beckmann, et al., 2003) and psychology (e.g. Krull and MacKinnon, 2001). The system properties are then constituted by the simple aggregation of individual ones. The issue with this modelling technique is that for computational reasons it only allows for an indirect interaction between individuals. Indeed, a cyclic dependence within the same time step is forbidden, hence each subject evaluates the previous (step) macro-situation to inform its decision-making process. The subjects cannot base their decisions on the behaviours of others (Gilbert and Troitzsch, 2005). However, multilevel models mostly tended to be statistical fitting ones. One type of multilevel model, i.e. random effects model, will be introduced later in the text.

3.2.2.5. Cellular Automata

Cellular Automata (CA) consists in a regular grid composed of identical cells. Every cell has a property that defines its state (e.g. "on" or "off"; "alive or "dead") and its state changes according to that of its neighbouring cells. The simulation time is divided in step units, and at each time step the state of a cell changes according to the rules of the system. The rules are homogenously applied to every cell in the grid. Squazzoni (2012) describes the main advantage of using CA as "[CA] reduces the problem of interaction between dispersed micro entities to a single homogenous parameter" (Squazzoni, 2012, p. 19). However, the same author also argues that "the idea of synchronous updating of agent behaviour is a poor approximation to understanding complex social interactions" (Squazzoni, 2012, p. 20), an opinion that is also shared by Gilbert and Troitzsch (2005). Indeed, although synchronous updating is a good representation of reality as people make different choices all at the same time, it is the differences in their circumstances that drive those choices and that creates complexity in the system. However, this perspective is challenged by other experts who argue that complex social interactions can also be simulated by a synchronous system as different agents need not be repeating the same behaviour at each update. In addition, the grid structure that characterises CA can be a useful approximation of space. Since CA finds its most suitable application in the analysis of macro-level outcomes starting from the simulation of micro-level interactions between units, this modelling approach is mainly implemented in areas such as physical science, biology, mathematics and social science (Gilbert and Troitzsch, 2005; Squazzoni, 2012).

3.2.2.6. Agent-based models

Agent-based models (ABMs) were developed in the 1990s, with the spread of artificial intelligence technology and the spread of object-oriented software. Gilbert (2008) defines ABMs as "a computational method that enables a researcher to create, analyse, and experiment with models composed of agents that interact within an environment" (Gilbert, 2008, p. 2). Squazzoni (2008) gives a more detailed definition of ABMs: "an ABM is a computational method that allows the use of computer to investigate a given macro-level social phenomenon through the representation of micro-level behavioural rules. These will be followed by a group of agents which interact inside a bounded macro-environment limited by either geographical, spatial, structural and/or institutional boundaries" (Squazzoni, 2008, p. 8)[8]. ABM has also been defined as an "aid-intuition" (Axelrod, 2003), as a "magnifying glass" (Terna, 2009) and as a "mindset", where a system is described from the perspective of its components (Bonabeau, 2002). The first two terms derive from ABM's transparent modelling structure, which allows the modeller to infer where a specific pattern originates from, isolate it and run further analysis. Furthermore, both Squazzoni (2008) and Gabbriellini (2011) identify ABM's valuable contribution to the modelling field in being "a virtual or artificial laboratory", where "generative experiments" can be carried out.

ABMs are widely acknowledged as an instrument especially appropriate to simulate SESs (Gilbert and Terna, 2000; Gilbert, 2008; Thiele, et al., 2011; Railsback and Grimm, 2012; Filatova, et al., 2013) because they include the following elements (Bravo, et al., 2013): i) an environment, i.e. a set of objects the agents can interact with, ii) a set of interactive agents, iii) a set of relationships linking objects and/or

[8] Note that this quote was translated from the author of this thesis.

agents and finally iv) a set of operators that allow the interaction between the agents and the objects.

The main characteristics of ABM that distinguish this from other modelling techniques is that they allow to: i) have an ontological correspondence between model and real world dynamics as a result of the simulation. This is possible due to the opportunity of grounding agents' cognitive and social characteristics on real behaviours (Squazzoni, 2012); ii) shape heterogeneous agents, all with a specific set of properties distribution (Bonabeau, 2002; Swinerd and McNaught, 2012); iii) analyse nonlinear agent interaction at the micro-level, which results in macro-level patterns (Grimm, 2008). These outcomes can also be studied "as bottom-up emergent properties from local interaction" (Squazzoni, 2012, p. 11); iv) recreate a highly detailed representation of the environment in which agents interact (geographical boundaries, institutional rules, and/or social structures) and how these affect agents' behaviour and interaction; v) clearly visualise the on-going simulation as well as its results, allowing the researcher to analyse the dynamics of agents' interactions (Gilbert, 2008; Squazzoni, 2012); vi) introduce an element of stochasticity to the behaviours of the agents instead of using a noise term added to the equations of the system (Bonabeau, 2002).

3.2.3. Abstract vs Empirical (or applied) models

Another important general distinction between different types of models is that of abstract and empirical or applied models. Abstract models are theoretical models built to investigate a general phenomenon and do not rely on empirical data. This type of models is generally used to formulate a theory or to generalise one (Squazzoni, 2012). The way data is introduced in this type of models is mainly based on the concept of relative change and abstract values of variables. Conversely, empirical or applied models constitute a highly detailed replica of a real system and require real data as an input. The main use of this type of models is to inform decision-making processes (Squazzoni, 2012).

In extreme situations, empirical modelling may simply constitute a statistical fit to data raising a whole different set of concerns about the reliability of data, whereas an abstract model might hypothesise a mechanism (e.g. Schelling's segregation model, Schelling, 1969) based on some notional ideas about how a system is constituted.

However, a mechanistic model without data, and a data-based model without mechanism might both be seriously in error. In either case there are typically sets of (possibly hidden) theoretical assumptions built into the model structure which need to be taken into account while presenting the results from the model to facilitate understanding.

The increasing importance of impact in academic research has driven academics to engage on a more frequent basis with policy- and decision-makers. At the same time, a new generation of policy- and decision-makers search for science and research to inform their decisions. However, there is often a mismatch between these two groups which involves the language used by research and the expectations for ‘solutions’ from the policy side. A change is needed: academics need to provide scientific results that can be easily understood and related to and policy-makers need to engage with terms such as ‘uncertainty’ and ‘variability’. The ultimate aim of the research being presented here is to influence and inform decision-making as related to possible challenges involving the scarcity of natural resources and conflict, mainly to investigate and provide evidence for this connection. For this reason, the empirical approach was preferred to the abstract. Another reason for this choice was the great availability of empirical data. The GRO Project compiled a database of country-level annual data for several fields of information (social, economic, environment and finance) by gathering data from freely available sources such as the FAO, WB and the United States Energy Information Administration (EIA) (GSI, 2015). In addition, this choice was led by Principle 2 of the project, that required all the models to be data-led.

3.2.4. Selection of a modelling paradigm

The previous sections outlined the different methods that could be (and have been) used to model complex systems. As mentioned in Section 3.2.1 of this chapter, “The analysis of a system as complex as the one being studied here required a mix of methodologies that could represent and disentangle complexity, while respecting the principles dictated by the GRO project”. Indeed, all the methods that have been listed so far are characterised by both advantages and drawbacks, which is why different methods have been implemented to undertake different parts of the research. In particular, statistical and econometric techniques have been implemented to explore the data that were either collected or sourced from the GRO database and other respected organisations. The results from these analyses were used to inform some of the relationships between the different variables included and to build estimates for some of the key parameters of the ABMs.

The most important choice concerned the modelling approach to use. From the brief review of modelling paradigms presented in Section 3.2.2 it appears clear that the two approaches that were most suitable for the study of this complex system were SD and ABM. These are the only modelling paradigms well suited to study complex dynamics of big systems, where the focus is on the patterns that result from the simulations.

Bonabeau (2002) lists instances when ABM is recommended as a modelling approach: i) when the behaviours of the components of the system are non-linear, present thresholds and when the system is suitable to being simplified with if-then rules; ii) when the behaviours of the individuals in the system present learning and adaptation capabilities; iii) when individuals are heterogeneous in their preferences and behaviours and when interaction is a key component of the system.

The research questions that this study proposed to investigate perfectly applied to the list of instances reported by Bonabeau (2002): firstly, as described in the previous chapter SESs are characterised by non-linearities and thresholds. Moreover, this research involved the study of national fragilities and how countries react to scarcity of natural resources and the increase in their price. Heterogeneity was thus another condition that the modelling approach selected needed to be able to simulate. Finally, the interaction between individual behaviours and non-linear dynamics made it clear that the emergent properties that characterise ABMs were critical for this research, making this modelling technique the most suitable.

One of the main advantages of using ABMs to study complex systems is their generative approach: these models recreate the system from the bottom-up, which allows them to provide insights on the emerging properties of the system (Bonabeau, 2002). In ABMs the dynamics of the complex system are recreated by shaping the individual processes and entities it is known to rely on, which can result in non-linear aggregated behaviours different from those of the individuals' (Pourdehnad, et al., 2002; Janssen and Ostrom, 2006). Their structure is in line with Aristotle's quote

“The whole is greater than the sum of its parts” [Aristotle, 384 BC - 322 BC]. As opposed to bottom-up approaches, in top-down (e.g. SD) the focus is on averaged and general patterns that are broken down in rough estimates for the singular entities of the system. ABM’s attention to detail also constitutes one of its major limitations. It is indeed easy to lose focus of the research and add too many components to the system, hence building complex simulation models whose outcomes are difficult to interpret (Bonabeau, 2002). This attention to detail also entails the need for large computational power, which sometimes could constitute a drawback of this modelling approach (Bonabeau, 2002). Another consequence of this is the challenging calibration and sensitivity analysis that characterises this type of models: the higher level of detail used by ABM likely translates in a larger number of components and behaviours captured by the system. These need to be ‘fitted’ to reality, which may prove challenging and time-consuming (Filatova, et al., 2013). Finally, Bonabeau (2002) suggests caution in the interpretation of the results from ABMs. This is due to the characteristics of the systems that are subject of the research. Indeed, SESs involve decisions made by human agents, who implement complex, sometimes irrational, subjective behaviours, which are difficult to model and simulate. Although this constitutes one of the possible challenges posed by ABM, this modelling approach is one of the methods that can deal with these issues (Bonabeau, 2002). Uncertainty in the model results is hence key, both how it is accounted for and communicated. It is in fact important to highlight the purpose of the model: quantitative results generated from an ABM whose purpose is to qualitatively describe a behaviour or demonstrate a theory, should be handled with caution and vice versa.

Another reason to prefer an ABM approach to SD was because part of this research involved the aggregation of findings from different fields, i.e. geopolitics, environmental economics, macroeconomics and international economics, and hence interdisciplinarity was a fundamental condition for the modelling approach that would finally be chosen. Because of its characteristics, ABM is most useful when studying interdisciplinary subjects, as it can promote integration and interaction between different fields of study (Jager, 2000; Voudouris, et al., 2011). ABM has been applied to a wide variety of sectors (Bonabeau, 2002; Balbi and Giupponi, 2009; Garro and Russo, 2010). For instance, in the agricultural sector ABM has been applied to model technology diffusion (e.g. Berger, 2001), micro-scale market dynamics (e.g. Arsenault, et al., 2012), scenario and policy testing (e.g. Bastardie, et al., 2010), land use change (e.g. Zhang, et al., 2013), decision-making (e.g. Ng, et al., 2011) and land price dynamics (e.g. Filatova, et al., 2009). In addition, this modelling approach has also been applied to social dynamics (e.g. Gilbert and Troitzsch, 2005; Bravo, et al., 2013), political systems (e.g. Cioffi-Revilla and Rouleau, 2009), transport (Jin and Jie, 2012; Natalini and Bravo, 2013), change in land use in agriculture (e.g. Matthews, et al., 2007; Polhill, et al., 2013), ecology (e.g. Bousquet and Le Page, 2004), finance (e.g. Tesfatsion, 2002; Cincotti, et al., 2010), product-service sustainable business model (e.g. Bianchi, et al., 2009) and industrial sustainability (e.g. Tonelli, Evans and Taticchi, 2013), just to name a few.

However, as highlighted above and in the previous chapter, to the best of my knowledge an ABM fully empirically grounded aimed at investigating the connection between scarcity of food and fuel and conflict has never been developed before. This, in addition to the lack of a systemic view of how scarcity of natural resources can translate in an increased probability of the occurrence of riots in the world, constitutes the gap in literature that this research aims at addressing. The novelty of this research consists in the questions addressed and the results obtained, the methodological framework and the systemic approach used to understand and quantify the relationships between the different variables considered, in addition to the ABMs developed.

3.3. The modelling journey

For scientific research to be academically sound, this has to be consistent, rigorous, transparent and replicable (Martensson and Martensson, 2007). Academic rigor can be achieved through the implementation of methodological standards. This is particularly important in ABM since, as Gilbert and Troitzsch (2005) argued “All research should be theoretically informed, methodologically sophisticated and creative. These qualities are especially necessary when doing simulations because the field is only about 20 years old, so there are no well-established traditions to rely on […]” (Gilbert and Troitzsch, 2005, p. 1). A methodological standard is defined as "a constructive framework that provides a socially shared system of principles, rules and practices which defines how research should be performed [...]" (Squazzoni, 2012, p. 131). In the modelling field, following a methodological standard can make the difference between building a model that is correctly coded and achieves its objective and one that does not, and can produce models that are more transparent, manageable, testable and replicable.

Different methodological frameworks have been proposed by the ABM literature. In particular those of Squazzoni (2012), Gilbert and Troitzsch (2005) and Grimm and Railsback (2005) provide a reiterative list of steps to build consistent and reliable models. These methodologies were very general and have hence been adapted to fit this research, in particular to incorporate the work that went into developing different databases that have been used to inform the models. A brief description for each point in the list will follow.

3.3.1. Formulate a research question

As mentioned before in this chapter, the correct formulation of the research question is of utmost importance towards building a 'good' model (Gilbert and Troitzsch, 2005). This step allows the definition of boundaries for the research to improve clarity and focus the research effort. As stated above, the research questions that this research aimed to address regarded the investigation of how scarcity of natural resources, their international prices and national political fragility affect the occurrence of food and fuel riots, also taking into account trade of natural resources. In addition, this research aimed at developing three fully data-led ABMs, one focussing on food, one on fuel and an integrated version of the two, which will be called Food ABM, Fuel ABM and Food and Fuel ABM, respectively.

3.3.2. Building a conceptual model

Building a conceptual model is a key step in building any model (Wilson, 2001) because it visually formalises the key variables, connections and feedbacks present in the system. A conceptual model is a simplified version of the system that is the target of the simulation. Usually it is represented with a flowchart or similar simple visualisation techniques. For reasons of space and synthesis Figure 3.1 provides a simplified version of the conceptual model for the Food and Fuel ABM.

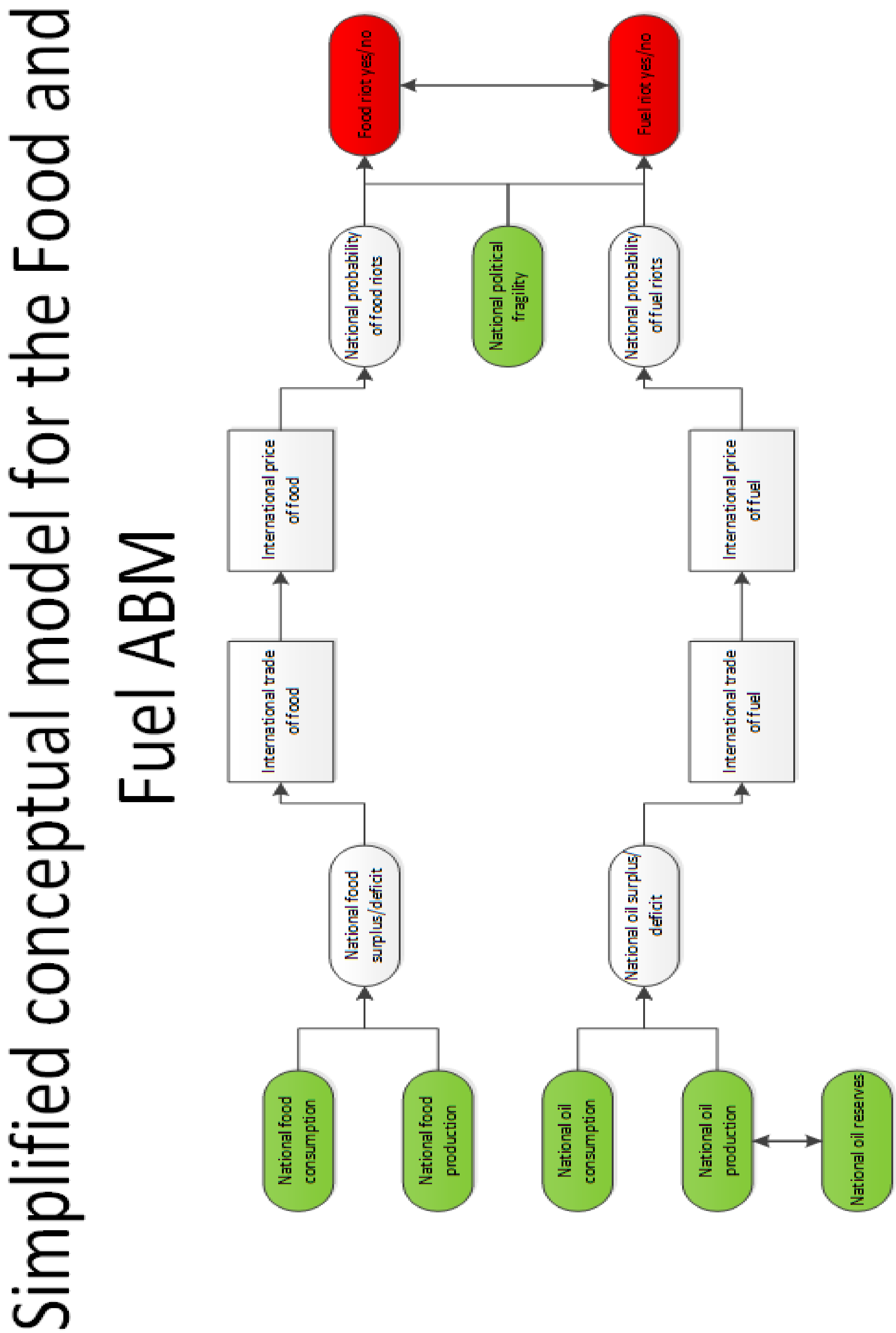

Figure 3.1 – simplified version of the conceptual model for the Food and Fuel ABM. The green boxes identify the variables that have been estimated via trend-lines (as will be explained in the following chapters) and the red boxes identify the final variables. The rectangular boxes identify processes that take place at the 'global' level, whereas round boxes represent national processes (own elaboration).

3.3.3. Specification of the properties of the model

The specification of the properties of the model clearly identifies the theories on which the model relies. This research was approached as constituted by building blocks, i.e. the main components of the ABMs. These were identified as: i) consumption and production of natural resources, ii) international prices for natural resources iii) national political fragility, iv) international trade of natural resources, and, finally, v) the occurrence of food and fuel riots as related to the previous dynamics. These dynamics will be investigated and analysed in the following chapter.

3.3.4. Data collection

Collecting the data needed to build a model can prove to be challenging. The data used have to be consistent and sourced from a reliable institution if not produced as part of the research through surveys or alternative methods. In this case, the data that have been used to develop the ABMs was both collected ad-hoc (data for the occurrence of food and fuel riots) and the remainder was sourced from internationally acknowledged institutions (e.g. WB, FAO, UN) that made them freely available on the institution's websites and from the database compiled as part of the GRO Project. This step is particularly important when building an empirically grounded model: the lack of data or its low accuracy can sometimes result in having to edit the conceptual model or even to having to reformulate the research questions. This occurred to be true for this research and led me to edit my conceptual model in a few instances.

3.3.5. Data analysis

Analysing the data collected is again particularly important when building empirically grounded models. This step can provide initial findings that could better specify some parts of the model or their development. Econometric techniques have been employed to explore the data to inform the ABMs and these will be listed in the next section. In addition, the data collected from the GRO Project included some gaps across the years that were filled using simple interpolation and are part of a larger database held and kept up-to-date by the GSI. The techniques that have been applied to the data are summarised in Jones and Phillips (2015).

3.3.6. Model implementation, execution and verification

During this step the theoretical basis, the conceptual model and the outcomes from the data analysis are translated in the language of the chosen software (Squazzoni, 2012). Previous experience in building models of complex systems taught me that the best way to approach the development of the model was that of building blocks. Firstly, the components that would constitute the final ABM were identified and built in isolation, subsequently adding complexity to the main model as new parts were developed separately. In addition, standard repeatable tests for each component were built to detect code errors possibly introduced with subsequent additions. The outcomes of these tests are known, to ensure the software is performing as expected. This process is also called 'unit testing' (Gilbert and Troitzsch, 2005). This process also helps to distinguish emerging patterns from anomalies once the final model is built and run. In particular, this research first focussed on food riots and the dynamics that cause these events, subsequently incorporating the knowledge produced in the development of the Food ABM. Then the same analysis was applied to the study of fuel riots, which led to the development of the Fuel ABM. Finally, the analysis focussed on the interaction between the two types of riots, subsequently integrating the two versions of the ABM whilst including the knowledge generated from the data analysis.

3.3.7. Model calibration and sensitivity analysis of the parameters

When the purpose of the model is to replicate and investigate real world phenomena, the model needs to be calibrated using reported data to ensure it is a good representation of reality. Two important approaches during this phase are sensitivity analysis and calibration or parameter fitting (Thiele, et al,, 2014). Sensitivity analysis tests the sensitivity of the model outputs to changes in the parameters in order to investigate and report the robustness of the model outcomes as relates to uncertainty in the definition of the parameters (Thiele, et al., 2014).

Calibration is the process of defining boundaries for the values of selected parameters in the model and organise a series of model runs to explore these ranges and select the values for these parameters that better fit the data. The use of these practices is still relatively low in ABM (Thiele, et al., 2014). The reasons probably being: i) lack of data; ii) uncertainty in the theories applied; iii) more abstract than empirical models;

iv) the complexity of the agents' decision making; v) scarce familiarity of a large part of the modelling field with computer science; indeed, non-experts are increasingly interested in computer modelling, although not being familiar with the standard practices and processes required, which hence are often overlooked; vi) agent-based modellers dedicate more attention to the explorative aim of ABM rather than to its explanatory potential, for which empirically soundness is key (Lorscheid, et al., 2012; Thiele, et al., 2014). Recently published books and academic papers (e.g. Kleijnen, 1997; Saltelli, 2000; Saltelli, et al., 2004; Helton, et al., 2006; Kleijnen, 2007; Saltelli, et al., 2008; Cournede, et al., 2013; Gan, et al., 2014; Thiele, et al., 2014) try to address the scarce methodology on how to implement these methods. As it will be detailed in Chapter 5, the development of a fully data-led model results in very deterministic outcomes. In this case sensitivity analysis could not be implemented in the 'common' fashion. As will be explained in Chapter 5, sensitivity analysis of a model is usually performed by varying key parameters within certain ranges, thus analysing the sensitivity of the results to changes in the parameters. The deterministic nature of the main dynamics that lead to the estimates for production and consumption of natural resources calculated in the model and the fact that there is no free parameter included, meant that the standard procedure could not be implemented in this case and an alternative procedure was implemented. The calibration of the ABMs will also be presented in Chapter 5.

3.3.8. Analysis of the outcomes of the model

The model runs generate a large amount of data that then needs to be analysed using statistical software to extrapolate the results. The software selected for the development of the ABMs was NetLogo (Wilensky, 1999), a piece of software originally designed for teaching, but now increasingly used for research (Thiele, et al., 2014). NetLogo is increasingly used in combination with R (R Core Team, 2013), which was used both to analyse the data that was then used to inform the models, as well as to analyse the results from the ABMs.

3.3.9. Model validation

The validation process is aimed at ensuring that the results of the model match the system that it simulates to test its consistency and facilitate its replicability (Squazzoni, 2012). Squazzoni (2012) lists three types of validation techniques: i) internal validation; ii) cross-validation; iii) empirical validation. He defines internal validation as "the process by which the coherence between explananda and explanandum is scrutinised, possibly also by peers" (Squazzoni, 2012, p. 137). In this case empirical data is not required to validate the model and this approach is hence more suitable for abstract or theoretical models. Cross-validation, is defined as "the process by which the explanatory power of models which look at the same or similar issue is tested comparatively according to a given criterion, for example, simplification or empirical adherence" (Squazzoni, 2012, p. 137). Empirical validation is defined as "the process by which model results are confronted and corroborated with empirical data" (Squazzoni, 2012, p. 139). To improve the validation power of this technique, the author introduced the concept of multilevel empirical validation, which he defines as "the process by means relevant model parameters are informed by and simulation findings are evaluated against empirical data" (Squazzoni, 2012, p. 139). According to this last approach, empirically grounded models can use databases to both inform their simulations and to validate their results. To do this, the database being used must be split either horizontally (using a given number of records as inputs for the model and the remainder to test the model results) if the data is time-independent (when the time variable is not included in the model and/or does not affect the simulations and/or its results) or vertically (using a given number of time-series to inform the model and the remainder to test the model results) if the data is time-dependent (when the model uses time-series time-series).

Another methodology that can be used to validate ABMs is Pattern Oriented Modelling (POM) (Wiegand, et al., 2003; Grimm, et al., 2005). This is particularly indicated to address the two main challenges that characterise the bottom-up modelling nature of ABMs, i.e. complexity and uncertainty. POM is aimed at unpacking the information relative to the internal organisation of the system. To do so, this procedure focusses on identifying and validating specific, multiple patterns that are simulated in the system, which highlight the underlying assumptions and dynamics incorporated in the model. This method can reduce the uncertainty related to the model results by developing a realistic simulation of the structure of the system. Grimm et al. (2005) prescribe that to implement this method, the patterns that will be eventually validated need to be identified ahead of the model's development. For this reason, the authors recommend the development of a conceptual model before coding. In the case of this research, the development of the ABMs was preceded by a detailed preparation process, which will be presented in the following chapter.

As mentioned before, the ABMs developed as part of this research were fully data-led, i.e. reported time-series were analysed and used as input for the behaviours and parameters included in the models. This means that the ABMs are already internally validated, also through the unit testing process mentioned above (Squazzoni, 2012). Both POM and multilevel validation had features that could help validate the ABMs, hence the two techniques were combined and tweaked to better meet this research's needs. As for multilevel validation, differently from the procedure specified above, due to the short time frame that was used for this analysis and scarcity of data, it was decided to validate the different versions of the ABM on the same database used to calibrate them, although focusing on different variables to check the validity of the models' results. This research could have taken into account a longer period, however the food and fuel riots were concentrated in 2008 and 2011 because of the global crisis that occurred in this time frame, which was unique in its genre (Homer-Dixon, et al., 2015). The only crisis of similar proportions goes as far back as 1929, for which data is scarcely available for the variables analysed in this work. The procedure implemented to overcome this methodological issue will be better detailed in the next chapter. The assumption underlying this procedure, which is common practice in the modelling field, is that if the model was able to recreate part of the past, then it will be able to 'tell a story' about the future. Another important part for the validation of the ABMs was the recreation of specific patterns. For instance, the Food ABM needed to be able to recreate politically fragile situations like the Arab Spring, which saw a period of high international food prices coupled with an increased occurrence of food riots. For this, the data produced by the model was analysed, checking for a correspondence between the countries that actually experienced food riots in the period 2008-2011 (the Arab Spring) and those that recorded a food riot in the model simulations. I appreciate that the data that was used as input in the model to allow it to recreate Arab-Spring-like events referred to the very events happened in 2008-2011, i.e. the data used as input and to calibrate the model were the same data used to validate its results. However, a model that is 'mechanistically correct' should be able to recreate future events, but only to the extent that the mechanisms that drive the dynamics observed in reality have been correctly identified and are sufficient for the future cases. The validation techniques implemented evaluated the accuracy of the ABMs at reproducing past patterns. As for whether the past patterns will be similar to future ones, only time will tell.

3.3.10. Reporting and publication

Documenting and publishing the model and its results is critical both for communicating the model results and for its replication. In order to allow peers in the field to replicate and further analyse a model, the publication of its theoretical basis and results has to be undertaken in the most transparent and methodologically sound way. Recently, high-impact ABM journals stressed the need for the development and use of standards to document and publish this type of studies and the most famous in the field of ABMs is the Overview, Design concepts and Details (ODD) protocol (Polhill, et al., 2008; Grimm, et al., 2010), which was implemented in Chapter 5 to present the ABMs.

3.3.11. Replication

Replication is another critical step to ensure the soundness of a model. Squazzoni (2012) defines this procedure as a "process by means a given model is independently scrutinised by peers by re-running it" (Squazzoni, 2012, p. 140). Moreover, as Squazzoni (2012) argues, replication is critical for verification, internal validation and cross-validation. In other words, the real importance of this step is the contribution that it may give to theoretical progress: if several scholars replicate the same model obtaining the same results from diverse simulations, they may be facing a progress in science that they could formalise in a new theory.

Although in research the trend is to categorise, formalise and provide steps to improve research practices, rarely the modelling process is as clear-cut as described above. In fact, the list of steps just described could be represented as a conceptual model in itself and as such the modelling process can be outlined with a flowchart as shown in Figure 3.2.

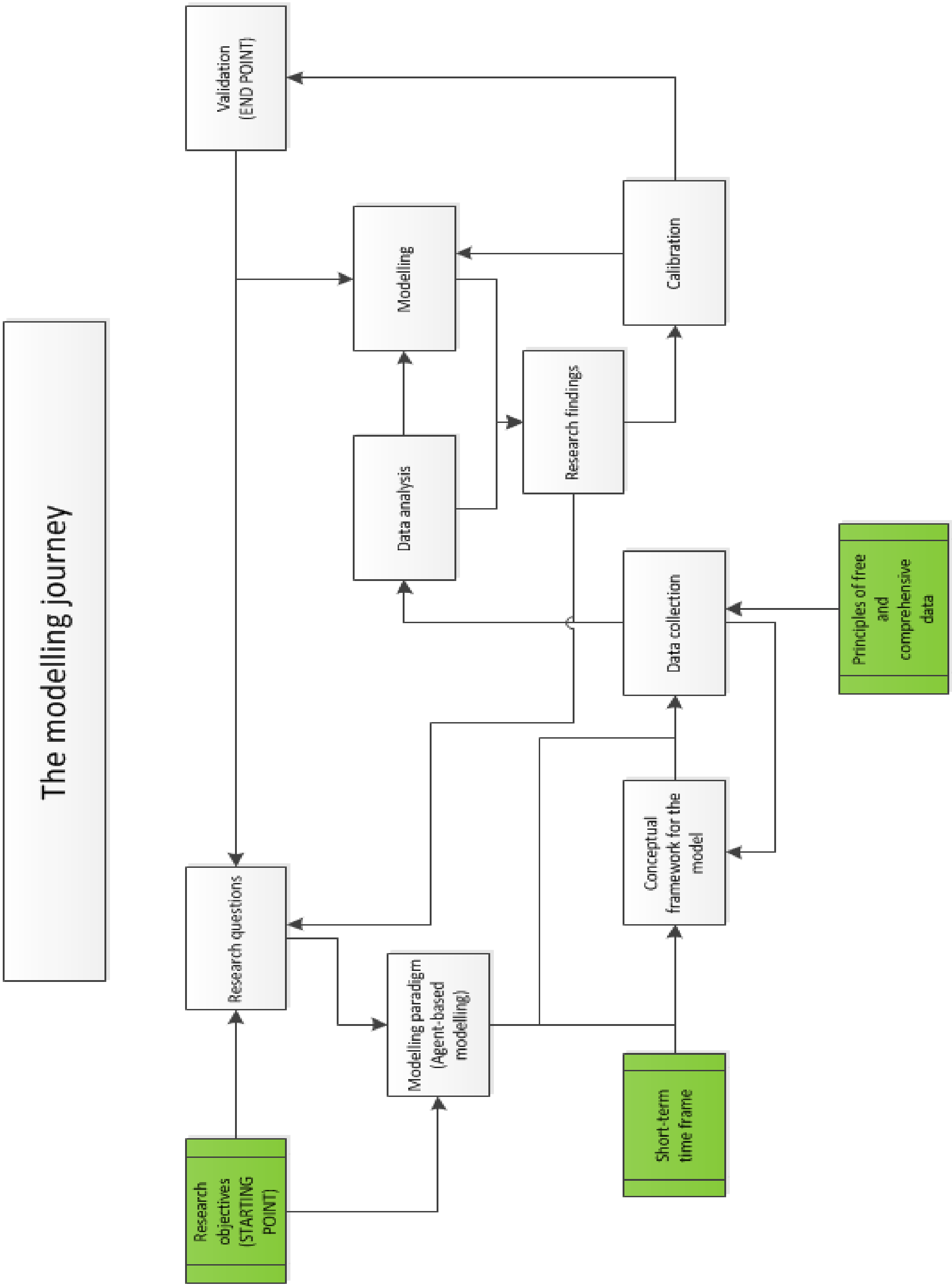

Figure 3.2 – Flow-chart of the modelling journey. The green boxes identify the GRO principles outlined in the introduction to this chapter (own elaboration).

3.4. Architecture of the models

As mentioned before, this research produced three versions of an ABM, one modelling the global food system, one focussed on the fuel system and finally a model integrating the dynamics of the previous two ABMs. The aim of the models was to simulate how scarcity of natural resources, i.e. food for the Food ABM, oil for the Fuel ABM and both resources for the Food and Fuel ABM[9], their international prices and national political fragility influence the occurrence of food and fuel riots in countries. Since the models are empirically grounded, the first step was to collect data for these variables and analyse them. The results were subsequently implemented in the model to inform the dynamics. Although the analysis on riots that informed the models will be presented in detail in the following chapter, it is important to briefly introduce the methods that have been applied during this initial phase and why these have been chosen.

In particular, the methodological steps applied in the analyses on riots are the following:

1. Creation of databases of riots
2. Random effects logistic linear regression (RE) to test the relationship between international price of the resource and riots
3. Calculation of a threshold for the international price of the resource beyond which riots are more likely to occur in countries, based on the previous point
4. Hazard model (survival analysis) (HZ) on periods above the price threshold to evaluate the relationship between whether a country is a net importer or exporter of the resource, national political fragility and the occurrence of riots in countries
5. Regression tree with random effects for longitudinal (panel) data (REEM) to operationalise international price threshold and categories of fragility to calculate probability of riots. Results were compared with RE models on the same variables
6. Evolutionary Tree (ET) to predict the formation of international prices of natural resources in the ABMs starting from the availability of resources.

The analysis of the data on riots required (a mix of) methods that could deal with sparse, longitudinal data. Longitudinal or panel data is characterised by a set of individuals as the subject of the study $i \in \{1, \ldots, n\}$ and whose observations are recorded at times $t \in \{1, \ldots, m\}$. Therefore an observation is (i, t). Longitudinal data hence observes the same subjects over a period of time, rather than different observations for different individuals as in cross-sectional analyses. This type of study

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[9] The Food and Fuel version of the ABM also includes production and consumption dynamics for coal and natural gas, as will be explained in more detail in Chapter 5.

can help to understand and predict specific patterns and behaviours in the subjects (Sela and Simonoff, 2012). In this case, the subjects of the study were the 213 countries of the world, which have been modelled as agents in the different versions of the ABM. Time in the analyses was either represented in years or months. All the most common methods usually applied in statistics could not be applied in this case as panel data violates a fundamental assumption these all share – that the observations and the errors for each individual are statistically independent between different data points. Indeed, data for prices and other national variables investigated in this study is usually autocorrelated over time, hence the need for a method that could deal with this property. Failure of accounting for this would have led to a bias in the analysis by either overestimating the strength of the relationship between dependent and independent variables or choosing the wrong model. In conclusion, the methods that were needed for this study had to be able to handle statistical dependence of the data, autocorrelation and that could generate predictions based on time series. Econometric and machine learning methods were hence the most appropriate methods that were explored.

3.4.1. Random effects logistic linear regression

As for the second study[10] between prices and riots, the method that was to be selected needed to be able to quantify the relationship between international prices of natural resources and the occurrence of riots, whilst being able to identify a threshold for the price over which the probability for these events to happen is significantly higher. In a situation where the data was of cross-sectional type and non-panel, this study would have used classic regression. A similar method for panel data exists and it is called RE linear regression.

In a RE model (also called multilevel model) RE are estimated for every observation to account for the presence of relevant subgroups. This model assigns, for example, a different intercept for each group to try to capture the variation due to the different groups within the sample. These are different from Fixed Effects (FE) models that look for systematic connections between dependent and independent variables: RE refer to either variables that are not themselves modelled or measured (and thus can

[10] The first study consisted in the gathering of data for food and fuel riots and did not require the use of any specific method. This collection procedure will be presented in the following chapter.

only be modelled as randomly varying), or parameters kept constant amongst different groups. Literature is rather confusing about when to use either RE or FE, however Gelman and Hill (2006) recommend to always use RE models for their specific characteristics.

In particular, Gelman and Hill (2006) recommend this method when the aim of the study is: i) to account for variation both at the individual- and group-level while estimating the regression coefficients at the group-level, ii) to model the variation between regression coefficients at the individual-level and across groups, providing predictions for new groups and accounting for the variation in the uncertainty at the group-level for individual-level coefficients and iii) estimate coefficients for the regression on specific groups returning acceptable estimates even with small sample sizes.

The characteristics of RE models were in line with the study on the relationships between international prices and the occurrence of riots. Indeed, the possibility of RE models to account for autocorrelation and provide estimates for different groups (in this case the countries), was suitable for this study. In addition, the maximum-likelihood function resulting from the model could be used to estimate a threshold for the international price, which was the aim of the third study. This method was hence selected and implemented by using the pglm() R package (Croissant, 2013).

3.4.2. Hazard models (survival analysis)

The aim of the fourth study was to capture the information generated from the previous study on prices and riots and add another level of complexity by testing the effect of national food scarcity and political fragility on the occurrence of riots. In particular, the method to be selected needed to be able to statistically ascertain the time it takes for a riot to occur according to conditions set at different scales of analysis, i.e. at the global (for international prices) and national (for availability of food and political fragility) levels.

The method deemed most suitable for this task was Hazard Models (HZ). The name of this method varies greatly according to the academic field of implementation. Other examples are Survival Analysis or Event History Analysis (Vermunt and Moors, 2005). HZ is a type of statistical regression that implements the maximum-likelihood estimation method (like the others presented in this section) aimed at predicting the risk for an event to occur given a set of covariates. In particular, these models estimate how long it takes for a particular event to happen, also explaining why some individuals are more at risk than others (Vermunt and Moors, 2005). HZ analyse the rates of occurrence for a particular event that can affect all the subjects of the study, who are all in the same state during a risk period (Vermunt and Moors, 2005).

In this analysis, the countries were the subjects of the study and the rate of occurrence of the event being ascertained was the riots. The condition that countries all shared was the international price of the natural resource being above the threshold and the duration of this condition constituted the risk period of the analysis. As mentioned in the previous chapter, countries greatly subsidise the price of natural resources to allow their populations to enjoy reasonable prices. The reasoning behind the implementation of this type of models relies on the dynamic that was identified as the main cause of food and fuel riots[11]: whenever the price of the resource crosses the threshold calculated in the previous study, governments' expenditures to control prices increase. When this condition is sustained for a prolonged period, wealthy countries – or countries that have access to credit or other monetary sources – can afford to maintain the subsidies in place, whereas poorer countries are forced to cut the subsidies, hence causing discontent in the population and subsequent riots.

HZ allows estimation of survival and hazard functions, i.e. the probability of an individual to survive to time *t* or the instantaneous rate of 'death' at time *t* (Kleinbaum and Klein, 2006). In the study, the HZ model implemented was the Cox Proportional Hazards Model (Cox PH) with the R package survival() (Therneau and Lumley, 2016) which focuses on the hazard function. The Cox PH model is a class of HZ and it allows to compare the risk experienced by different individuals and to test the effect of continuous covariates (Kleinbaum and Klein, 2006).

3.4.3. Regression trees with random effects for longitudinal data

For the fifth study, the method that was to be selected needed to be able to quantify the probability of a country to experience a riot according to different conditions, i.e. whether the international price of the resource was either above or below the

[11] See Chapter 4 for a more detailed explanation.

threshold and the category of political fragility the countries belonged to, and provide probabilities for each condition for direct implementation in the ABMs, i.e. operationalise the results. For this reason, both RE and REEM models were explored.

REEM models are a machine learning method that allows the exploration of panel and clustered data whilst accounting for autocorrelation and can deal with missing data. These are a version of regression trees and represent a generalisation of linear models with mixed effects (Sela and Simonoff, 2012).

Tree models generally look similar and use the same jargon. They identify breaks in data for the predictors which are called decision nodes with a true/false condition that lead to either further decision nodes or a leaf. The very first decision node is called 'root node'. A specific combination of conditions identified by the decision nodes in the model leads to a leaf, which represents a specific value for the target variable. Generally, this is an iterative process applied recursively to each node identified as significant by the tree, which stops if a certain condition or threshold is met.

Regression trees are machine-learning methods that generate prediction models from data and are implemented to estimate or predict a response. This type of tree-based method applies to cases where the target variable is quantitative.

Regression trees were clearly particularly suitable for the research being presented here. This is because the dependent variables used in the analysis, i.e. food and fuel riots, were discrete ordered variables and the aim was to estimate the odds for each of the possible values taken by the response variable.

Sela and Simonoff (2012) developed REEMtree, which is a regression tree estimation method that uses a tree structure to estimate mixed effects models and that incorporates individual-specific RE. With this method, the nodes can split on any attribute and, as a result, observations for the same individual can be included in different nodes. Since this method integrates RE with an algorithm similar to expectation maximisation (EM) using regression trees, this is called RE-EMtree (REEM). EM is an algorithm employed to estimate parameters in probabilistic models with incomplete data (Do and Batzoglou, 2008).

In general, the use of tree methods is recommended when coupled with simulation models such as ABM (Sánchez-Maroño, et al., 2015). This is because the breaks (nodes) that identify splits in the data that lead to a specific leaf correspond to 'if' clauses with a 'true' or 'false' response, which are widely implemented in any programming language. In addition, REEM models were particularly suitable for this particular study as the results from the models were already implementable in the ABMs. This is because REEM returns the probability for each value of the target variable to occur in relation to specific clauses, i.e. nodes. The implementation of this method and the comparison of its results with RE models will be presented in the following chapter.

3.4.4. Evolutionary Trees

Another tree-based machine learning technique that was implemented in this research was ET. The sixth study undertaken on riots involved the prediction of the regime of international prices, i.e. either above or below the threshold identified in the second study, according to a set of variables relative to the natural resource the price referred to. Once again, a tree-based method was preferred to other techniques due to its convenient applicability to computer models.

ETs have been developed by Grubinger, et al. (2011), who operationalised this technique in the R package evtree() (Grubinger, et al., 2014). This method implements evolutionary algorithms to predict specific values in the target variable. Evolutionary algorithms are a type of stochastic optimisation method and 'are inspired by Darwinian evolutionary theories for the natural environment, implementing concepts such as inheritance, mutation and natural selection' (Grubinger, et al., 2011, p. 2). By applying an evolutionary algorithm to the partitioning procedure, ETs allow a comprehensive exploration of the tree's parameters space, leading to global optima if only one exists. This is accomplished by considering all the nodes further down the tree to identify splits in the data.

By implementing evolutionary algorithms, ETs should yield globally optimal results and can be more effective at optimising the trade-off between accuracy and complexity as compared to other partitioning methods.

ETs are characterised by several limitations. Firstly, the global exploration of the tree's parameters can be computationally intensive, affecting computation time and the memory required and hence can only be effectively applied to small datasets. Secondly, the evtree() R package cannot handle missing values, hence forcing to shrink further the size of databases that present gaps in the data. The last limitation of

ETs is related to the random nature of the algorithm on which these are based. When applied to large databases, different model runs can yield trees whose structure can differ greatly, which is acceptable when the purpose of the study is only to predict the target variable, although less so when the interpretation of the tree is important (Grubinger, et al., 2011).

Although these limitations are generally important, these did not apply to the study on international prices as the database used was very small. In fact, the database used contained one record per year between 2005 and 2013 (8 records in total), one target variable and two predictors and did not present missing values. Most likely, any tree-based partitioning method could have been applied effectively to such a small database. Although the interpretation of the tree resulting from the model was an important factor, the aim of the study was mainly to predict the international prices of natural resources. In addition, as it will be explained in Chapter 5, the structure of the trees was stable across different runs. Possible alternatives were the implementation of an existing study on price formation of the resources or the exogenous introduction of the prices in the ABMs. However, the first alternative was excluded due to the high complexity involved in the prediction of prices (see Chapter 2.8) and as for the second alternative, an endogenous generation of prices was preferred. For all these reasons, ET was the method implemented in this study.

This chapter provided a detailed outline of the methodology and methods that have been used to structure and undertake this research. This will form the basis for the following chapters that will delve deeper into the structure of the model and its components.

4. Parameterisation of the agent-based models

As outlined in Chapter 1, one of the principles this research had to follow was that the research needed to be mainly data-led, i.e. Principle 2 of the GRO Project. This implies that the relationships between the different variables needed to be empirically based and grounded in real data. To do so, a range of different techniques were applied to explore and quantify the dynamics that lead from food and fuel scarcity to the increased probability of experiencing food or/and fuel riots for countries. The knowledge and the numerical outcomes of the analyses have subsequently been used to inform the ABMs.

Moreover, to satisfy principle 3 of the GRO Project, i.e. delivering free scenarios and forecasts, the analyses only used open-source and free to use data. When this was not possible or data was not available, new databases were collected and managed. This research used different sources for data. The main one is a database created within the framework of the GRO Project and maintained by colleagues at the GSI. The GRO database holds a collection of data sourced from trusted open-access databases such as WB and FAO (i.e. institutions that implement robust methodologies in the collection and manipulation of data they release) and further manipulated by researchers from the GSI to improve consistency and to complete the gaps (e.g. missing data for years and/or countries). The full database is freely available on the GSI's website (GSI, 2015). As part of this research, three more databases were compiled to allow the econometric analysis that will be described in the next sections of this chapter, two recording the number of food riots, i.e. one was created for an earlier version of the study on food riots and a second for an updated version of the same study, and another on fuel riots.

The next section of this chapter will present the statistical analyses undertaken to parameterise the drivers of food riots. In particular, it will present an early version of this analysis that was published in Natalini, et al. (2015b) and subsequently updated in a paper submitted to the 2015 BHP Billiton Sustainable Communities/UCL Grand Challenges Symposium on Global Food Security and accepted for presentation (Natalini, et al., 2015a). The PowerPoint presentation related to the talk can be found on the website of the Symposium (Natalini, 2015). The analysis from this last paper will not be presented here as the second part of this section constitutes a further update of Natalini, et al. (2015a) and is submitted to the journal Food Security in Natalini, Bravo and Jones (TBP). The second section of this chapter will present the same analysis on the parameterisation of the drivers for fuel riots, whereas the third section will present the results from the analysis of the interactions between food and fuel riots. The quantitative analyses presented in this chapter used a combination of software: Excel was used to carry out basic statistics, tables and figures. R (R Core Team, 2013) was used for the more complex statistics and to generate relevant output and figures.

4.1. Parameterising the food system and drivers of food riots

The analysis on food riots started by reviewing different databases containing records for these episodes, which eventually led to the decision of developing a new more comprehensive one. Subsequently, this database was used to evaluate with approximate calculations the relationship between scarcity of food and its international price, also testing the hypothesis of the existence of a threshold for the international price of food which, if surpassed, could contribute to the increase in the probability of food riots. These tests have been subsequently backed up with formal statistical tests. The same database has been used to evaluate the accuracy of several aggregated measures of national political fragility, which allowed identification of one as best performer. In addition, approximate calculations have been used to test whether a country being a net food importer contributes to that country's probability of experiencing a food riot, which was subsequently tested with formal statistical tests. Finally, these results have been integrated with approximate calculations to estimate different probabilities of food riots for when international prices are above or below the threshold and for different categories of fragility. After the release of a key database of food riots published by WB and an update of the database of food riots used here, the whole analysis has been updated and the results operationalised with the implementation of REEM models.

4.1.1. Compiling an initial database of food riots for the Arab Spring

This initial analysis covered a time frame that can be attributed to the Arab Spring, i.e. 2005 – 2011, as this period saw an unusually large occurrence of food riots, which have been widely acknowledged to be due to high prices of food (Lagi, et al., 2011; Gaub, 2012; Bleischwitz, et al., 2014) amongst other causes. This analysis started by reviewing different databases for food riots. The only database available at the time when this research was undertaken was included in Lagi, et al. (2011). A careful consideration and review of the paper carried out as part of this research concluded that this database was not accurate. In particular, some of the food riots included in the study lacked a clear connection to any food-driven cause and/or any form of violence used in the protest. In addition, the method used to calculate a threshold for the FAO FPI over which food riots are more likely to occur was not reported, casting doubts about the validity of the authors' findings. Hence this research compiled a database of monthly food riots occurrences in African, Middle-Eastern and Asian countries during the period between 2005 and 2011, which largely corresponds to the Arab Spring. The definition of food riots used to compile the database was provided in Chapter 2.7.1 [12]. Data was collected by carrying out a simple search using combinations of different keywords to find newspaper articles in English that clearly stated the occurrence of violent demonstrations in response to the increase of the price of food or its scarcity, i.e. food riots, in African, Middle-Eastern and Asian countries. The countries resulting from this research are organised in Table 4.1.

Country	**2005**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**
Burundi	April (BBC News, 2005)							
Somalia		June (USA TODAY, 2007)	May (NBC News, 2008)			August (Pflanz, 2011)		
India		October (Majumdar, 2007)	August (Mukherjee, et al., 2008)					
Mauritania		November (Mail and Guardian, 2007)						

[12] This definition was sourced from a WB report. Through personal correspondence with the main author of the report I discovered that himself and his team of research were using this definition to compile a database that would be used by the WB and its Food Price Observatory, which was undergoing internal review before being released on their website. Aligning the definition used for my research to that used by WB increased the chances of this research being used by the institution and potential collaborations with its researchers. The Food Price Observatory database of food riots, i.e. Food Riot Radar, (WB, 2015a) was only released after the first publication related to this PhD was published in Natalini, et al. (2015b), which led to an update of the analysis at a second time. However, as it will be discussed in the next section, aligning the definition of food riots to that of the report from the WB did not result in identical results for the episodes included. In fact, my database, once updated, included more records, which have been notified to the main author of the report and editor of the Food Price Watch Newsletter, but there has been no response from the team of researchers.

Cameroon			February (Healy and Munckton, 2008)					
Burkina Faso			February (Healy and Munckton, 2008)					
Senegal			February (Healy and Munckton, 2008)					
Ethiopia			February (Healy and Munckton, 2008)					
Cote d'Ivoire			April (BBC News, 2008b)					
Haiti			April (Christie, et al., 2008)					
Yemen			March (Worth, 2008)					
Morocco			February (Worth, 2008)					
Lebanon			February (Worth, 2008)					
Egypt			April (BBC News, 2008a)			January (Rianovosti, 2011)		
Tunisia			June (Schneider, 2008)			January (Aburawa, 2011)		
Sudan			August (Sanders, 2008)			January (McDoom, 2011)		
Mozambique					September (Mangwiro, 2010)			
Algeria						January (The Daily Telegraph, 2011)		
Oman						February (Aljazeera, 2011)		
Iraq						February (Al-Salhy, 2011)		
Uganda						April (Kron, 2011)		

Syria						September (Asian Correspondent, 2013)		
Bangladesh			February (The Times of India, 2008)					
Guinea			June (Schneider, 2008)					
Kenya			May (Schoen, 2011)					

Table 4.1 – Database of food riots from Natalini, et al. (2015b). Each cell contains the month(s) during which each country experienced a food riot during the year listed in each column.

Each year therefore experienced the following number of food riots: 2005 (1), 2007 (3), 2008 (17), 2010 (1), 2011 (9) that amounted to a total of 31 food riots and 2008 and 2011 as the years that saw the highest number of food riots throughout the period considered.

4.1.2. Calculating an initial threshold for international price of food

Using the database for food riots presented in the previous section, Natalini, et al. (2015b) evaluated and estimated a threshold for the international price of food beyond which countries are more likely to experience food riots. The relationship between food price and food riots can already be seen in Figure 4.1, which plots the FAO FPI in both its nominal (blue line) and deflated (red line) versions against the number of food riots recorded in the database (green columns). Data for the FAO FPI was sourced from FAO (FAO, 2015). The figure shows an evident increase in the number of violent food-related episodes for high levels of the FAO FPI.

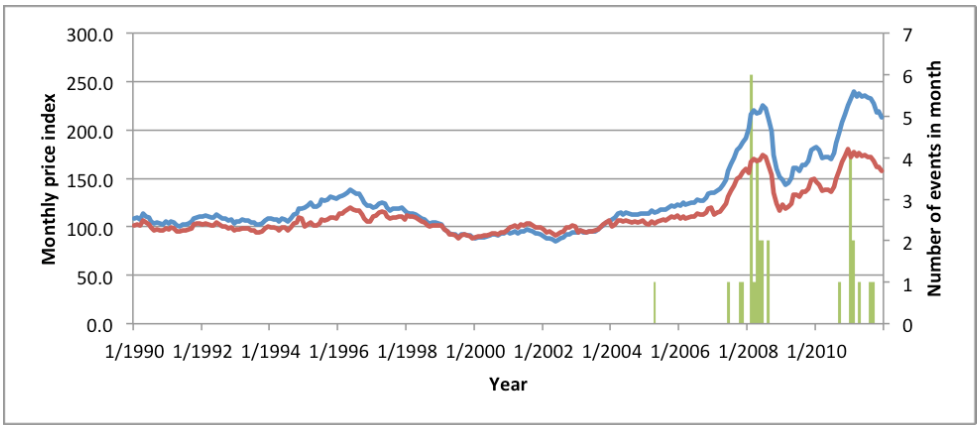

Figure 4.1 - The FAO monthly price index (nominal prices in blue and deflated in red) for food between 1990 and 2011 compared to the number of violent demonstrations that were associated with food over that month (shown in green) (Natalini, et al., 2015b).

Following the example of Headey (2011), the paper implements a simple mathematical approach for both the nominal and deflated versions of the FAO FPI (FAO, 2015) to test the existence of a threshold for the international price of food beyond which food riots are more likely to occur. The authors found two different regimes for the FAO FPI for its monthly and annual and deflated and nominal versions. These regimes are significantly different according to a one-tailed t-test. By graphically comparing the different regimes, the authors initially identify the following thresholds: 200 for the nominal annual FAO FPI and 140 for the deflated FAO FPI. The threshold for the monthly, deflated version of the FAO FPI was found at 130.

Subsequently, the monthly threshold for the deflated version of the FAO FPI was further tested by introducing the database including only the countries that actually experienced a food riot in the period of the analysis in a logit model with random effects for country and time, with time expressed as the number of months since January 2005. The maximum likelihood estimations resulted in a highly significant positive coefficient for the monthly, deflated FAO FPI, which aids support to the idea of a direct causal relation between the increase of food prices and food riots. Table 4.2 reports the results of the analysis.

	Estimate	**SE**	***t*-value**	***p*-value**
(Intercept)	−14.434	2.165	−6.667	0.000***
FAO FPI deflated	0.066	0.013	5.091	0.000***

σ	0.000	0.294	0.000	1.000
Log-Likelihood	−138.114			
No.	2,100			

Table 4.2 - Random effects logit regression model estimates (Natalini, et al., 2015b). Sig. codes: 0 '***'; 0.001 '**'; 0.01 '*'; 0.05 '.'; 0.1 ' '.

The threshold for the deflated, monthly FAO FPI estimated from the model was calculated by evaluating Equation 4.1 with x = 0.01 to find the value for the international price of food above which the probability of a random country to experience a food riot is greater than 1%. The Betas in the equation were substituted with the coefficients resulting from the econometric model, i.e. -14.434 and 0.066.

$$F_{(x)} = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x)}}$$

Equation 4.1 – Formula for logistic function probability (Own elaboration).

The resulting value for the FAO FPI threshold was 148. More precisely, the 148 threshold represents the value for the monthly, deflated FAO FPI above which the probability for a random country to experience a food riot is >1%. The 1% probability is an arbitrary threshold that was chosen to signify a probability of riots ≠ 0.

4.1.3. Selecting a measure of national political fragility

To test the relationship between national political fragility and the occurrence of food riots, the first step of the analysis involved choosing a measure that could capture the political fragility of countries. Because this measure would ultimately be included in the ABMs, hence adding another layer of complexity, the main requirements were practicality and ease of replication. This reasoning is in line with the idea that the most useful computer models are the ones that recreate the dynamics of the system which is the object of the study in the most simple, yet accurate, manner. National political stability or fragility can depend on a very large number of factors (Carment, et al., 2011) and modelling the dynamics that determine whether a country is politically stable or fragile was beyond the scope of this research. The method to be applied hence needed to encapsulate this information in a concise form. An index approach was the most suitable for this analysis as this approach is particularly used when there is a need to summarise different measures into a single figure. A report from The United Nations Development Programme (UNDP) focusing on national political fragility reviewed some of the freely available indices and provided a clear and comprehensive overview of the methodology used by each of these measures (UNDP, 2009). The indices included in the report that met the criteria of this research (see below) were hence included and their accuracy at capturing food riots was evaluated. Finally, the index that performed best was selected as a measure of national political fragility.

Since this measure was going to be used in further developments of the research, i.e. the evaluation of the relationship between national political fragility and fuel riots, only aggregated indices of political fragility were evaluated, avoiding sector- or resource-specific measures of fragility (e.g. food security indicators). In addition, the index that would eventually be used in this research needed to abide by Principle 3 of the GRO Project, i.e. only use open-access sources, which further restricted the pool of possible measures of fragility that could be implemented.

The review of indices started from UNDP (2009), a report collecting data and methodology for several indices. Table 4.3 presents the final list of indices of political fragility whose accuracy in capturing food riots was assessed.

Index	Producer	No. of Countries Covered	Years Available
Bertelsmann Transformation Index State Fragility Index (BTI-SFI) (Bertelsmann Stiftung, 2008)	Bertelsmann Stiftung	119 (2006)–128 (2012)	2006, 2008, 2010, 2012
Fragility Index of the Country Indicator for Foreign Policy project (CIFP) (CIFP, 2008)	Carleton University	30 (2008)–197 (2010)	2006–2008, 2010
Failed States Index (FSI) (Fund for Peace, 2008)	Fund for Peace	76 (2005)–177 (2012)	2005–2012
Global Peace Index (GPI) (Institute for Economics and Peace, 2008)	Institute for Economics and Peace	120 (2007)–158 (2012)	2007–2012
Index of state weakness in the developing countries (ISW) (Rice and Patrick, 2008)	Brookings Institute	141	2008
Peace and Conflict Instability Ledger (PCIL) (Hewitt, et al., 2008)	University of Maryland	162 (2008)–163 (2012)	2008–2012
Political Instability Index (PII) (EIU, 2007)	The Economist Group	165	2007, 2010
State Fragility Index (global reports) (SFI global) (Marshall and Cole, 2009)	George Mason University	159 (2006)–164 (2010)	2006–2008, 2010
State Fragility Index (excel file) (SFI xls) (Center for Systemic Peace, 2014)	George Mason University	164 (2004)–167 (2012)	2004–2012
Worldwide Governance Indicators: Political Instability and Absence of Violence	The World Bank	207 (2004)–212 (2012)	2004–2012

(WGI) (WB, 2015c)

Table 4.3 - Summary of the indices used in this study with time series available and the number of countries covered (adapted from Natalini, et al., 2015b).

Two indices of political fragility included in the UNDP (2009) publication were excluded due to a comparatively low number of countries covered: (i) the Country Policy and Institutional Assessment (CPIA)/International Development Association (IDA) Resource Allocation Index (IRAI) developed by the World Bank (WB, 2014); (ii) the Harvard Kennedy School Index of African Governance developed by the Harvard Kennedy School (Rotberg and Gisselquist, 2009); As for the BTI, the index as produced by the Bertelsmann Stiftung originally included two different indices: the Status Index and the Management Index, which both rely on further indicators (Bertelsmann Stiftung, 2008). UNDP (2009) extracted two indicators from the index built by Bertelsmann Stiftung and rearranged them in a new fragility index called the State Fragility Index (BTI-SFI). The two measures selected in the report to create this new index were: (i) monopoly on the use of force; and (ii) basic administration (security area and political area). This research employs the BTI-SFI and not the index as developed by its producer. Moreover, since UNDP (2009) only provided one year for the BTI-SFI, i.e. 2008, the missing time-series[13] were calculated following the methodology used in the report.

In addition to this list of indices, GDP per capita (GDP pc) in both its 'current' and 'constant 2005 dollars' versions were included and their accuracy as possible indicators of food riots. Since different authors have argued that the Arab Spring and in particular food riots may be partly due to the conditions of poverty that countries suffer (Gaub, 2012), the most common indicator of a country's wealth was evaluated alongside other indicators of political fragility. The data for these two variables was sourced from the GRO Database (GSI, 2015).

The evaluation of the different indices of political fragility followed several stages: i) which index ranked as most fragile the highest number of countries that experienced a food riot the same year the riot was recorded, i.e. best descriptor of food riots; ii) which index ranked as most fragile the highest number of countries that experienced a

[13] Since the original BTI index is published biannually and this analysis covered the period 2005 – 2011, the BTI-SFI was calculated for the years 2006, 2010 and 2012.

food riot the year before the riot was recorded, i.e. best predictor of food riots; iii) test whether the indices suffer from a one- (or more) year time lag in the data for the indicators on which they rely.

The indices included in this analysis had different purposes: some were aimed at simply describing the current fragility of countries, others claimed predictive power, i.e. forecast situations of fragility or unrest, and still others claimed to be able to do both. In addition, most institutions that develop this type of indices warn possible final users not to rely on their products for decision-making. Despite this recommendation, indices are commonly used as part of the decision-making process as relates to future international policies, investments and aid (Carment, et al., 2011). For all these reasons, the year 2004 was included in this analysis in order to evaluate whether the indices were indeed able to predict the food riots occurred in 2005 and every following year.

The analysis of the indices encountered several methodological issues: i) the indices used different definitions of political fragility; ii) the indices used different categories to classify the political fragility of countries between years; iii) the indices used different approaches to divide the countries in categories; iv) different ranking techniques have been applied to the indices and to different versions of the same index (e.g. the SFI as provided with the excel spreadsheet downloaded from the George Mason University website and as provided by the Centre for Systemic Peace Global Reports); v) the time series available for the indices did not cover the whole period of this analysis, and data often presented missing values for some countries (e.g. Somalia in the Political Instability Index). For instance, the CIFP for 2006 and 2008 provides only the top 30/40 most-at-risk countries and only the rank of the countries (and not the scores) for the year 2010. This and other similar examples made the cross-index comparison methodologically challenging.

To partially overcome these issues, the analysis of the accuracy for the indices only involved a specific number of countries per index. This was selected by comparing the number of countries included in the categories most at risk of the indices that provided defined categories of fragility. In particular, the categories that were taken into account were: (i) very high alert, high alert and alert for the FSI; (ii) failed states, very fragile states and fragile states for the BTI-SFI; (iii) top 30/40 for the CIFP; (iv) top 20% least at peace for the GPI; (v) failed states, critically weak states and weak states for the ISW; (vi) top 25 countries for the PCIL (as reported in Hewitt, et al., 2008; Hewitt, et al., 2010); (vii) very high risk and high risk for the PII; and (viii) extreme fragility and high fragility for the SFI. As shown in Figure 4.2, which presents the number of countries in the categories of interest for each country/year, this number ranged between 6 – 94 and the average 31.5. The analysis hence focused on the top 30 most fragile countries for each index. The analysis was also extended to the top 40 most fragile countries to evaluate whether this affected the results. Albeit this method solved some of the methodological issues characterising the cross-index comparison, the data available for the indices did not allow the employment of a formal, standardised and sound quantitative method for the cross-index comparison. For this reason, approximate estimates were calculated in the first instance to evaluate the accuracy of the different indices and the results were subsequently validated with formal quantitative methods.

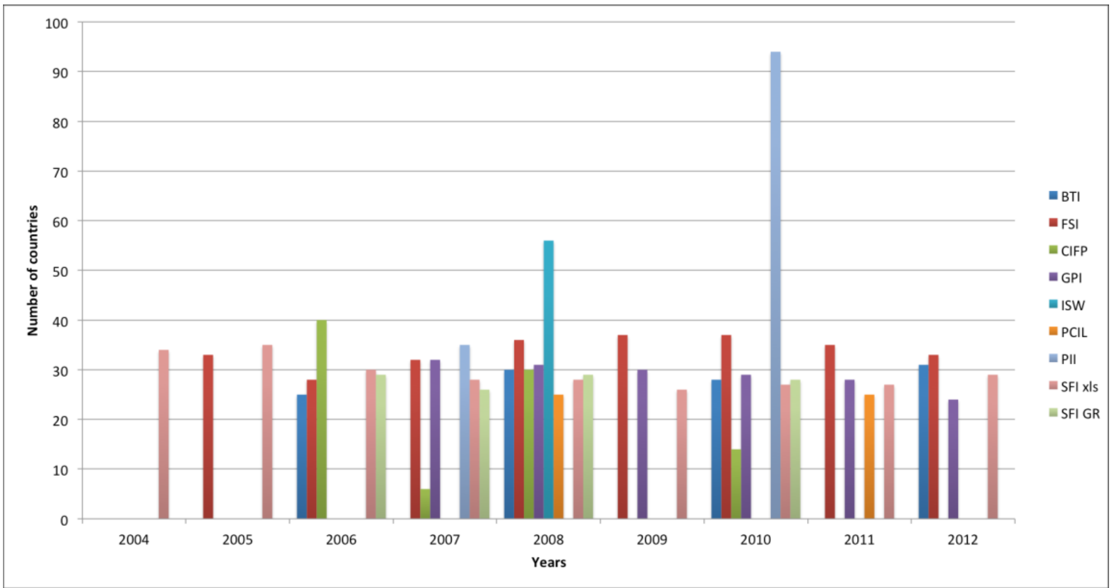

Figure 4.2 – Number of countries in the categories of interest for each index of fragility. The columns represent each index (see legend), for each year (own elaboration).

The accuracy of the indices at predicting and describing food riots was tested by comparing the ranking given to each country by the indices and the actual food riots recorded in the database presented in Table 4.1. In particular, their accuracy was computed by calculating the proportion of countries that experienced a food riot out of the top 30/40 countries most fragile as ranked by the indices. This was done both for the year prior to the food riots recorded to test the forecasting power of the indices and for the same year to test their descriptive power. For example, if an index was assigned with 50% accuracy for the top 30 countries most at risk, this meant that half of the countries listed as the 30 most fragile countries from that index experienced a food riot. For reasons of brevity Table 4.4, provides as an example the results of the accuracy analysis for the indices for the year 2008, i.e. the year with the largest number of food riots.

Name of the Index	**2007 Year Prior**		**2008 Same Year**	
Descriptive Indices:	**Top 30**	**Top 40**	**Top 30**	**Top 40**
SFI xls	41%	47%	41%	59%
SFI global	41%	53%	47%	53%
GPI	35%	47%	35%	53%
ISW	NA	NA	47%	47%
BTI	NA	NA	47%	53%
WGI	**65%**	**65%**	59%	65%
Descriptive and predictive indices:				
CIFP	53%	59%	47%	NA
FSI	53%	77%	**59%**	**77%**
Predictive indices:				
PCIL	NA	NA	41%	65%
PII	41%	41%	NA	NA
GDP per capita:				
GDP pc (current $)	35%	41%	35%	47%
GDP pc (2005 const $)	29%	35%	35%	41%

Table 4.4 - Example of accuracy test carried out on the indices for the food riots occurring in 2008 (best data coverage: food riots recorded in 15 countries) (adapted from Natalini, et al., 2015b).

The same procedure was employed for each year considered in the analysis. The indices that proved to be most accurate – both as predictors and as descriptors of food riots – are reported in Table 4.5. Since 2008 and 2011 saw the largest number of food riots, these years were considered as more important for this analysis.

Purpose of	**Year of Food Riots**

the Index	2005	2007	2008	2010	2011
Predictor	WGI, SFI xls, GDP pc (current $), GDP pc (2005 constant $)	SFI xls, CIFP	WGI	PCIL, GDP pc (current $), GDP pc (2005 constant $)	WGI, SFI xls
Descriptor	WGI, SFI xls, FSI, GDP pc (current $), GDP pc (2005 constant $)	WGI, SFI xls, CIFP	FSI	PCIL, GDP pc (current $), GDP pc (2005 constant $)	WGI

Table 4.5 – Most accurate indices divided by year for food riots (adapted from Natalini, et al., 2015b).

The WGI was the most accurate index throughout the period, correctly categorising as highly fragile the largest number of countries that experienced food riots for three years out of five, both as a predictor and descriptor. Second was the SFI xls, which resulted most accurate three years out of five as predictor and two years out of five as descriptor. The FSI resulted the third most accurate index, with two years out of five as descriptor, along with both versions of the GDP pc (current $ and 2005 constant $), which jointly came first alongside other indices two years out of five in both categories. Therefore, the other indicators can be considered as no better than general GDP measures as a tool to predict and capture the occurrence of food riots.

Since the two years that saw the largest incidence of food riots were 2008 and 2011, i.e. 17 and 9, respectively, this analysis suggests the WGI as the best predictor of food riots, even if its purpose was only descriptive. The descriptive power of WGI and FSI is apparently equal. Two out of four indices whose aim is to forecast political fragility of countries were the most accurate only one year out of five (alongside other non-predictive indices): the CIFP and the PCIL. As for the other two predictive indices, the FSI was better at describing rather than forecasting food riots, whereas the PII did not perform well in either category. Interestingly, these indices were most accurate at predicting food riots in years that saw a very low number of events recorded, which leads one to question the ability of these indices to capture the outbreak of violent events. To justify this statement it is worth remembering here that, as highlighted in Chapter 2, food riots have a negative impact on the political stability of countries. This dynamic should be captured by indices of political fragility and alike by definition.

To investigate the presence of time lags in the data underlying the indices, the time-series of the rankings for the countries that experienced food riots as given by the indices were plotted. For each index, the simple average ranking for every year for those countries was calculated. This was done only for the countries that experienced food riots in 2008 and 2011 because of the larger number of observations, i.e. food riots, during these years.

This assessment was carried out for both indices with the highest accuracy score. The WGI and FSI averages are provided in Figures 4.3 and 4.4, respectively. Since the ranking scale used by the indices was different, the WGI's was inverted to allow comparison between the two indices. In the figures, the higher the fragility of a country, the higher its ranking.

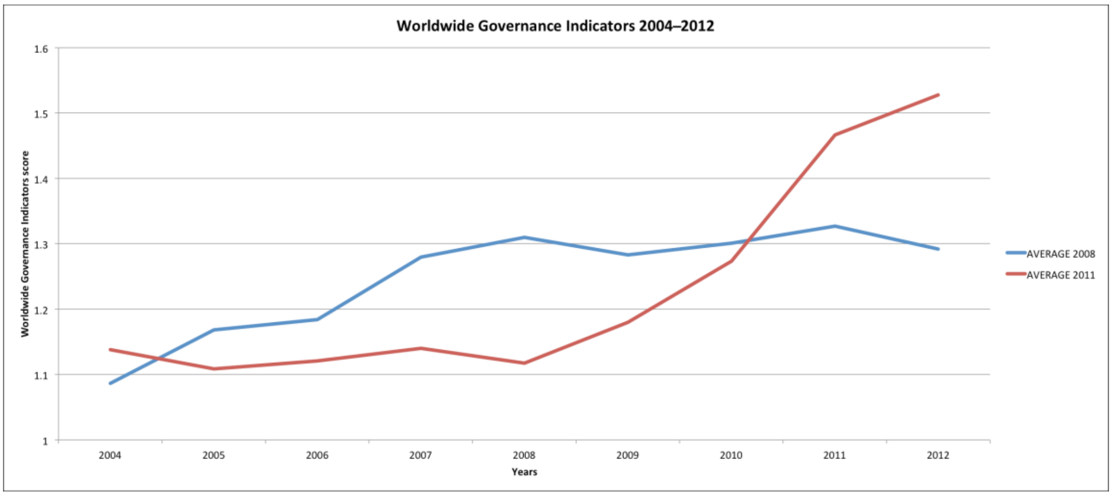

Figure 4.3 – Plot of the WGI average scores each year from 2004 until 2012 for the countries that experienced food riots in 2008 (blue line) and those that experienced food riots in 2011 (red line) (Natalini, et al., 2015b).

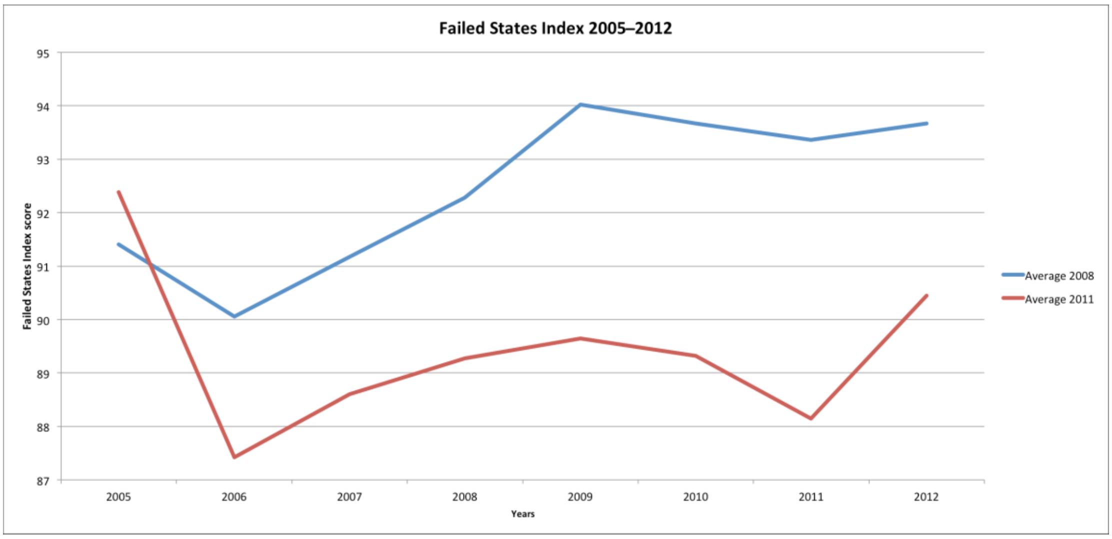

Figure 4.4 – Plot of the FSI average scores each year from 2004 until 2012 for the countries that experienced food riots in 2008 (blue line) and those that experienced food riots in 2011 (red line) (Natalini, et al., 2015b).

If the indices were able to accurately capture the increased political fragility due to the occurrence of food riots in the selected countries, we would expect to see a peak in their rankings in correspondence to the years 2008 and 2011 for the indices with descriptive purpose, i.e. both indices, and a peak in correspondence to the years 2007 and 2010 for the index has a predictive purpose, i.e. the FSI. The plot for the WGI shows a peak in 2008 with no delay, whereas it continues to rise into 2012 after the 2011 food riots, which could indicate a delay or that other factors affecting political fragility more generally could be associated with this increase. As for the FSI, the plot shows a one-year delay in capturing the food riots for 2008, and again, the 2011 line increases in 2012. This further shows the inability of the FSI to fulfil its aim as a predictor, at least in capturing food riots. This analysis suggests the WGI as the most accurate index amongst those evaluated, as it best captures the underlying conditions (Gaub, 2012) for food riots.

4.1.4. *Initial evaluation of net food production as potential indicator for food riots*

As reported in Chapter 2, another main driver of food riots is believed to be the level of food security in countries. Countries that are reliant on the international food market to source the part of national food demand that they cannot meet internally are more likely to experience food riots when the international price of food increases, as they are more exposed to the higher prices (Lagi, et al., 2011). To test this hypothesis, the WGI was used in conjunction with a measure of national self-sufficiency for food availability (and hence as a measure of national reliance on the international food market) to evaluate the contribution of food security to the occurrence of food riots.

To carry out this analysis, the countries were divided into categories of political fragility. As the WB does not provide categories of fragility for the WGI, these were calculated as equal intervals based on the range of the fragility scores for the whole period of analysis and sorted in a decreasing order of fragility, i.e. the first category is the most fragile and the last the least fragile. Countries were further divided in two categories, according to their net food production throughout the years: (i) countries with positive net production of food (net food exporters, self-sufficient countries); and (ii) countries with negative net production of food (net food importers, not self-sufficient countries). Net food production was calculated as the difference between countries' national food production and consumption using the variables Food Production (1000 MT) and Food Consumption (1000 MT) sourced from the GRO database (GSI, 2014). The following countries were excluded from this analysis due to missing data for food production/consumption: French Guiana, Réunion, Martinique, Taiwan (China), Nauru, Netherland Antilles and Anguilla.

Similarly to the measure of accuracy computed in the previous section, this test calculated the proportion of countries that experienced a food riot as compared to the number of countries in each category of fragility for the WGI. This was done for both categories of food availability, for every year when a food riot was recorded, i.e. 2004, 2006, 2007, 2009, 2010 when the index was used as predictor and 2005, 2007, 2008, 2010, 2011 when used as descriptor. An example is provided in Table 4.6. For instance, a measure of 50% in the first quartile of the WGI for countries with negative net food production implies that half of the countries included in the first category of the WGI that were net food importers experienced a food riot in that year.

WGI Proportions of Food Riots in 2008				
Categories	**1st**	**2nd**	**3rd**	**4th**
WGI as predictor				
Net food importers	67%	21%	13%	0%
Net food exporters	40%	24%	5%	0%
WGI as descriptor				
Net food importers	50%	27%	13%	0%

Net food exporters	33%	29%	4%	0%

Table 4.6 - Proportions of net food importers/exporters that experienced food riots divided in categories of fragility for the WGI in 2008 (adapted from Natalini, et al., 2015b).

To provide an approximate estimate for the whole period, the proportion of the countries belonging to each category of food availability and to each category of fragility that experienced a food riot were averaged across the reference period of the analysis. The results are presented in Table 4.7 alongside the range, which is provided as a measure of dispersion of the results.

WGI Average Proportions of Food Riots				
Categories	**1st**	**2nd**	**3rd**	**4th**
WGI as predictor				
Net food importers	20%	6%	3%	1%
Range	0-67%	0-15%	0-13%	0-4%
Net food exporters	10%	7%	1%	0%
Range	0-25%	0-25%	0-5%	0-1%
WGI as descriptor				
Net food importers	10%	8%	4%	0%
Range	0-50%	0-22%	0-13%	0%
Net food exporters	8%	8%	2%	0%
Range	0-20%	0-30%	0-4%	0%

Table 4.7 - Average proportions of net food importers/exporters divided in categories of fragility for the WGI that experienced food riots (adapted from Natalini, et al., 2015b).

The results in Table 4.7 show a slightly higher accuracy of the WGI as predictor than as descriptor. Although net food importers registered a slightly higher rate of food riots than net food exporters, the range for the proportions for every category of fragility are large and indicate an extreme variability in the occurrence of food riots in either category of food availability. This makes it difficult to draw any conclusion from this analysis and it also implies that the occurrence of food riots was only marginally affected by national annual availability of food. This may be due to a number of different factors, including a higher degree of corruption, seasonal variation in the availability of food or lack of infrastructure in those fragile countries (see, for example, Bretthauer, 2014), that can all lead to inadequate distribution of food within countries, which might not show in annual variables such as the ones used in this analysis. In conclusion, this analysis suggests that annual food availability within a country is not a reliable indicator for food riots alongside the condition of being an existing fragile state.

4.1.5. Formal quantitative test to validate previous results

To validate the previous indicative analyses and their conclusions on the threshold for the FAO FPI, on the WGI as best indicator to capture food riots and on the national availability of food not being a reliable indicator of food riots alongside national political fragility, a more formal statistical approach was implemented. This was possible because, notwithstanding the low number of food riots used in this analysis, data for the WGI and for the variables used to derive countries' net food production presented very few missing values. The method selected was HZ using a Cox PH regression model. In the case of this research, the events were the food riots, and the time variable introduced in the HZ recorded the months during which the monthly, deflated FAO FPI was above the 148 monthly threshold as calculated with the RE model in Section 4.1.2. Throughout the time frame considered for this study, i.e. 2005–2011, there were in total 32 non-continuous months above the threshold: i) September 2007–September 2008; ii) November–December 2009; iii) August 2010–December 2011. The covariates tested were the national political fragility of countries as represented by the WGI and countries' net food production as proxy for national availability of food. The variable net food production was recoded in a binary variable which equalled 0 for countries that were net food importers, i.e. countries with negative net food production, and 1 if net food exporters, i.e. countries with positive net food production.

Since the majority of food riots recorded in the database were concentrated in the period September 2007–September 2008, i.e. 19 events, this was used as reference period for the analysis. In line with the standard use of HZ, countries were right-censored as they experienced a food riot, i.e. if a country experienced a food riot in June 2008, its observations were only included in the database for the first ten months. Countries that experienced more than one food riot during the period of analysis were hence only counted once. Since the time frame selected was in between the years 2007 and 2008 and the variables used as covariates were annual estimates, the model used an average estimate for the WGI for each country and data for 2008 to calculate national net food production. This last choice was due to inconsistencies in data for the variables used for the calculations between the two years.

Table 4.8 shows the results from the HZ, which remarkably confirm the findings from the previous sections. Although the availability of food in a country has a negative impact on the occurrence of food riots, this relationship is not significant. Conversely, the relationship between WGI and food riots is positive and highly significant: for every unit increase in the WGI estimate, i.e. higher political fragility of countries, the likelihood of experiencing a food riot increases on average by a factor of 2.75. The Concordance Index provides a very positive result as any value above 0.5 for this index implies a good ability of the covariates at predicting the observed data. The other measures of goodness of fit, i.e. Wald, likelihood ratio and score (log rank), are significant, which means that the null hypothesis that the betas equal 0 can be rejected with 95% confidence.

Covariates	**Regression Coefficient**	**Exponentiated Coefficient**	**Standard Error (Coef)**	**Robust Standard Error**	**z**	**p-value**
Net food production (2008)	−0.1286	0.8793	0.4807	0.4690	−0.274	0.784
WGI average (2007/2008)	1.0103	2.7465	0.2066	0.1543	6.548	$5.83e^{-11}$ ***

Notes: N = 202; number of events = 18 (9 observations deleted because they were missing); concordance = 0.826 (se 0.069); R-squared = 0.114 (max possible = 0.609); likelihood ratio test = 24.44 on 2 df; p = $4.92e^{-06}$; Wald test = 46.59 on 2 df; p = $7.626e^{-07}$; score (log rank) test = 29.91 on 2 df; p = $3.206e^{-07}$; robust = 12.77, p = 0.001688; Sig. codes: 0 '***'; 0.001 '**'; 0.01 '*'; 0.05 '.'; 0.1 ' '.

Table 4.8 – Hazard model calculated on the months between 2007 and 2008 when the monthly, deflated FAO FPI was above the threshold of 148 using countries' reliance on the international food market and national WGI as covariates (adapted from Natalini, et al., 2015b).

To further examine the effect of WGI estimates for a country on the probability of that country to experience a food riot when the FAO FPI is above the 148 monthly threshold, the hazard ratios were calculated assuming the relationship between WGI and food riots as linear. These are plotted in Figure 4.5.

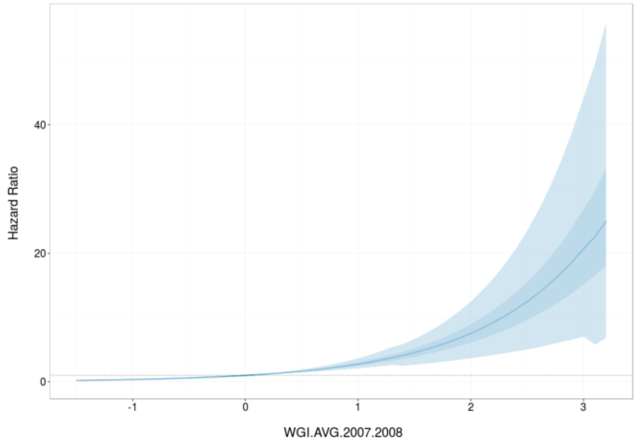

Figure 4.5 – Plot of the hazard ratios for the hazard model on the 2007-2008 period of analysis, where the hazard ratios are plotted on the y-axis and the covariates on the x-axis. Note that the plot was generated taking into account both covariates. Since Net food production 2008 is not significant, the whole impact on the occurrence of food riots can be attributed to the WGI alone. The shaded areas represent the σ and 2σ probability intervals, respectively (Natalini, et al., 2015b).

As Figure 4.5 shows, countries that are more politically fragile have a relatively higher probability of experiencing food riots than those that are less politically fragile. For instance, Somalia, who had an average WGI of 3.28 in the years 2007–2008, was around 21-times more likely to experience a food riot than Malawi, whose average WGI was 0.00. This estimate was calculated by evaluating the maximum likelihood equation provided by the model with $x = 3.28$.

4.1.6. Proportion of food riots for different WGI categories when FAO FPI is above the threshold

This section aims at bringing together findings on the threshold for the FAO FPI and on the accuracy of the WGI by calculating the average proportions of countries that experienced a food riot for each category of fragility as determined by the WGI for the years when the international price of food was above the threshold. This was only done for the annual versions of the FAO FPI as the WB does not provide monthly data for the fragility of the countries.

The selection of the years when the FAO FPI was above the annual threshold incurred another methodological challenge: by using the threshold on the nominal value of the FAO FPI, the years above the threshold during the timeframe considered in this study were two, 2008 and 2011, whereas using the deflated version of the index the years above the threshold were three, 2008, 2010 and 2011. Tables 4.9 and 4.10 present the proportions of food riot for each category of the WGI when the price was above the threshold for the nominal and deflated versions of the FAO FPI, respectively. Both tables provide the range for each figure as a measure of dispersion of the results.

	WGI classes of fragility			
Categories	**1st**	**2nd**	**3rd**	**4th**
Proportions of food riots	37%	18%	5%	0%
Range	33-40%	8-28%	2-8%	0%

Table 4.9 - Average proportions of food riots for the categories of the WGI when the FAO FPI was above the 200 threshold on the annual, nominal version of the FAO FPI (adapted from Natalini, et al., 2015b).

	WGI classes of fragility			
Categories	**1st**	**2nd**	**3rd**	**4th**
Proportions of food riots	24%	12%	4%	0%
Range	0-40%	0-28%	1-8%	0%

Table 4.10 - Average proportions of food riots for the categories of the WGI when the FAO FPI was above the 140 threshold on the annual, deflated version of the FAO FPI (own elaboration).

Both tables show a clear trend: the proportions decrease alongside the decrease in fragility. The proportions in from Table 4.9 are higher than those reported in Table 4.10 and, in addition, the range of the results from the first table are rather narrow, which denotes a clear trend in the relationship between these two variables and a high confidence in these results. This is due to the fact that the years taken into account to generate this table, i.e. 2008 and 2011, were the years when the largest number of food riots was recorded.

In Table 4.10 the inclusion of 2010, which only recorded one food riot during the timespan and geographical area considered in this analysis, resulted in a considerable increase in the range of the figures. This brings into question the validity of these results and of the method implemented for this analysis.

Finally, it is worth noting that fragility is not confined to the most fragile categories, but also relatively politically stable countries that fall in the third category can still experience violent events under specific circumstances.

However promising and interesting the findings presented in the previous sections may be, this analysis presented several methodological issues. In particular, the very low number of food riots recorded in the database used poses questions about the reliability of the results from the statistical models that have been implemented. In addition, the different proportions for the categories of the WGI obtained using either the threshold on the nominal or deflated versions of the FAO FPI called for further investigation.

4.1.7. An updated analysis on food riots

Following the mixed and sometimes contradictory results provided by the initial analysis on food riots, this was replicated on a larger database. By extending time- and geography-wise the scope of the analysis more food riots were included in the analysis, which provided more robust and confident results that remarkably confirmed those from the initial analysis. In addition, the new version of the database also included updated data for food production and consumption for countries, always sourced from the GRO database (GSI, 2015) and for the WGI estimates, sourced from the WB (WB, 2015c). This larger database was used to rerun the statistical tests presented in the previous sections. The analysis was also extended to include further statistical tests to operationalise the results and include them in the Food and integrated Food and Fuel ABMs.

4.1.7.1. An updated database of food riots

This updated analysis now included a reference period of 9 years, i.e. 2005 –2013, and the geographical area was extended to the whole world. This was done also to include the observations from a key database on food riots created by the WB Food Price Observatory programme, i.e. Food Riot Radar (WB, 2015a). The previous version of the food riot database and the Food Riot Radar database presented some inconsistencies. Although the same definition of food riots was used to collect data, the database included some food riots that weren't captured by the Food Riot Radar database. For this reason, it was updated to include all the records from the WB's database, but also a new keyword Internet search was performed following the same methodology reported in Section 4.1.1. The final version of the database for food riots presented in Appendix 1 included more records than the Food Riot Radar database.

Each year therefore experienced the following number of food riots: 2005 (1), 2007 (3), 2008 (27), 2009 (1), 2010 (3), 2011 (11), 2012 (4), 2013 (2) that amounted to a total of 52 food riots, with 2008 and 2011 as the years that saw the highest number of food riots throughout the period considered. This update added 21 records to the previous database.

4.1.7.2. An updated threshold for the FAO FPI

To overcome the discrepancy obtained in the previous section while selecting the years above the FAO FPI threshold, from here on the analysis was focused exclusively on the deflated version of the FAO FPI. This is justified by the fact that the deflated version is purified from the effect of inflation and other short-term price dynamics. In addition, the analysis on the FAO FPI threshold only focused on annual estimates to simplify the analysis and to allow for consistency between different parts of the analysis.

The same RE model presented in Section 4.1.2 was fit to the new database over the timeframe 2005 – 2013. During this time period new countries formed: Montenegro gained independence in 2006, Kosovo in 2008 and South Sudan in 2011. These three countries have been included in the database from the year following their independence because of the better reliability of annual data. As found by Natalini, et al. (2015a) the maximum likelihood estimations resulted in a highly significant positive coefficient for the deflated FAO FPI (Table 4.11). Applying Equation 4.1 the new annual threshold on the deflated version of the FAO FPI above which countries start to experience food riots was found at 140, slightly lower than the one found in the previous analysis, but, due to the larger database used, more accurate.

	Estimate	**SE**	***t*-value**	***p*-value**
(Intercept)	-11.689	1.785	-6.549	$5.79e^{-11}$***
FAO FPI deflated	0.051	0.011	4.526	$6.02e^{-06}$***
σ	1.524	0.397	3.842	0.000***
Log-Likelihood	-217.185			

Table 4.11 - Random effects logit regression model estimates (Natalini, et al., 2015a). Sig. codes: 0 '***'; 0.001 '**'; 0.01 '*'; 0.05 '.'; 0.1 ' '.

4.1.7.3. An updated formal test for the relationship between WGI, import/export and food riots

The results from the Cox PH analysis was updated as well fitting the same model presented in Section 4.1.5 to the new data. The periods when the deflated version of the FAO FPI was above the 140 threshold were the following: i) August 2007 – September 2008 that corresponds to 14 months and 28 food riots (although India and Peru experienced more than one food riot during this timeframe, only the first riot occurred in either country was accounted for and data after that was right-censored as is standard practice in HZ models); ii) November 2009 – February 2010 that corresponds to 4 months and no food riots; iii) July 2010 – November 2014. Since this timeframe goes beyond the period considered for this analysis, only the period July 2010 – December 2013 was considered. This corresponds to 42 months and 20 food riots. This analysis focused on the periods 2007-2008 and 2010-2013 as these were the only timeframes when the FAO FPI was above the threshold and food riots were recorded.

Differently from Natalini, et al. (2015b) and from the analysis reported in Section 4.1.5, this update used national data from the first year, i.e. 2007 and 2010 for the first and second period above the price threshold respectively, rather than data averaged for the two (or more) years, as this is more common practice in the use of HZ. In addition, this updated analysis provides the controls to check whether the covariates meet the assumption of proportionality required by the Cox PH model, which was tested using the cox.zph() function (Grambsch and Therneau, 1994) provided with the survival package for R (Therneau and Lumley, 2016) based on weighted residuals. This control tests the null hypothesis $H_0\colon \beta = 0$ that the covariates included in the model do not meet the assumption of proportionality. The test was run with the argument *global* = *True*, which also tests whether the model as a whole meets the proportionality of hazard assumption. The results of this test for both covariates are presented in Table 4.12 for the first period and in Table 4.13 for the last period considered in this analysis.

Covariates	$\boldsymbol{\rho}$	$\mathbf{X^2}$	**p-value**
Importer/exporter 2007	0.014	0.005	0.942
WGI 2007	0.361	1.948	0.163
Global	NA	1.973	0.373

Table 4.12 – Test for the proportionality of the hazards for the covariates included in the Cox model for the period 2007-2008 (own elaboration). Sig. codes: 0 ‘***’; 0.001 ‘**’; 0.01 ‘*’; 0.05 ‘.’; 0.1 ‘ ’.

Covariates	ρ	X^2	**p-value**
Importer/exporter 2010	-0.123	0.295	0.587
WGI 2010	0.061	0.055	0.815
Global	NA	0.416	0.812

Table 4.13 – Test for the proportionality of the hazards for the covariates included in the Cox model for the period 2010-2013 (own elaboration). Sig. codes: 0 ‘***’; 0.001 ‘**’; 0.01 ‘*’; 0.05 ‘.’; 0.1 ‘ ’.

As the tables above clearly show, both the p-value for the single covariates and for the model as a whole are > 0.05. This is true for both periods considered in this analysis. Therefore, the null hypothesis of the hazards for the covariates not being proportional can be confidently rejected and the alternative hypothesis of the proportionality of the hazards for the covariate is accepted.

Having ensured that the covariates met the assumptions of the Cox PH model, the models could be fit to the data for both periods when the FAO FPI was above the 140 threshold. The results for the models are reported in Table 4.14 for the period 2007-2008 and in Table 4.15 for the period 2010-2013.

Covariates	**Regression Coefficient**	**Exponentiated Coefficient**	**Standard Error (Coef)**	**Robust Standard Error**	**z**	**p-value**
Importer/exporter 2007	-0.3983	0.6715	0.3929	0.3823	-1.042	0.297
WGI 2007	0.8614	2.3664	0.1628	0.1338	6.436	$1.23e^{-10}$***

Notes: N = 202; number of events = 27 (9 observations deleted because they were missing); concordance = 0.796 (se 0.057); R-squared = 0.129 (max possible = 0.754); likelihood ratio test = 27.82 on 2 df; $p = 9.111e^{-07}$; Wald test = 45.95 on 2 df; $p = 1.055e^{-10}$; score (log rank) test = 33.38 on 2 df; $p = 5.633e^{-08}$; robust = 17.62, p = 0.0001492; Sig. codes: 0 ‘***’; 0.001 ‘**’; 0.01 ‘*’; 0.05 ‘.’; 0.1 ‘ ’.

Table 4.14 – Hazard model on the period August 2007 – September 2008 when the deflated version of the FAO FPI was above the 140 threshold using whether the countries were net importers/exporters and WGI as covariates (own elaboration).

Covariates	**Regression Coefficient**	**Exponentiated Coefficient**	**Standard Error (Coef)**	**Robust Standard Error**	**z**	**p-value**

Importer/exporter 2010	-0.3206	0.7257	0.4554	0.4545	-0.706	0.48
WGI 2010	0.9427	2.5669	0.2106	0.1897	4.970	$6.71e^{-07}$***

Notes: N = 204; number of events = 20 (8 observations deleted because they were missing); concordance = 0.769 (se 0.065); R-squared = 0.099 (max possible = 0.644); likelihood ratio test = 21.18 on 2 df; $p = 2.513e^{-05}$; Wald test = 27.67 on 2 df; $p = 9.809e^{-07}$; score (log rank) test = 24.31 on 2 df; $p = 5.249e^{-06}$; robust = 10.62, $p = 0.004935$; Sig. codes: 0 '***'; 0.001 '**'; 0.01 '*'; 0.05 '.'; 0.1 ' '.

Table 4.15 – Hazard model on the period July 2010 – December 2013 when the deflated version of the FAO FPI was above the 140 threshold using whether the countries were net importers/exporters and WGI as covariates (adapted from Natalini, et al., 2015a).

The results from the HZ model were very similar for both periods and were consistent with those found by Natalini, et al. (2015b). Although the relationship between being a net food exporter and food riot was negative, this was not significant. Conversely, even with a longer period of analysis and a larger food riots database, higher levels of political fragility positively and significantly affect the probability of food riots in countries. In particular, according to the exponentiated coefficients for the covariate in both periods, any unit increase in the WGI of a country more than doubles the probability of that country to experience a food riot. As for the tests provided with the Cox model, the Concordance Index provided a very positive result as any value above 0.5 for this index implies a good ability of the covariates at predicting the observed data. The other measures of goodness of fit, i.e. Wald, likelihood ratio and score (log rank), were significant, which means that the null hypothesis that the betas equal 0 can be rejected with 95% confidence.

To further examine the effect of WGI estimates for a country on the probability of that country to experience a food riot when the FAO FPI is above the 140 annual threshold, the hazard ratios were calculated. These are plotted in Figure 4.6 and Figure 4.7 for the 2007-2008 and 2010-2013 periods, respectively.

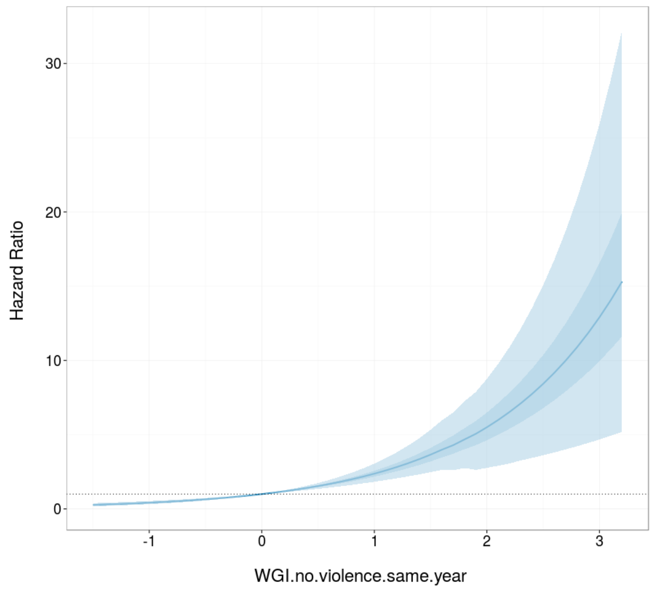

Figure 4.6 – Plot of the hazard ratios for the hazard model on the 2007-2008 period of analysis, where the hazard ratios are plotted on the y-axis and the covariates on the x-axis. Note that the plot was generated taking into account both covariates. Since Importer/Exporter 2007 is not significant, the whole impact on the occurrence of food riots can be attributed to the WGI alone. The shaded areas represent the σ and 2σ probability intervals, respectively (own elaboration).

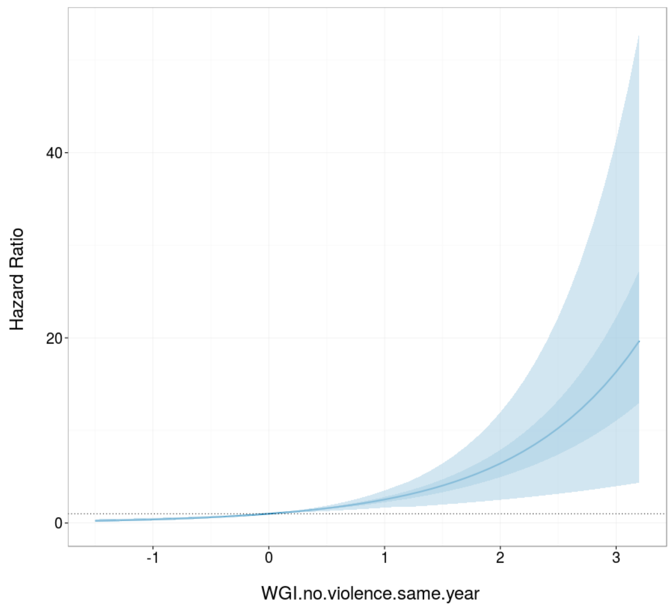

Figure 4.7 – Plot of the hazard ratios for the hazard model on the 2010-2013 period of analysis, where the hazard ratios are plotted on the y-axis and the covariates on the x-axis. Note that the plot was generated taking into account both covariates. Since Importer/Exporter 2010 is not significant, the whole impact on the occurrence of food

riots can be attributed to the WGI alone. The shaded areas represent the σ and 2σ probability intervals, respectively (Natalini, et al., 2015a).

As Figures 4.6 and 4.7 show, countries that are more politically fragile have a relatively higher probability of experiencing food riots than those that are less politically fragile. Following these results, the WGI was selected as the preferred method to simulate countries' political fragility for the other parts of this analysis and in the ABMs.

4.1.7.4. Selection of a method to implement food riots probabilities in the Food and integrated Food and Fuel versions of the ABM

This section aims at operationalising the findings reported so far. Once tested the influence of the international price of food and national political fragility on the occurrence of food riots, this information needed to be translated in a functional probability for each variable that would subsequently be included in the ABMs. This could have been done with different methods, whose applicability was comparable, but whose accuracy and practicality differed greatly. For this reason two different methods were implemented and their accuracy at predicting food riots was compared to finally select one. The selected method was then implemented in the Food and Food and Fuel ABMs to calculate the probability for each country to experience a food riot. Since this whole analysis was repeated to parameterise fuel riots and subsequently operationalise the findings and implement them in the Fuel and Food and Fuel ABMs, consistency between the two analyses was critical. The method selected needed to be the same for food and fuel riots and the integrated analysis, which is why the final choice will be made in the Discussion Section of this chapter.

The methods selected for the comparison were: i) RE and ii) REEM. Both methods used a binary variable that recorded whether each country experienced a food riot in a given year as dependent and two new independent variables: one binary variable that modelled the international price of food through two regimes, i.e. above/below the threshold, by classifying each year as either below or above the 140 threshold for the FAO FPI and an ordinal scale variable that assigned each country to one of four homogenous categories of fragility according to their WGI estimate for each year. These categories were calculated by computing homogenous breaks for the WGI estimates using the whole range of possible estimates given by the index for the whole period, i.e. 2005 – 2013. The categories were arbitrarily called: high fragility; medium-high fragility; medium-low fragility; low fragility. Although, as it will be shown below, the original independent variables for the FAO FPI and WGI used in their continuous form generated better predictions for the probability of food riots, these were translated in discrete variables because of how these variables are modelled in the ABMs. In line with the modelling approach, the ABMs were structured to be kept as simple as possible, although still able to reproduce some of the dynamics that lead to the occurrence of food riots. International price of food and national political fragility are amongst these and hence needed to be included in the models. However, since both the variables that capture this information, i.e. FAO FPI and WGI, depend on complex dynamics themselves, which were not necessarily the aim of this research, the dynamics that lead to international food price fluctuations and change in countries' political fragility were not modelled or only modelled partially. This means that the figures for these variables generated by the ABMs would be inaccurate estimates. To avoid the provision of specific figures that would be meaningless, it was preferred to provide classes for each of the variables, hence reducing the possibility of error.

Firstly, a RE model (M1) using the continuous versions of the FAO FPI and of the WGI tested these variables' influence on the dependent variable Food Riots. The results presented in Table 4.16 show that both variables have a positive, significant influence on the occurrence of food riots in countries and the accuracy of this model at predicting food riots was used as a baseline to show the loss of information due to the transformation of the independent variables from continuous to discrete.

	Estimate	**SE**	***t*-value**	***p*-value**
(Intercept)	$-1.189e^{01}$	1.786	-6.658	$2.79e^{-11}$***
FAO FPI deflated	$5.153e^{-02}$	$1.132e^{-02}$	4.551	$5.35e^{-06}$***
WGI	1.070	$1.421e^{-01}$	7.528	$5.14e^{-14}$***
σ	$3.190e^{-11}$	$7.342e^{-01}$	3.842	1
Log-Likelihood	-187.2191			

Table 4.16 – Results for RE model M1 with FAO FPI and WGI included as continuous variables used as baseline for comparison with other models (own elaboration). Sig. codes: 0 '***'; 0.001 '**'; 0.01 '*'; 0.05 '.'; 0.1 ' '.

Secondly, another RE model (M2) was developed using the discrete versions of the two independent variables. The results presented in Table 4.17 show that the variables, even in their discrete version have a significant influence on the occurrence of food riots in countries. As expected, each class of fragility has a positive influence on the occurrence of food riots, which is stronger as the fragility of the classes – and hence of the countries belonging to each class – increases. This can be noted by the increasing values of the estimates, i.e. the β, for each class. In addition, this model provides a comparison of the significance between the classes of each variable using the below-the-threshold price regime for the FAO FPI and the low-fragility category for the WGI as benchmarks. The model results highlight a significant difference for all the categories included in each variable from the respective benchmark. Therefore, this model was selected and its accuracy compared with a REEM model using the same variables.

	Estimate	**SE**	***t*-value**	***p*-value**
(Intercept)	-7.250	$8.246e^{-01}$	-8.792	$< 2e^{-16}$***
FAO FPI regime	1.975	$4.759e^{-01}$	4.150	$3.33e^{-05}$***
Medium-low WGI	2.142	$7.484e^{-01}$	2.862	0.004213**
Medium-high WGI	2.886	$7.443e^{-01}$	3.878	0.000105***
High WGI	3.653	$7.874e^{-01}$	4.639	$3.49e^{-06}$***
σ	$-6.854e^{-12}$	1.475	0	1
Log-Likelihood	-196.2663			

Table 4.17 – RE model M2 with discrete variables for FAO FPI threshold and WGI categories (own elaboration). Sig. codes: 0 '***'; 0.001 '**'; 0.01 '*'; 0.05 '.'; 0.1 ' '.

Subsequently, a REEM model was fit to the data using the variable food riots as dependent and the discrete variables for FAO FPI and WGI as independent to find different 'paths' or combinations of values that lead to different probabilities of food riots for countries. The continuous variables were not tested with this method as the algorithm would have identified splits in the variables, hence leading to discrete variables. The results of the model are presented in Figure 4.8.

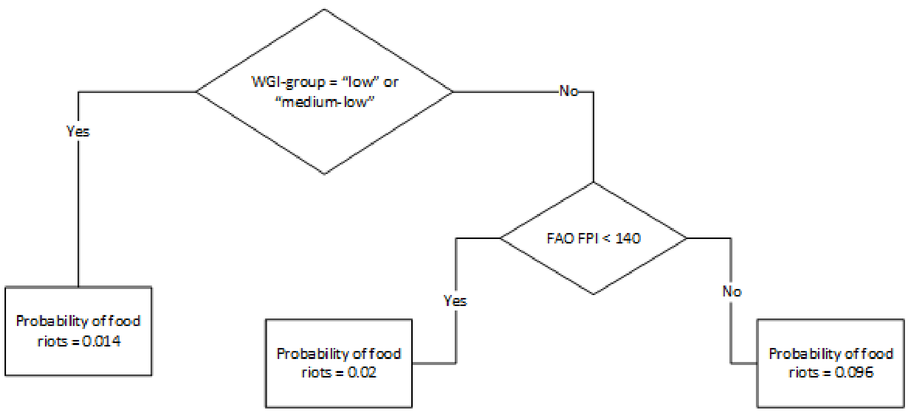

Figure 4.8 – REEM model with discrete variables for FAO FPI threshold and WGI categories (adapted from Natalini, et al., 2015a). Notes: n = 1904; intercept = 0.0001082515; Estimated variance of errors = 0.0251652781120792; Log likelihood = 789.545285468834.

REEM models only return leaf nodes that are statistically significant (Sela and Simonoff, 2012). Positively, the structure of the tree looks very simple, splitting on both variables and identifying only three 'paths' that lead to different probabilities of food riots for countries. In particular, countries belonging to low or medium-low category of fragility for the WGI will have the same probability of experiencing a food riot independently from the FAO FPI regime. This only significantly affects the probability of food riots for the countries belonging to the categories with higher levels of fragility as defined by the WGI. Interestingly, the splits calculated by the REEM model suggest that the variable WGI that was arbitrarily split in four categories with different levels of fragility could potentially be split in only two classes, as far as the probability of food riots for countries is concerned. This is different from the results of the model M2, which suggest that each category of the WGI is significantly different from the benchmark 'low' fragility.

The accuracy of these three models was compared alongside model M0, which always predicts 0 for the variable Food Riot. In addition, two versions of the model REEM were tested, one without RE (REEM) and another which included them (REEMre). The random effects estimated for each country were extracted with the function ranef () of the R package REEMtree (Sela and Simonoff, 2011). The accuracy of the models was tested by running 1000 iteration of an R script which generated predictions on whether each country included in the full database would have experienced a food riot according to the likelihood functions generated by each model for each year and compared them with the database on reported food riots. The script recorded for every run and for every model the percentage of food riots correctly predicted out of the total number of food riots occurred, i.e. comparison of only the 1s included in the variable food riot, and the percentage of records correctly predicted out of the total number of records present in the database, i.e. comparison of both 0s and 1s in the variable food riot. The records that presented missing values in any of the variables of interest were omitted from the database used for the comparison. Because of the variability built in the predictions generated by each model, each of the 1000 iterations was slightly different and the mean for both percentages was calculated. Table 4.18 presents the mean percentages of correctly predicted food riots and correctly predicted records for each model.

Models	Food riots predicted	Total correct
M0	0	97.21%
M1	13.59%	94.92%
M2	53.90%	79.46%
REEM	5.61%	94.81%
REEMre	6.39%	94.83%

Table 4.18 – Results of the accuracy test for the different models evaluated in this analysis. The second column reports the mean of the percentage of food riots correctly predicted by each model throughout the 1000 iterations, whereas the third column reports the mean of the percentage of any record, i.e. food riot yes or no, correctly predicted by each model throughout the 1000 iterations (own elaboration).

Table 4.18 clearly shows that model M1 was overall the most accurate by predicting the largest percentage of records, i.e. both whether countries experienced or did not experience a food riot. Model M2 was the most accurate at predicting food riots, despite losing accuracy in the percentage of total records correctly predicted. This is probably due to the fact that Model M2 simply attributed to countries a high probability of experiencing a food riot, hence increasing the number of false positives, i.e. countries that were predicted to experience a food riot according to the likelihood function generated by the model, but did not in reality. REEM models maintain a total accuracy comparable to that of M1, although underestimating the probability of food riots. Once RE for each country are added to the predictions of the model, i.e. REEMre model, the accuracy at predicting food riots increases by almost 1%.

4.2. Parameterising the fuel system and the dynamics that lead to fuel riots

As discussed in Chapter 2, research on riots related to oil and other energy resources is absent to the best of my knowledge. However, this type of events does happen, as testified by the several online newspaper articles that report the occurrence of the so-called ‘fuel riots’.

Due to this lack of academic knowledge, the approach taken by this thesis was to test whether the same dynamics that are true for food riots also apply to fuel riots. Since the previous sections already identified the WGI as the index of political fragility most accurate at capturing riots, the analysis on fuel riots only used this.

4.2.1. Compiling a database for fuel riots

Similarly to the analysis on food riots, the aim of this analysis was to evaluate if and how scarcity of fuel, international fuel prices and national political fragility impact the occurrence of fuel riots in countries. As mentioned in Chapter 2.7.1, the Collins English Dictionary defines as 'fuel' 'every conventional non-renewable energy resource' (Collins, 2016). Following this definition, this research included coal, natural gas and oil as the energy resources to be modelled. Although fuel riots have been occurring until recently, this analysis focused on the period between 2005 and 2013 to provide results comparable to those from the analysis on food riots. Due to the lack of research and academic literature in the field, no databases on fuel riots were available at the time when this thesis was being written. For this reason, the same methodology used for food riots was implemented to collect data on fuel riots. A database of monthly fuel riots that occurred anywhere in the world during the period between 2005 and 2013 was created. The definition of fuel riots used to collect data was provided in Chapter 2.7.1. Data collection followed the same process as for food riots and a table summarising the fuel riots included can be found in Appendix 2.

Each year experienced the following number of fuel riots: 2005 (2), 2006 (2), 2007 (2), 2008 (13), 2010 (4), 2011 (8), 2012 (4), 2013 (9) that amounted to a total of 44 fuel riots and 2008, 2011 and 2013 as the years that saw the highest number of fuel riots throughout the period considered.

4.2.2. A threshold for the international price of fuel

This section presents tests on the relationship between the international price of fuel and the occurrence of fuel riots, in particular trying to identify the presence of a threshold for the international price of fuel over which fuel riots are more likely to occur. Although fuel riots, as explained in previous section, can relate to any energy resource, only the relationship between the international price of crude oil and the occurrence of fuel riots was evaluated in this thesis. This decision was due to different reasons: firstly, oil is the only energy resource for which an international market has fully developed. The international trade of natural gas is mostly 'continental', i.e. traded within continents, because of storage and transportation challenges (Davoust, 2008; Phillips and Natalini, TBP) with prices that vary greatly between different markets (Davoust, 2008) and although evidence of an international market for coal was found (Ellerman, 1995), this finding has been challenged for more recent data (Wårell, 2006). In addition, most of the coal produced is mainly consumed in the same country where it is produced, with international trade accounting for only 15% of coal consumption worldwide in 2012 (US EIA, 2016); secondly, most of the analyses on price behaviours of energy resources focused on US prices due to the high availability of data and long time-series for this country (see for example Pindyck, 1999; Serletis and Xu, 2016), which makes it challenging to draw conclusions on the relationships between the different energy sources at the international level. However, it is common knowledge that the prices of coal, natural gas and oil are correlated, at least at the national level (see for example Serletis and Xu, 2016) with evidence that markets of crude oil, coal, and natural gas are cointegrated in the long run in the US (Bachmeier and Griffin, 2006) and UK (Asche, et al., 2006). In particular, there is evidence of an indirect link between prices of natural gas and crude oil in the US (Hartley, et al., 2008). Because oil is the only energy resource with a real international market and international price and retains the world's largest share of total primary energy supply (IEA, 2016), only its international price was evaluated as potential cause of fuel riots. However, to allow future versions of the ABM to implement prices for the other energy resources, production and consumption dynamics for natural gas and coal are included in the Food and Fuel ABM.

Data for the international price of crude oil was sourced from the US Energy Information Administration (EIA) (US EIA, 2015b). EIA provides free to use time series for crude oil spot prices for the two main international hubs where crude oil is exchanged and which are used as benchmarks for the international price of crude oil, one based in the US and one in Europe: Cushing, Oklahoma (WTI) and Brent, London (Brent). Although the prices recorded for the two benchmarks slightly differ, research found that the international market for crude oil is highly globalised and the two benchmark prices tend to move together (Hammoudeh, et al., 2008; Reboredo, 2011). For this reason, the fuel price used as independent variable in this analysis (hereafter called EIA fuel price) was the simple average between the two benchmark prices.

The relationship between the international price of fuel and fuel riots can already be seen in Figure 4.9, which plots the EIA fuel price (blue line) against the number of fuel riots recorded in the database (green columns). The Figure shows an evident increase in the number of violent fuel-related episodes for high levels of the EIA fuel price.

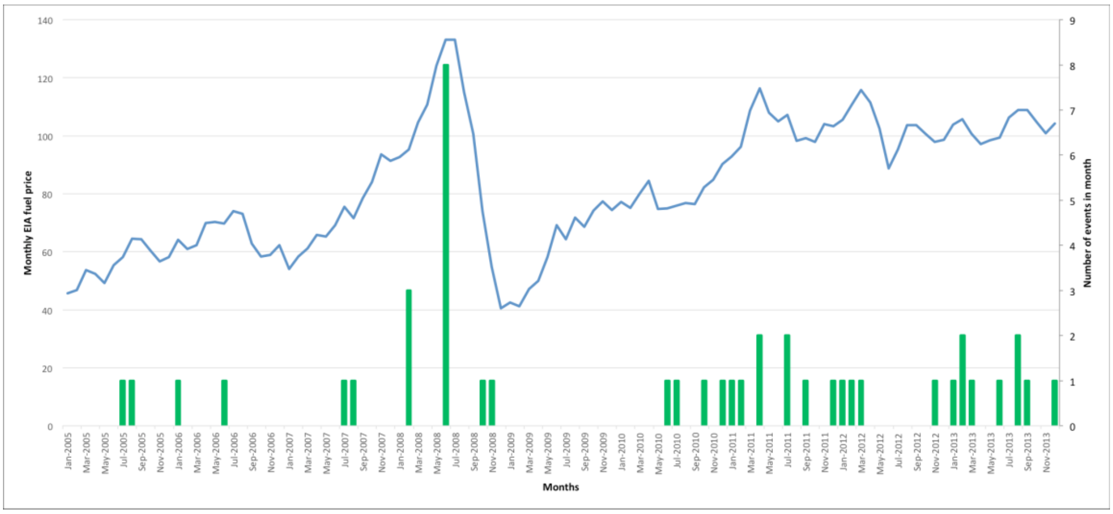

Figure 4.9 - The EIA fuel price between 2005 and 2013 (blue line) compared to the number of violent demonstrations that were associated with fuel over each month (green columns) (own elaboration).

An RE model for fuel riots was fit to the data for fuel following the procedure presented in the food riots section. The results are presented in Table 4.19.

	Estimate	**SE**	***t*-value**	***p*-value**
(Intercept)	− 8.847	1.175	− 7.530	$5.08e^{-14}$***
EIA fuel price	0.046	0.012	4.038	$5.39e^{-05}$***
σ	2.095	0.427	4.902	$9.47e^{-07}$***
Log-Likelihood	-182.48			

Table 4.19 - Random effects logit regression model estimates for EIA fuel price influence on the occurrence of fuel riots (own elaboration). Sig. codes: 0 '***'; 0.001 '**'; 0.01 '*'; 0.05 '.'; 0.1 ' '.

The maximum likelihood estimations resulted in a highly significant positive coefficient for the EIA fuel price, which provides initial evidence of a direct causal relationship between the increase in the international price of fuel and the occurrence of fuel riots. Similarly to the analysis on food riots, Equation 4.1 was implemented and the threshold for the EIA fuel price was found at $93 per barrel.

4.2.3. Testing the relationship between WGI, import/export and fuel riots

As for the analysis on food riots, the method selected to test the relationship between fuel scarcity, WGI and fuel riots was Cox PH. In this case, the events whose probability was being estimated were the fuel riots, and the time variable introduced in the HZ model recorded the months during which the monthly version of the EIA fuel price was above the $93 annual threshold. Throughout the time frame considered for this study, i.e. 2005–2013, there were in total 44 non-continuous months above the threshold: i) November 2007; ii) February–September 2008; iii) January 2011–May 2012 and iv) July 2012-December 2013.

The analysis focused only on the second, third and fourth period excluding the first, as this only involved one month and no fuel riots. In addition, the third and fourth periods were considered as a single continuous interval as they are divided by only one month, i.e. June 2012. This decision is justified by the fact that treating the two periods as a single interval allowed the model to run on three whole years, including 18 fuel riots (India and Indonesia experienced more than one fuel riot during this time frame and the records for these countries were right-censored after the first fuel riot they experienced as is standard practice in HZ models). Moreover, June 2012 fell below the threshold because of the averaging procedure implemented: the month recorded a price well above the threshold for the Brent spot price, whereas the WTI was below the threshold, resulting in an international price below the threshold when averaged. Therefore, two HZ models were fit to the data: one for the period February–September 2008, which included 11 fuel riots, and another for the period January 2011–December 2013, which included 18 fuel riots.

The model tested the effect of two covariates on the probability of the occurrence of fuel riots: the net oil production of countries, i.e. proxy for a country's reliance on the international oil market for the part of oil consumption that cannot be met internally, hence defining a country as either net importer or net exporter of oil, and the WGI. The variable net oil production consisted in the simple difference between the variables Total Petroleum Consumption (Thousand Barrels per day) and Total Oil Supply (Thousand Barrels Per Day) sourced from the GRO database (GSI, 2015) for each country, for each year and was recoded in a binary variable which equalled 0 for countries that were net oil importers and 1 if net oil exporters. The data used for the covariates related to the first year of each period that was analysed, i.e. 2008 and 2011 for the first and second period above the price threshold, respectively.

The results for the tests checking whether the covariates met the assumption of proportionality required by the Cox model for both covariates are presented in Table 4.20 for the first period and in Table 4.21 for the last period considered in this analysis.

Covariates	ρ	X^2	**p-value**
Importer/exporter 2008	-0.545	3.415	0.0646
WGI 2008	0.371	0.626	0.4289
Global	NA	3.619	0.1637

Table 4.20 – Test for the proportionality of the hazards for the covariates included in the Cox model for the period 2008 (own elaboration). Sig. codes: 0 '***'; 0.001 '**'; 0.01 '*'; 0.05 '.'; 0.1 ' '.

Covariates	ρ	X^2	**p-value**
Importer/exporter 2011	0.0661	0.069	0.793
WGI 2011	0.1245	0.174	0.677
Global	NA	0.231	0.891

Table 4.21 – Test for the proportionality of the hazards for the covariates included in the Cox model for the period 2011-2013 (own elaboration). Sig. codes: 0 '***'; 0.001 '**'; 0.01 '*'; 0.05 '.'; 0.1 ' '.

As the tables above clearly show, both the p-value for the single covariates and for the models as a whole are > 0.05, although the Imporer/Exporter covariate for the period 2008 is very close to the acceptance threshold. This is true for both periods considered in the analysis. Therefore, the null hypothesis of the hazards for the covariates not being proportional can be confidently rejected and the alternative hypothesis of the proportionality of the hazards for the covariates is accepted.

HZ models were then run on both periods when EIA fuel price was above the $93 threshold. The results are reported in Table 4.22 for the period 2008 and in Table 4.23 for the period 2011-2013.

Covariates	**Regression Coefficient**	**Exponentiated Coefficient**	**Standard Error (Coef)**	**Robust Standard Error**	**z**	**p-value**

Importer/exporter 2008	- 1.2115	0.2978	1.0577	1.0734	-1.129	0.259
WGI 2008	0.3524	1.4225	0.2727	0.2190	1.609	0.108

Notes: N = 202; number of events = 11 (9 observations deleted because they were missing); concordance = 0.661 (se 0 0.09); R-squared = 0.014 (max possible = 0.438); likelihood ratio test = 2.83 on 2 df; p = 0.2427; Wald test = 3.3 on 2 df; p = 0.1923; score (log rank) test = 2.73 on 2 df; p = 0.2555; robust = 2.92, p = 0.232; Sig. codes: 0 '***'; 0.001 '**'; 0.01 '*'; 0.05 '.'; 0.1 ' '.

Table 4.22 – Hazard model on the period February–September 2008 when the EIA fuel price was above the $93 threshold using whether the countries were net importers/exporters and WGI as covariates (own elaboration).

Covariates	**Regression Coefficient**	**Exponentiated Coefficient**	**Standard Error (Coef)**	**Robust Standard Error**	**z**	**p-value**
Importer/exporter 2011	- 0.071	0.932	0.531	0.484	-0.146	0.884
WGI 2011	0.960	2.611	0.218	0.193	4.978	$6.41e^{-07}$***

Notes: N = 205; number of events = 18 (8 observations deleted because they were missing); concordance = 0.787 (se 0.068); R-squared = 0.089 (max possible = 0.604); likelihood ratio test = 19.04 on 2 df; $p = 7.324e^{-05}$; Wald test = 24.97 on 2 df; $p = 3.778e^{-06}$; score (log rank) test = 21.61 on 2 df; $p = 2.025e^{-05}$; robust = 11.7, p = 0.00288; Sig. codes: 0 '***'; 0.001 '**'; 0.01 '*'; 0.05 '.'; 0.1 ' '.

Table 4.23 – Hazard model on the period January 2011 – December 2013 when the EIA fuel price was above the $93 threshold using whether the countries were net importers/exporters and WGI as covariates (own elaboration).

The results for the periods differed greatly. Although the HZ model for the 2008 period found a negative relationship between a country being a net importer or exporter of oil and fuel riots and a positive one between the WGI and fuel riots, neither of these were significant. This may be due to the fact that the period considered was shorter than that used for the other models and did not cover an entire year, i.e. only 9 months. Conversely, the results from the HZ model run on the second period, i.e. 2011 – 2013 were very positive and similar to those found in the analysis on food riots: the relationship between being a net oil exporter and fuel riots was not significant, conversely from WGI and fuel riots. In particular, according to the exponentiated coefficient for the covariate in the last period, any unit increase in the WGI of a country more than doubles the probability of that country to experience a fuel riot. As for the tests provided with the Cox Model, the results for the period 2008 are negative for all the tests presented. Conversely, those provided for the period 2011 – 2013 are positive: the Concordance Index provides a very positive result as any value above 0.5 for this index implies a good ability of the covariates at predicting the observed data. The other measures of goodness of fit, i.e. Wald, likelihood ratio and score (log rank) are significant, which means that the null hypothesis that the betas equal 0 can be rejected with 95% confidence. Figure 4.10 shows the hazard ratios for the period 2011 - 2013. Countries that are more politically fragile have a relatively higher probability of experiencing fuel riots than those that are less politically fragile. Following these results, the WGI was confirmed as accurate at capturing both food and fuel riots and hence was used as the preferred method to simulate countries' political fragility for the other parts of this analysis and in the ABMs.

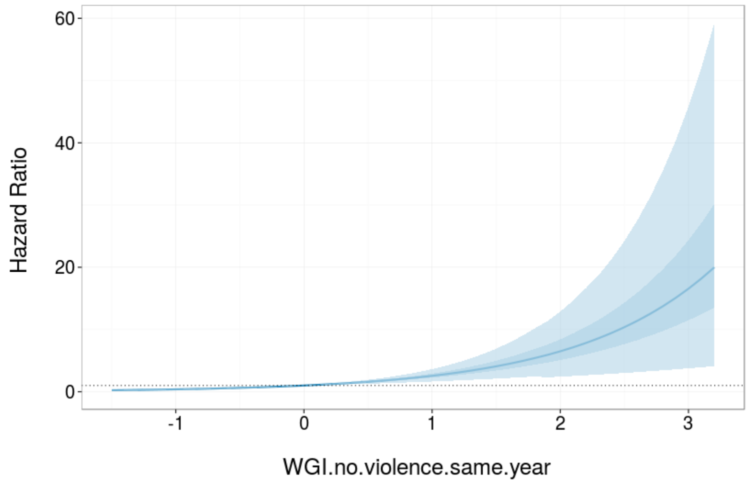

Figure 4.10 – Plot of the hazard ratios for the hazard model on the 2011-2013 period of analysis, where the hazard ratios are plotted on the y-axis and the covariates on the x-axis. Note that the plot was generated taking into account both covariates. Since Importer/Exporter 2011 is not significant, the whole impact on the occurrence of fuel riots can be attributed to the WGI alone. The shaded areas represent the σ and 2σ probability intervals, respectively (own elaboration).

4.2.4. Selection of a method to implement fuel riots probabilities in the fuel version of the ABM

This section aims at operationalising the findings reported in the previous sections on the analysis for fuel riots. To maintain consistency between the two analyses, the same methods evaluated for the analysis on food riots, i.e. RE and REEM, have been compared here evaluating their accuracy at predicting fuel riots to finally select one.

Both methods used a binary variable that recorded whether each country experienced a fuel riot in a given year as dependent and two new independent variables: one binary variable that modelled the international price of fuel through two regimes, i.e. above/below the threshold by classifying each year as either below or above the $93 threshold for the EIA fuel price and an ordinal scale variable for the four categories of the WGI. As for the analysis on food riots, the continuous versions of the independent variables for the EIA fuel price and WGI were compared with their discrete versions.

Firstly, a RE model (M1) using the continuous versions of the EIA fuel price and of the WGI tested these variables' influence on the dependent variable Fuel Riot. The results presented in Table 4.24 show that both variables have a positive, significant influence on the occurrence of fuel riots in countries and the accuracy of this model at predicting fuel riots was used as a baseline to show the loss of information due to the transformation of the independent variables from continuous to their discrete form.

	Estimate	**SE**	***t*-value**	***p*-value**
(Intercept)	-8.936	1.185	-7.543	$4.59e^{-14}$***
EIA fuel price	0.046	0.011	4.046	$5.21e^{-05}$***
WGI	0.851	0.204	4.170	$3.05e^{-05}$***
σ	1.789	0.413	-4.329	$1.50e^{-05}$***
Log-Likelihood	-171.4708			

Table 4.24 – Results for RE model M1 with EIA fuel price and WGI included as continuous variables used as baseline for comparison with other models (own elaboration). Sig. codes: 0 '***'; 0.001 '**'; 0.01 '*'; 0.05 '.'; 0.1 ' '.

Secondly, another RE model (M2) was developed using the discrete versions of the two independent variables. The results presented in Table 4.25 show mixed results for the variables in their discrete version: all the classes for international price of fuel regimes and WGI groups have a positive impact on the occurrence of fuel riots. Similarly to the analysis on food riots, the comparison of significance between the classes of each variable highlights that the two price regimes are significantly different from each other, whereas the classes 'low' and 'medium-low' of the WGI are not significantly different from each other. This suggests that potentially these two classes could be merged, although the estimated coefficients vary. Therefore, this model was selected and its accuracy compared with another REEM model using the same variables.

	Estimate	**SE**	***t*-value**	***p*-value**
(Intercept)	-6.2282	0.610	-10.208	$< 2e^{-16}$***
EIA fuel price regime	1.583	0.398	3.976	$7.02e^{-05}$***
Medium-low WGI	0.282	0.574	0.492	0.622822
Medium-high WGI	1.609	0.541	2.976	0.002925**

High WGI	2.309	0.688	3.355	0.000793***
σ	-1.652	0.408	-4.054	5.03e^{-05}***
Log-Likelihood	-171.3897			

Table 4.25 – RE model M2 with discrete variables for EIA fuel price threshold and WGI categories (own elaboration). Sig. codes: 0 '***'; 0.001 '**'; 0.01 '*'; 0.05 '.'; 0.1 ' '.

Subsequently, a REEM model was fit to the data using the variable fuel riots as dependent and the discrete variables for EIA fuel price and WGI as independent. The results of the model are presented in Figure 4.11.

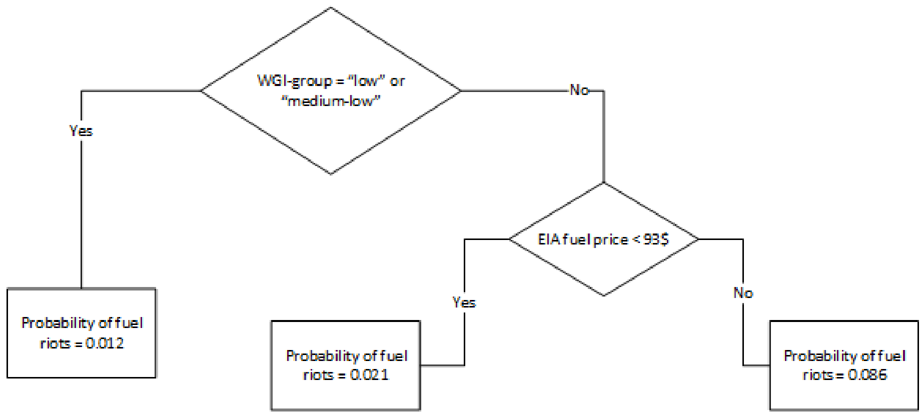

Figure 4.11 – REEM model with discrete variables for EIA fuel price threshold and WGI categories (own elaboration). Notes: n = 1904; intercept = 0.001367006; Estimated variance of errors = 0.0195820602281012; Log likelihood = 980.769632178929.

Positively, the structure of the tree is remarkably similar to the one resulted from the analysis on food riots presented in Section 4.1.7.4. The low and medium-low categories of the WGI will have the same probability of experiencing a fuel riot independently from the EIA fuel price regime. Price regime only significantly affects the probability of fuel riots for higher levels of fragility. Also in this case, the REEM model suggests that the variable WGI could potentially be split in only two classes. This is in line with the results from model M2 which suggest that the WGI could be divided in three classes of fragility rather than four.

The accuracy of these models was compared alongside model M0, which always predicts 0 for the variable Fuel Riot. The procedure followed the analysis on food riots with two versions of the REEM model being tested, one without RE (REEM) and another which included them (REEMre). Table 4.26 presents the mean percentages of correctly predicted fuel riots and correctly predicted records for each model.

Models	Fuel riots predicted	Total correct
M0	0	97.67%
M1	3.30%	96.61%
M2	1.60%	96.80%
REEM	5.25%	95.67%
REEMre	11.29%	95.93%

Table 4.26 – Results of the accuracy test for the different models evaluated in this analysis. The second column reports the mean of the percentage of fuel riots correctly predicted by each model throughout the 1000 iterations, whereas the third column reports the mean of the percentage of any record (fuel riot 0s and 1s) correctly predicted by each model throughout the 1000 iterations (own elaboration).

Table 4.26 provides results that differ greatly from those of the same models fit to data on food riots. The percentages representing the total number of records correctly predicted by each of the model tested is remarkably similar. The comparison between the accuracies of models M1 and M2 shows that recoding the variables for EIA fuel price and WGI in a discrete form results in a loss of predicting power. However, the percentage of fuel riots correctly predicted was very low as compared to the REEM models, in particular the version including RE. Indeed, once RE for each country are added to the predictions of the model, i.e. REEMre model, the accuracy at predicting fuel riots increases by 6%. REEMre model was hence undoubtedly the most accurate at predicting fuel riots in countries using the variables tested in this analysis.

4.3. Interaction between food and fuel riots

This section tested whether countries that experienced a food riot were more likely to experience a fuel riot as well and vice versa. This analysis was interesting for different reasons: firstly, as shown in the food and fuel riots databases in Appendices 1 and 2, respectively, multiple countries experienced both food and fuel riots; secondly, food and fuel as resources are partly interdependent. Indeed, fuel is one of the inputs needed to grow food and, at the same time, specific crops can be transformed in biofuel, which can create competition in the use of these crops between the two sectors, hence impacting the price of either resource. Related to this last point, multiple sources indicated the US expansive policy on biofuels as one of the major causes of the spike in the international price of food in 2008 and 2011 (See Chapter 2.8). Finally, food and fuel are also basic needs (alongside water), so any rise in the cost of these resources will impact households' budgets similarly.

Once again, the analysis tested the same methods that were used for both the food and fuel riots analyses. Both methods whose accuracy at predicting either riots was tested used a binary variable that recorded whether each country experienced a fuel or a food riot in a given year as dependent and another binary variable recording the other type of riots as independent.

Firstly, a RE model (M1) testing the effect of Fuel Riot as independent variable on the variable Food Riot was fitted to the data from the full database. The results presented in Table 4.27 show that the variable Fuel Riot has a positive, significant influence on the occurrence of food riots. The accuracy of this model was hence evaluated and compared alongside the others.

	Estimate	**SE**	***t*-value**	***p*-value**
(Intercept)	-4.05	0.272	-14.877	< $2e^{-16}$***
Fuel Riot	2.454	0.452	5.435	$5.47e^{-08}$***
σ	-1.1	0.435	-2.527	0.0115*
Log-Likelihood	-221.54			

Table 4.27 – Results for RE model M1 with the variable Fuel Riot used as independent variable to predict the occurrence of food riots (own elaboration). Sig. codes: 0 '***'; 0.001 '**'; 0.01 '*'; 0.05 '.'; 0.1 ' '.

Secondly, another RE model (M2) was developed to test the inverse relationship between the two variables, i.e. testing the effect of Food Riot as independent variable on the variable Fuel Riot. The results presented in Table 4.28 show that the variable Food Riot has a positive, significant influence on the occurrence of fuel riots. The accuracy of this model was hence evaluated and compared alongside the others.

	Estimate	**SE**	***t*-value**	***p*-value**
(Intercept)	-4.741	0.361	-13.144	< $2e^{-16}$***
Food Riot	2.427	0.493	4.925	$8.46e^{-07}$***
σ	-1.788	0.409	-4.374	$1.22e^{-05}$***
Log-Likelihood	-183.4802			

Table 4.28 – RE model M2 with the variable Food Riot used as independent variable to predict the occurrence of fuel riots (own elaboration). Sig. codes: 0 '***'; 0.001 '**'; 0.01 '*'; 0.05 '.'; 0.1 ' '.

Subsequently, a REEM model (REEMfood) was fit to the data using the variable Food Riot as dependent and the variable Fuel Riot as independent. The results of the model are presented in Figure 4.12.

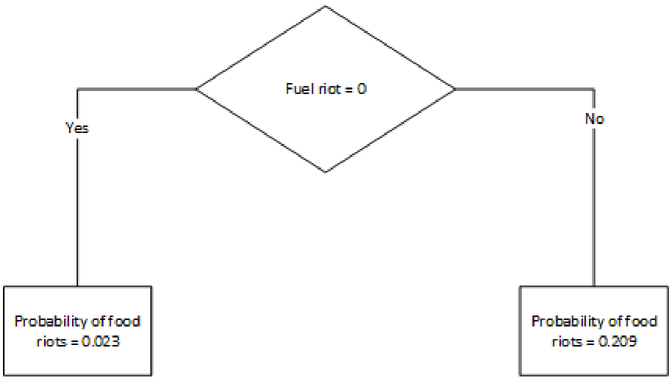

Figure 4.12 – REEMfood model testing the effect of fuel riots on the occurrence of food riots (own elaboration). Notes: n = 1904; intercept = 0.0005401692; Estimated variance of errors = 0.0247643227790632; Log likelihood = 793.817352564094.

The REEM tree identifies the variable Fuel Riot as significant and the split identifies two different probabilities for countries to experience a food riot according to whether the country previously experienced a fuel riot or not. In particular, the model assigns a probability close to zero if the country did not experience a fuel riot, whereas the chances for a country to experience a food riot increase substantially if that country had previously experienced a fuel riot.

The inverse relationship was tested with another REEM model (REEMfuel), which was fit to the data using the variable Fuel Riot as dependent and the variable Food Riot as independent. The results of the model are presented in Figure 4.13.

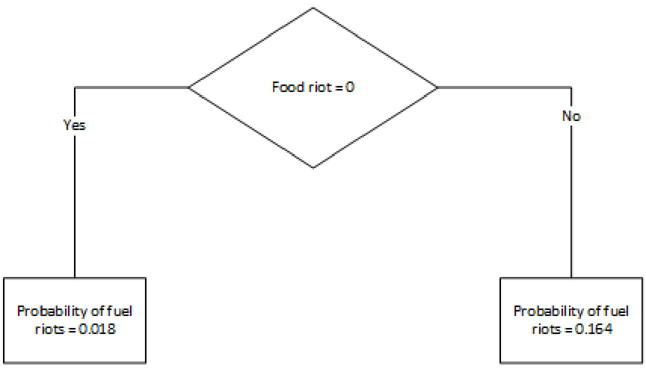

Figure 4.13 – REEMfuel model testing the effect of food riots on the occurrence of fuel riots (own elaboration). Notes: n = 1904; intercept = 0.001469882; Estimated variance of errors = 0.0194768047140661; Log likelihood = 986.414684322138.

Similarly to the previous REEM tree model on food riots, the REEM tree for fuel riots identifies the variable Food Riot as significant and the split identifies two different probabilities for countries to experience a fuel riot according to whether the country previously experienced a food riot or not. In particular, the model assigns a probability close to zero if the country did not experience a food riot, whereas the chances of the country to experience a fuel riot increase substantially if that country had previously experienced a food riot.

The accuracy of the models distinguishing between those using Food Riot and Fuel Riot as dependent variables and was compared alongside model M0, which always predicts 0 for the variables Food and Fuel Riot). Mirroring the previous analyses on riots, two versions of the REEM models were tested, one without RE (REEM) and another which included them (REEMre). Table 4.29 presents the results for the models using Food Riot as dependent variable and reports the mean percentages of correctly predicted food riots and correctly predicted records for each model.

Models	**Food riots predicted**	**Total correct**
M0	0	97.21%
M1	0.34%	97.19%
REEMfood	5.78%	94.87%
REEMfoodre	7.77%	94.91%

Table 4.29 – Results of the accuracy test for the different models using Food Riot as dependent variable. The second column reports the mean of the percentage of food riots correctly predicted by each model throughout the 1000 iterations, whereas the third column reports the mean of the percentage of any record (food riot 0s and 1s) correctly predicted by each model throughout the 1000 iterations (own elaboration).

The results shown in Table 4.29 differ greatly from the comparison provided for the models on food riots and resembles that on fuel riots. In particular, here the RE model captures a negligible percentage of food riots, whereas the REEM model captures a larger amount. As for the total amount of records, the REEM model performs worse as compared to the RE model, although losing only 3% of accuracy. As for the previous analyses on riots, adding the country-specific random effects to the REEM model, i.e. REEMfoodre, increases both the percentage of correctly predicted food riots and the overall records. In particular, including the random effects in the REEM model increases the percentage of correctly predicted food riots by 2%.

Table 4.30 presents the results for the models using Fuel Riot as dependent variable and reports the mean percentages of correctly predicted fuel riots and correctly predicted records for each model.

Models	**Fuel riots predicted**	**Total correct**
M0	0	97.21%
M2	0.26%	97.72%
REEMfuel	4.86%	95.68%
REEMfuelre	12.10%	96.04%

Table 4.30 – Results of the accuracy test for the different models using Fuel Riot as dependent variable. The second column reports the mean of the percentage of fuel riots correctly predicted by each model throughout the 1000 iterations, whereas the third column reports the mean of the percentage of any record (fuel riot 0s and 1s) correctly predicted by each model throughout the 1000 iterations (own elaboration).

Similarly to the previous table, Table 4.30 differs greatly from the comparison provided for the models on food riots and resembles that on fuel riots. Also here the RE model captures a negligible percentage of fuel riots, whereas the REEM model resulted more accurate at predicting the fuel riots. As for the total amount of records, the REEM model performs worse as compared to the RE model, although losing only 2% of accuracy. As for the previous analyses on riots, adding the country-specific RE to the REEM model, i.e. REEMfuelre, increases both the percentage of correctly predicted fuel riots and the overall records. In particular, including the RE in the REEM model increases the percentage of correctly predicted fuel riots by a remarkable 8%.

4.4. Discussion

This chapter presented findings from initial approximate calculations and formal statistical tests that evaluated and quantified the effect of different variables on the occurrence of food and fuel riots. Interestingly, the analyses on each type of riot was perfectly in line with the other.

The results presented found a positive, statistically significant relationship between the international price of food – as modelled by the FAO FPI – and the occurrence of food riots, also identifying 140 as the threshold for the annual, deflated version of the FAO FPI over which the probability of food riots increases significantly. In addition, an accuracy analysis identified the WGI as the best predictor of food riots. This finding was later confirmed by more robust econometric analyses. In particular, a Cox PH HZ model was fit to the data for two different time frames and both models found a positive, significant relationship between national political fragility – as modelled by the WGI – and the occurrence of food riots. Conversely, national food availability, i.e. national net food production used as a proxy for a country's reliance on the international market for the supply of food, does not significantly affect the occurrence of food riots according to the same model. Subsequently, different econometric models, i.e. RE model and REEMtree model, were tested to integrate and quantify the previous findings, with the final aim of operationalising the information for their inclusion in the food and food and fuel versions of the ABM. The results show that the translation of the variables for the FAO FPI and WGI in their discrete versions leads to a substantial loss of information, which in the case of this thesis was necessary due to how these variables are modelled in the ABMs (see Chapter 5). The RE model M2 was able to capture more than half of the food riots which occurred in the period considered, although losing predictive power once accounting for both prediction of food riots and non food riots, i.e. once asked to identify both countries that did and did not experience a food riot. The REEM model accounted for only 5% of food riots with an overall prediction power similar to the best model with continuous variables M1. Its accuracy at predicting food riots increased by almost 1% once the RE assigned from the model to each country were included in the predictions.

The analysis on fuel riots led to very similar results: a RE model fit to the data highlighted a positive, significant relationship between the international price of fuel – modelled as the price of crude oil averaged between two spot prices, WTI and Brent, sourced from the US EIA – and the occurrence of fuel riots, also identifying $93 per barrel as the threshold over which the probability of fuel riots increases significantly. In addition, a Cox PH model was fit to the data for two different time frames and led to mixed results. The Cox PH model for 2008 found that the singular relationships between the WGI and fuel riots and national fuel availability, i.e. national net oil production used as a proxy for a country's reliance on the international market for the supply of fuel – modelled as the difference between national oil production and consumption – and fuel riots are not significant. Conversely, the Cox PH model fit to the data for the time frame 2011 – 2013 found a positive, significant relationship between national political fragility and the occurrence of fuel riots. National fuel availability does not significantly affect the occurrence of fuel riots according to the same model. The findings from the last period are in line with those found between the same covariates and food riots. One of the possible reasons why the model fit to the data for 2008 did not produce significant results is because the period considered was very short, not covering a whole year, hence potentially biasing the estimates calculated by the Cox PH model. Indeed, all the variables analysed were annual figures and, in general, the analysis of a longer period allows to better capture the dynamics underlying prices and fragility. This is confirmed by the positive results from the analysis on the 2011 – 2013 period. For this reason the results for the last period were selected as more robust as this covered a time frame of three whole years. Subsequently, an RE model and a REEM model were tested to integrate and quantify the previous findings, with the final aim of operationalising the information for their inclusion in the fuel and food and fuel versions of the ABM. Differently from the analysis on food riots, the results of the models applied to fuel riots show that the translation of the variables for the EIA fuel price and WGI in their discrete versions leads to a minimal loss of information. In this case the REEM model was more accurate at predicting fuel riots as compared to both RE models. In particular, the RE model using discrete variables correctly predicted 3% of fuel riots as compared to 5% predicted by the REEM model. All three models had a comparable overall accuracy. Once accounting for country-specific random effects, the predictive power of the REEM model reached 11%, still maintaining an overall accuracy comparable to that of the other models.

The integrated analysis between food and fuel riots found a positive, mutual influence between these two types of event, i.e. countries that experience either a food or a fuel riot are more likely to experience an event of the opposite type during the same year. This was highlighted by fitting RE models that used alternatively food and fuel riots as dependent and independent variables. The analysis compared once again the accuracy of RE and REEM models at capturing the mutual influence between food and fuel riots. As for the models generating predictions for food riots using fuel riots as independent variable, the RE model performed very poorly, correctly predicting less than 1% of food riots. The REEM model performed remarkably better, correctly predicting 6% of food riots and its accuracy increased to 8% when including country-specific random effects. The overall accuracy of the models was comparable. The models generating predictions for fuel riots using food riots as independent variable performed similarly: the RE model performed very poorly, correctly predicting less than 1% of food riots. The REEM model performed remarkably better, correctly predicting 5% of the food riots and its accuracy increased to 12% when including country-specific RE. The overall accuracy of the models was comparable.

The different loss of information due to the transformation of the international price of the resources and the WGI in their discrete forms is an interesting finding in itself. Indeed, splitting the WGI in categories is positive when predicting food riots and it is detrimental to predictions for fuel riots will require further investigation in future research. The results of models M1 and M2 suggest that this is attributable to the WGI variable. In M2 for food riots the categories for the WGI are all significantly different from the benchmark category as opposed to the M2 for fuel riots, which suggests that the two low fragility categories could potentially be merged. This is due to the different distribution of food and fuel riots in the classes of the WGI: food riots are more evenly distributed between the classes of fragility than fuel riots, which are instead concentrated in the classes with highest fragility.

Interestingly, REEM models were more accurate than RE at predicting fuel riots and in the integrated analysis, whereas RE performed better at predicting food riots. Intuitively, this could be explained by the characteristics of the methods: the occurrence of food riots, being more evenly distributed between classes, can be approximated by a function with a clearer trend, as compared to fuel riots whose distribution is more similar to irregular functions such as moving average. Therefore, RE may be more suitable at reproducing a function that follows a clear trend, whereas REEM may be more accurate in the second instance. However, this statement requires further investigation.

Having evaluated the accuracy of each method at predicting food and fuel riots and their mutual influence, it was possible to select an approach that would be carried on in the following stages of the analysis to implement these findings in the different versions of the ABM. It is important to remember here that for reasons of consistency only one method was selected. REEM was the method finally selected for three main reasons: firstly, for all the analyses apart from the one on food, REEM outperformed

RE models and showed the largest increase in accuracy once country-specific random effects were considered in the predictions. Secondly, the probabilities of riots for each condition highlighted by the models as significant were immediately implementable in the ABMs. Indeed, these models are highly recommended when operationalising results to be included in ABMs (Sánchez-Maroño, et al., 2015). Finally, the trees resulting from the models showed an extremely simple structure, which further facilitated the implementation of these results.

5. Modelling food and fuel riots

One of the main characteristics of ABMs is the possibility of simulating a system while including interactions between micro (national, country-level in this case), and macro (global) levels of analysis. This was particularly important in this research as the system recreated in the models is made of individual agents (countries) whose decisions (in this case production, consumption and trade of cereals, oil, natural gas and coal) have international consequences in terms of global availability of cereals and oil. This influences the international prices of these resources, which in turn have national consequences in terms of occurrence of national food and fuel riots. Abiding by Principle 2 of the GRO Project, the Food, Fuel and integrated Food and Fuel versions of the ABM that are presented in this chapter are empirically grounded, meaning that all the data fed into the models as well as the parameters used have been informed using real data. The sections of this chapter relative to the Food version of the ABM constitute a further update of Natalini, et al. (2015a) and has been submitted to the journal 'Food Security' as Natalini, Bravo and Jones (TBP). In addition, the procedures related to international trade of natural resources and data that has been used to inform the social networks in the ABMs are partly based on Phillips and Natalini (TBP), submitted to the journal 'The World Economy'.

As mentioned before, three versions of the ABM were developed: i) the Food ABM only includes dynamics that represent the global food system and that lead to food riots; ii) the Fuel ABM only includes dynamics that represent the global oil system and that lead to fuel riots and finally iii) the Food and Fuel ABM that integrates the two previous versions and also includes dynamics for production, consumption and trade of other energy resources, i.e. natural gas and coal. The dynamics that lead to food and fuel riots included in the three versions of the ABM are based on the analysis presented in Chapter 4. Abiding by Principle 1 of the GRO Project, the ABMs were built to give short-term (5 years) predictions.

This chapter presents the different versions of the ABM to explain the dynamics included. Their description is provided following the Overview, Design concepts, Details (ODD) protocol developed by Grimm, et al. (2006) as it is common practice in the field of ABMs. The ODD only describes the basic dynamics and processes underlying the ABMs, whereas the calibration and validation of the models are summarised in Sections 5.2 and 5.3, respectively. Future forecasts are provided in Section 5.4 and Section 5.5 will present findings from the sensitivity analysis on the ABMs. Finally, Section 5.6 will discuss findings from this chapter.

The ABMs have been implemented and run with NetLogo version 5.2 (Wilensky, 1999), whereas the results from the models runs have been analysed with R (R Core Team, 2013).

5.1. Using the Overview, Design concepts, Details protocol to describe the ABMs

Describing a computer model using pseudo-code is a critical part of the research. Indeed, when deciding how to communicate the dynamics included in a model, the researcher is forced to reflect on all the choices they made while developing the tool, hence highlighting the assumptions made and the interconnections between the different parts of the model. In addition, a clear description of the model facilitates its reimplementation to replicate its results. A model whose results cannot be replicated is considered unscientific (Railsback and Grimm, 2012). To facilitate the description of ABMs, a large group of experienced modellers developed a standardised format called the Overview, Design concepts, Details (ODD) protocol, which was first published in Grimm, et al. (2006) and subsequently updated in Grimm et al. (2010). Its application has spread widely in the ABM community (Polhill, et al., 2008) and it will hence be used to describe the dynamics included in the ABMs developed in relation to this work as well.

The three different versions of the ABM are fundamentally similar and only differ for what type of riots the model generates predictions for, i.e. food, fuel or food and fuel riots. In particular, only three procedures differ between the models, all rest being equal. Although these could have been implemented in the same model and the type of riot alternatively selected via a ‘chooser’ dialogue from the model’s interface, the three versions of the ABM were developed as independent models for two main reasons: firstly, the development of the ABM was approached in stages. First the analysis and parameterisation of food riots was undertaken, alongside the development of the Food ABM. Subsequently the same analysis to parameterise food riots was applied to fuel riots and the Food ABM was converted to generate predictions for fuel riots. Finally, the analysis on mutual relationships between food and fuel riots was undertaken and the results were included in another version of the ABM to investigate whether adding this dynamic improved the accuracy of the model at predicting both types of riot. This integrated version also includes consumption and production dynamics for the other two natural resources, i.e. coal and natural gas, and four different social networks representing trade, one per each resource and constitutes the platform for further updates of the model. Because of the high similarity between the ABMs and the dynamics underlying it, the next sections will present one ODD protocol for all the models, specifying for each step which version of the ABM applies to.

Provided as attachments to this thesis are: i) database to initialise countries, ii) databases to initialise four international trade networks, iii) code of the integrated Food and Fuel ABM, iv) databases for ETs, for both food and fuel and for calculations on absolute and price variations (only for food). Only one version of the code is provided due to the high similarity of the different versions of the models and for reasons of brevity.

5.1.1. Purpose (all ABMs)

The ABMs are a first attempt to model some of the dynamics that lead to food and fuel riots. In particular, the purpose of the model is to test and quantify how scarcity of food and oil, their international prices and national political fragility influence the probability of food and fuel riots in countries.

5.1.2. Entities, state variables and scales (all ABMs)

Grimm, et al. (2010) define an entity as “a distinct or separate object or actor that behaves as a unit and may interact with other entities or be affected by external environmental factors” (Grimm, et al., 2010, p. 2763). The same authors define a state variable or attribute of an entity as “a variable that distinguishes an entity from other entities of the same type or category, or traces how the entity changes over time” (Grimm, et al., 2010, p. 2763). Below a list of entities with corresponding state variables for the ABMs is reported.

- Agents. One of the entities included in the ABMs are the agents that represent the 213 countries of the world, which constitutes the micro-level of analysis. The breed[14] of these agents is ‘country’. For reasons of brevity, the state variables and attributes that apply to more than one natural resource will be listed with a general heading. If not specified, the variable or attribute applies to each resource. The state variables and attributes of countries are listed in Table 5.1.

Variable	Resources	ABM version	Description
Code	-	All	ISO code for the country
Label	-	All	Name of the country
Birth-rate	-	All	Rate of birth for the country
Death-rate	-	All	Rate of death for the country
Population	-	All	Population for the country
Population growth	-	All	Rate of population growth for the country
<resource>-reserves	Energy	Fuel and Food and Fuel	Reserves of energy resources per country
<resource>-finds	Energy	Fuel and Food and Fuel	Energy resources endowments discovered every year within the country
<resource>-production-function	All	All	National estimates for production of natural resources
<resource>-consumption-function	All	All	National estimates for consumption of natural resources
<resource>-consumption-per-capita	All	All	National estimates for per capita consumption of natural resources
<resource>-stock-t-1	All	All	Previous tick’s stock of resources for the country
<resource>-exports-available	All	All	National exports available for trade
<resource>-imports-required	All	All	National imports required for resources
<resource>-imports-required-before-trade	All	All	National imports required for resources
<resource>-imported	All	All	Amount of resource imported
<resource>-production+exports	All	All	Total availability of resource for countries
<resource>-depleted	All	All	Binomial variable that defines whether resource is depleted
cereal-land	Food	Food and Food and Fuel	National amount of land available
food-SUR	Food	Food and Food	Stock-to-Use Ratio, the

[14] In NetLogo this term is used to refer to a category of agent, or, more formally, a class.

		and Fuel	ratio between the stock of food in a country and its annual consumption
desired-cereals-stock	Food	Food and Food and Fuel	Desired stocks of cereals for countries
food-scenario-parameter	Food	Food and Food and Fuel	See Section 5.1.7.5
lloyds-scenario-parameter	Food	Food and Food and Fuel	See Chapter 6.2.2
fuel-scenario-parameter	Energy	Fuel and Food and Fuel	See Chapter 6.2.3
WGI	-	All	National estimate for the WGI
WGI-function	-	All	WGI function for the country
WGI-group	-	All	WGI group of fragility for the country
food-crisis	Food	Food and Food and Fuel	Binomial variable that registers a food riot in the country
fuel-crisis	Energy	Fuel and Food and Fuel	Binomial variable that registers a fuel riot in the country
rnd-eff-food1	Food	Food and Food and Fuel	RE generated by the REEM model on only food riots
rnd-eff-fuel1	Fuel	Fuel and Food and Fuel	RE generated by the REEM model on only fuel riots
rnd-eff-food2	Food and Energy	Food and Fuel	random effects generated by the REEM model on influence between food and fuel riots
rnd-eff-fuel2	Food and Energy	Food and Fuel	RE generated by the REEM model on influence between food and fuel riots
lat-centroid	-	All	y coordinate for agents' location
long-centroid	-	All	x coordinate for agents' location
Size	-	All	size of the bubbles for countries that represent the size of their population in the ABMS' interface

Table 5.1 – List of variables included in the different versions of the ABM. The first column reports the name of the variable, the second to what resources it refers to, the third column reports the version of the ABM where it is included and finally a description (own elaboration).

- Links. Another type of entities is the directed links that connect the countries included in the models generating four different social networks, one for each natural resource modelled. These networks are used in the ABMs to model international trade of natural resources. Similarly to above, only the variables relevant to the food and fuel riots dynamics will be accounted here. The models include two breeds (types) of directed links, oil links and cereal links. The state variables and attributes of the links are: strength, zero-time (see Section 5.1.7.11).

The 'world' graphically recreated in the screen pane of the ABMs' interface represents an atlas of the world using latitude on the y axis and longitude on the x axis for an easier interpretation. Countries' location in space is determined by the coordinates of their centroids, which were sourced from Donnelly (2012). The temporal scale used in the ABMs is discrete and every time step represents one year. In NetLogo, these are represented with the procedure *tick* and the counter *ticks*, where the first advances the counter *ticks* by one unit at the end of each run. The models were run for nine years (2005 – 2013) for validation, reflecting the timeframe implemented in the studies on riots, and for thirteen years (2005 – 2017) to produce forecasts.

5.1.3. Process overview and scheduling

Figure 5.1 outlines the procedures run by each agent during one tick (year) and their interrelationships. Each rectangular box represents one of the procedures included in the different models. White boxes indicate procedures included in all the ABMs, green procedures are included in the Food ABM, yellow procedures belong to the Fuel ABM and the Food and Fuel ABM includes all the procedures (white, green, yellow and orange, the latter being specific for this model). Descriptions are provided in this section for simple procedures, whereas the more complex ones will be dedicated a section later in the text. For reasons of brevity, only the procedures that contain dynamics key to the occurrence of food and fuel riots and for the functioning of the ABMs have been included. The procedures are sequential, i.e. one country runs the whole procedure, followed by another country, etc., although the order in which the agents perform the procedure is random (USA can run procedure one before North Korea, whereas North Korea can run procedure two before USA). In Figure 5.1 boxes on the same level represent procedures whose order is not significant. Variables are immediately updated once their new value is calculated in the procedures, i.e. asynchronous update. Each agent will complete the first procedure before moving onto the next. At ticks 13, 15 and 17, which correspond to years 2007, 2009 and 2012 three new agents are introduced. These correspond to the years when Montenegro, Kosovo and South Sudan, were constituted, whose data was sourced from the GRO Database (GSI, 2015) for the corresponding year.

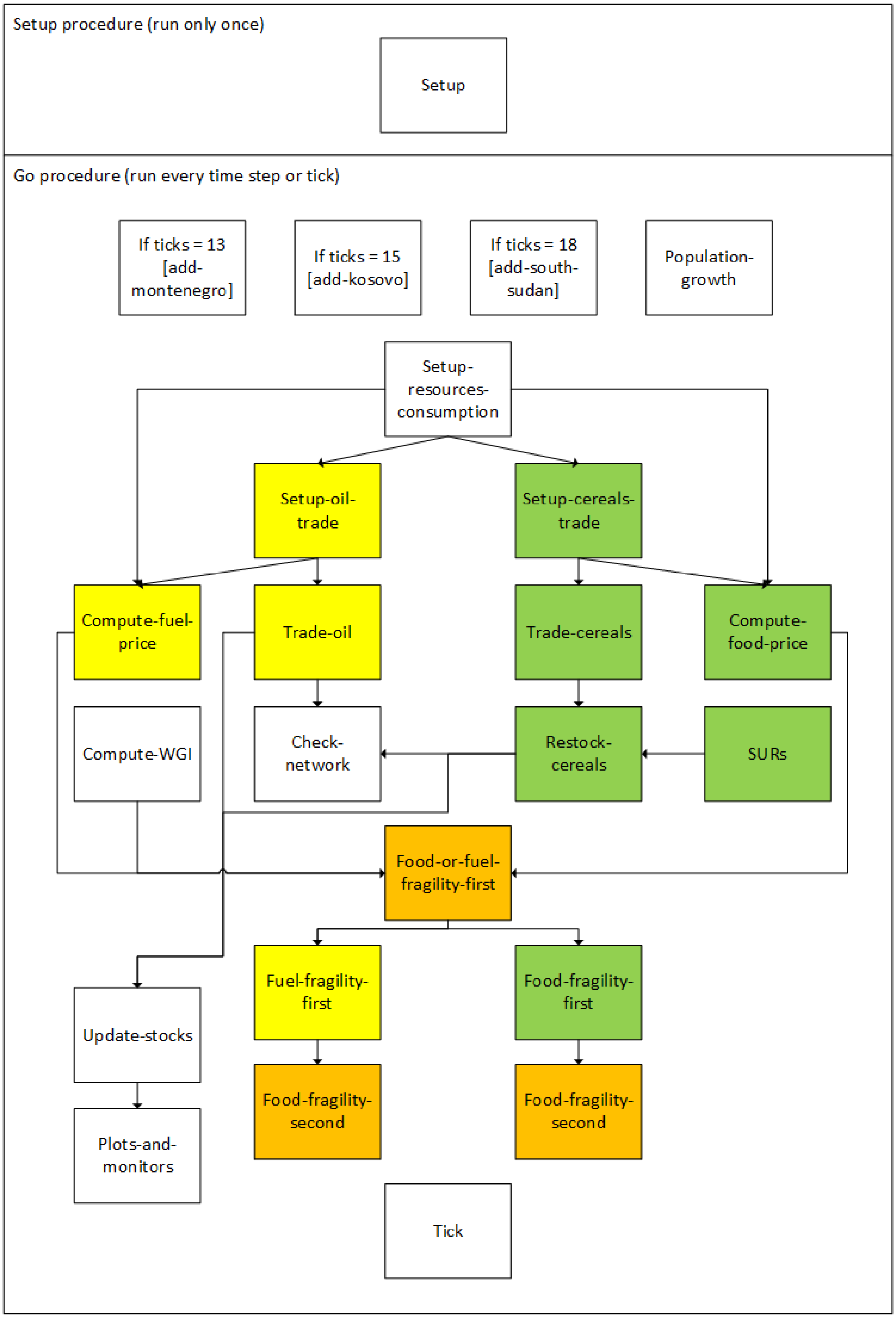

Figure 5.1 – Outline of the procedures included in the different versions of the ABM and their interrelationships. White boxes identify procedures that are included in all the ABMs, green boxes identify procedures that belong to the Food ABM, yellow are

procedures included in the Fuel ABM and the Food and Fuel ABM includes all the procedures, with the orange boxes being procedures specific for this model. Boxes on the same level represent procedures whose order is not significant (own elaboration).

5.1.4. Design concepts

5.1.4.1. Basic principles

As reiterated multiple times throughout the text of this thesis, the different versions of the ABM have been developed based on the findings from the quantitative analyses presented in Chapter 4. In addition, the ABMs are prototypes that can be further developed to improve the existing dynamics that lead to the occurrence of food and fuel riots, expanded to include more dynamics and different types of conflict and to improve the models' predictions. Therefore the aim of the ABMs is to explore the field of empirical ABMs and to encapsulate the findings produced while undertaking this research by introducing the quantitative relationships presented in the previous chapter. The models answer two main questions: firstly, whether adopting a fully data-led approach in developing an ABM generates a good model and, secondly, whether by introducing stochasticity, interaction between countries and the feedback between food and fuel riots improves the model's predictions as compared to the underlying statistical extrapolation.

5.1.4.2. Emergence

As explained in Chapter 3, emergent properties are dynamics that would not be captured if each component of the system was studied in isolation, but emerge from their interaction and the heterogeneity of the agents and their behaviours. Emergent properties in the different versions of the ABM can be found at different levels of analysis: firstly, in the distribution of national stocks of the resources because of the structure of international trade recreated in the ABMs. Countries are initialised with initial values for national stocks of natural resources that derive from reported data (GSI, 2015). Oil trade is simulated in only one round where countries exchange what they need to satisfy national consumption. The oil exports still available after trade become national stocks of the resource that will be carried over to the following time step. Trade of cereals, instead, is modelled in two rounds of international exchanges: the first to cover countries' annual consumption of cereals, and the second to cover their need for restocking. Because production and consumption of natural resources are deterministically defined in the model (see later in this section) the global production and consumption and global stocks of oil and cereals do not change between different runs of the model. However, how these are distributed between countries and which countries successfully meet their own consumption (for all the natural resources) and needs for stocks (only for cereals) before the availability of exports runs out is an emergent property of the models.

Emergence can also be found in the occurrence of food and fuel riots in countries. Because the probability of riots depends on several variables and feedbacks present in the models (see Chapter 4), the activation of different probabilities of riots in countries is an emergent property of the models. In addition, in the integrated Food and Fuel ABM, emergence can also be found in which type of riot countries experience first: as explained in Chapter 4, the probability for a country to experience a food or a fuel riot is also influenced by whether the same country experienced a riot of the other type during the same year. The decision determining which probability (for either food or fuel riots) is calculated first is randomised with a 50% probability (see Section 5.1.7.13). This can hence be considered as an emergent behaviour in the model.

Ideally, production and consumption of natural resources would be generated through endogenous processes included in the model. However, the dynamics that lead countries to select their consumption and production of natural resources was not the objective of this research and, in line with the modelling approach, the ABMs were structured to be kept as simple as possible and to focus on the research questions selected. As it is common practice in the field of computer modelling, a behaviour that is not the focus of the model, but which is critical for simulating the dynamics that lead to the research question that the model needs to answer, needs to be simulated in a simplified manner (Railsback and Grimm, 2012). For this reason, these variables were modelled by fitting trend lines to historical data for each country (see Section 5.1.7.3). As a result, the processes that determine national production and consumption of the different natural resources – and hence levels for international production, consumption and stocks – are deterministic, i.e. these variables are constant among different runs of the models.

The same reasoning was implemented while modelling national political fragility as represented by the WGI. The variables and sources used to construct this index are several and often not reproducible (e.g. expert analysis) (WB, 2015d) and include dynamics not modelled in the current versions of the ABM. For this reason, this index is modelled through trend lines fit to historical data for each country (see Section 5.1.7.12). As a result, the level of national political fragility for each country will be constant among different runs of the models.

5.1.4.3. Adaptation

Adaptation occurs during the procedures that model international trade of resources and restocking of cereals when countries seek a new trading partner. Countries adapt and widen their pool of trading partners when those they already share a connection with run out of exports available for the resources they need. This process is aimed at meeting countries' needs for natural resources, both in terms of consumption and desired stocks levels for cereals. However, if this is not possible due to lack of resources at the global level, there is no direct consequence for countries other than a change in the colour of their 'bubble' in the screen pane of the models' interface.

Adaptation also occurs in countries in terms of their probability of experiencing a food and/or fuel riot in relation to changes in price and own national political fragility. This process is not aimed at minimising countries' probabilities to experience these types of conflict, rather it simply reflects the dynamics estimated and presented in Chapter 4.

5.1.4.4. Objectives

Countries' objective is to meet their needs for natural resources to cover national consumption and desired stock level of cereals. While trading natural resources, importing countries maximise the imports of the resource in an attempt to meet their national consumption (both for cereals and oil) and their needs for cereals stocks.

5.1.4.5. Sensing

During the international trade of natural resources, importers 'sense' the exports availability of other countries, both those that they already share a connection with, but also when importers seek a new trade partner with exports still available if the exports availability for the resource has been depleted within their current network.

This remote sensing partly happens via the social networks countries are embedded in, which has an emergent structure as explained in detail in Section 5.1.7.8.

In addition, countries ‘sense’ the regime of the international price of each natural resource, i.e. either above or below the thresholds calculated in Chapter 4, which is determined at the global level. This in turn affects countries’ probability of experiencing food and/or fuel riots.

5.1.4.6. Interaction

Direct interaction between agents occurs through the social networks and particularly during two procedures: to trade-<resource> and to restock-cereals. See Sections 5.1.7.8 and 5.1.7.10 for an in-depth explanation of each procedure, respectively.

5.1.4.7. Stochasticity

Stochasticity is naturally embedded in the ABMs due to the use of NetLogo. One of the default characteristics of this piece of software is the randomness applied to the order in which each country performs each procedure, which results in stochastic processes.

Stochasticity is also introduced in the population model. Currently, population dynamics are modelled through birth and death rates for each country, to which ± 0.5‰ is added or subtracted. This is to avoid deterministic results, which are deemed to be inaccurate due to the very simplistic population model introduced. Also for this reason, population size has no impact on other parts of the ABMs, as it will be presented in Section 5.1.7.2.

In the current version of the integrated ABM for Food and Fuel, stochasticity is also introduced in the sequence in which the probabilities for food and fuel riots are calculated. As presented in Chapter 4, the occurrence of food riots in countries increases the probabilities of fuel riots to happen in the same country during the same year and vice versa. Since this influence is mutual, the order in which the procedures are run by the agents is randomised with a 50% probability for each outcome, resulting in a different sequence of what type of riots is calculated first.

Finally, all the versions of the ABM include stochasticity in the procedure that defines whether a country experiences any type of riot, since this is the result of a probability as presented in Chapter 4.

5.1.4.8. Collectives

The only informal aggregation of agents occurs during the international trade of resources and restocking of cereals in all the versions of the ABMs: when importing countries choose a trade partner whom to import what they need from, they create a temporary agentset with the pool of countries they already share a connection with, whose *<resource>-exports-available > 0*.

5.1.4.9. Observation

The variables saved from the simulations of the ABMs and subsequently analysed are: *Year*, *Country*, *Code*, *food-crisis*, *fuel-crisis, oil-stock and cereals-stock*. These are saved for each agent at the end of every time step. Importantly, food- and fuel-crisis are binary variables that register whether a food and/or a fuel riot occurred in a country during that particular time step, whereas oil- and cereals-stock record the amount of stocks for each resource still available in each country at the end of every time step. The variables *natural-gas-stock* and *coal-stock*, although present in the Food and Fuel version of the model, are not recorded, as these do not currently affect the dynamics of the system.

5.1.5. Initialisation

During the initialisation, 210 agents corresponding to the countries of the world present in 2005 are created in each version of the ABM. Data for the variables corresponds to reported data for those countries for the year 2005 and is sourced from the GRO database (GSI, 2015). The database used as input for the initialisation of countries' variables is provided as attachment. During the initialisation of the social networks for each of the natural resources, countries create links to their trade partners (see Section 5.1.7.1). These are based on reported data sourced from the UN Comtrade database (UN, 2014) and the four databases containing the links used to initialise the networks are provided as attachments. Kosovo, Montenegro and South Sudan are initialised in the code of the models, which can be found in the attachments.

5.1.6. Input data

As mentioned in the previous section, most of the data used to initialise the state variables for countries corresponds to reported data sourced from the GRO database

(GSI, 2015). For a comprehensive explanation of how data has been collected and handled, refer to the publication connected to the GRO database (Jones and Phillips, 2015). The WGI for countries was sourced from the WB website (WB, 2015c). As for production and consumption of natural resources and for countries' WGI, countries are provided with equations in function of ticks (years) that, once evaluated, result in the value of that variable for each specific country for that specific tick. This will be explained more in depth in Sections 5.1.7.3 and 5.1.7.4 for functions for consumption and production of natural resources, respectively, and Section 5.1.7.12 for countries' WGI. Reported data was also used to inform initial food stocks countries are initialised with. This was sourced from the United States Department for Agriculture (USDA) (USDA, 2015a). Finally, all the data was translated in the units used in the ABMs: 'Barrels' for oil data, 'Metric tonnes' for coal data, 'Cubic meters' for natural gas data and 'Kilograms' for cereal data.

As for data used to generate the four social networks included in the ABMs, the links again are based on real exchanges for 2005 recorded in the UN Comtrade database (UN, 2014). The same data was used in a recent publication from Phillips and Natalini (TBP) on a study on the evolution of the World Trade Web of Natural Resources (WTWNR), a term which was coined by the authors. The paper contains an in-depth account of how data was handled to account for coherence and inconsistencies (Phillips and Natalini, TBP) and an analysis of the past trends in the WTWNR. For the work related to this thesis, the countries recorded in the UN Comtrade database were matched with those included in the GRO database, deleting those that were not taken into account in the project and their labels modified for consistency. Subsequently, all export trade links from countries that did not have any endowments for that particular resource (just for oil, coal and natural gas) were ignored. This was in an attempt to capture the export of the raw resource (e.g. crude oil) and not the export of refined resources that had previously been imported from elsewhere. As analysed in Phillips and Natalini (TBP), UN Comtrade database contained several inconsistencies, which were particularly related to the weight and value of resources traded and which led to the choice of introducing and recreating only binary networks both in the paper and in the ABMs presented here. Finally, the countries that are introduced during the model runs, i.e. Kosovo, Montenegro and South Sudan, were deleted from the input database and are added during the simulation runs.

5.1.7. Submodels

The key procedures included in the models are reported and explained below, also specifying in which versions of the ABMs these have been implemented. When the procedures are fundamentally similar between models and resources and only the name of the variables used change, these will be aggregated for reasons of brevity.

5.1.7.1. Setup

The procedure Setup calls several sub-procedures aimed at initialising the ABMs. In particular, this procedure recalls a sub-procedure called to *countries-setup* where the shape 'circle' is assigned to the agents, i.e. countries, through the *set-default-shape* command and loads the database that is used to initialise the countries. The command *create-countries* creates one agent per each record contained in the initial database with the specifics for each country listed.

Through the sub-procedure to <resource>-network-setup, the different WTWNRs are loaded from the four databases containing the links for each country, subsequently initialising the WTWNRs. International trade is modelled from the importers' perspective, although the links are directed from the exporting to the importing countries. The database containing data for trade connections between countries is loaded during this procedure. The final database used in this thesis hence derives from the one used in Phillips and Natalini (TBP). The databases used in the ABMs (one for each natural resource) are composed of two columns, one with the name of the importing country and the second with the name of the exporter. This procedure will create one link for each record included in each of the databases, through the command *create-<resource>-link-from* run by the importer countries listed in the first column.

Ticks are initialised at tick 11 through the primitive *tick-advanced*. This is because, as it will be explained in Section 5.1.7.3 and 5.1.7.4, the equations for consumption and production of natural resources and WGI for each country have been calculated as a function of time starting from the year 1995 as this was the first year available from the GRO database and because using a longer time frame as a reference resulted in more accurate estimates. For consistency, 1995 was used as first year to calculate WGI equations as well.

The Setup procedure also initialises the visualisation of the models assigning a different colour to each type of link, i.e. the WTWNR for each natural resource will be coloured differently, and the choices made from the user through a chooser in the models' interface that controls which links and colours to show according to the natural resource selected, are operationalised here.

5.1.7.2. Population-growth (All ABMs)

Population in the model is introduced as a rough estimate and is assumed to vary only according to birth and death rates. Population and consumption of natural resources are decoupled in the current versions of the ABM. In addition, the ABMs do not take into account migration between countries and do not include any feedback between level of development of countries and their population size. This is obviously an oversimplification of real-world dynamics that will be improved in further developments of the ABMs (see Chapter 6).

5.1.7.3. Setup-resources-consumption (All ABMs, all natural resources)

For all the resources, this procedure is initialised with a check on countries' reserves to ensure that these didn't become negative during the previous time step. If so, *<resource>-reserves* is set to 0.

For energy resources, i.e. oil in the Fuel version of the ABM and also natural gas and coal in the Food and Fuel version of the ABM, in this procedure countries update their natural endowments with the current tick's (year) finds. For simplicity, finds of energy resources, i.e. any increase in the endowments of energy resources for countries, which includes actual discoveries of new deposits and correction of estimated reserves due to changes in extraction efficiency, have been assumed as constant throughout the period modelled and between countries. This was calculated as the yearly average percentage variation of reserves of energy resources amongst all the countries between 1995 and 2012 based on data from the GRO Database (GSI, 2014). Since data for the variation of energy reserves implicitly includes the production of energy resources that diminish countries' natural endowments, the average percentage ratio between production and reserves of each natural resource was added to the final estimate for the annual finds of each resource. The final parameter was included in the ABMs and represented the average percentage annual increase of energy reserves across the countries. This parameter equals 5.07% for oil, 3.55% for natural gas and 0.63% for coal. The variables *<resource>-finds* are then replaced with the result from the multiplication between the variables *<resource>-reserves* and the parameters reported above. The current tick's reserves for countries' energy resources are subsequently updated in the variable *<resource>-reserves* by adding the *<resource>-finds*.

In addition, countries also calculate the current tick's estimate for their consumption of each energy resource and cereals. Projections for consumption of all the resources for each country have been calculated by fitting polynomial regression trend lines on reported data available for the period 1995 – 2013 for each country included in the GRO database (GSI, 2015). Consumption hence is smoothed by the trend lines. The polynomial functions resulting from the trend lines have subsequently been included in the initial database loaded by the model. The equations for national consumption of all the resources are evaluated with x = current *tick* (year) and the national estimates for consumption are stored in the variable *<resource>-consumption* (see the attachments for the whole database used to initialise the ABMs). The data used to calculate the estimates for consumption of natural resources used different units than those used in the ABMs, in particular the GRO Database reported oil variables for production and consumption in 'Thousand barrels per day', coal in 'Thousand short tons' and natural gas in 'Billion cubic feet'. The variables *<resource>-consumption* are hence transformed in the units used by the ABMs, i.e. 'Barrels' for oil, 'Metric tonnes' for coal and 'Cubic feet' for natural gas. Finally, per capita values for the consumption of each natural resource are calculated and stored in the variable *<resource>-consumption-pc* by dividing *<resource>-consumption* by *pop* for each country.

5.1.7.4. Setup-<resource>-trade (Fuel and Food and Fuel ABMs, all energy resources, one procedure per resource)

This procedure is aimed at identifying countries as either net exporters or importers of energy resources. This procedure is initialised with a check on countries' reserves to ensure that these didn't become negative during the previous time step. If so, *<resource>-reserves* is set to 0. In addition, if *<resource>-reserves* = 0 countries move the previous tick's un-exported production of the energy resource from the variable *<resource>-stock-t-1* to *<resource>-production+exports*. This is because although countries may have exhausted their natural endowments of an energy resource, they might have not been able to export all of it, carrying it over to the following tick in the variable *<resource>-stock-t-1*, which is updated at the end of each tick.

The GRO Database from which data is sourced assumes that countries without natural endowments of energy resources have a production = 0. This assumption is reflected in the ABMs. This is also due to the fact that this research aims at simulating the dynamics of trade of raw natural resources and hence does not take into account refined products.

Subsequently, countries with *<resource>-reserves* > 0 calculate the current tick's national production for the resource. Countries evaluate the polynomial equations derived from reported data in function of time with x = current *tick* (year), and check whether this is < 0. If so, this is set to 0 otherwise the number is assigned to the variable *<resource>-production* and multiplied by 365,000 as the units used in the models are 'Barrels', differently from the original data sourced from the GRO database where the unit used is 'Thousand barrels per day'. Due to this estimate being a simple fit to past data in function of time and hence uncoupled from the amount of reserves for the resource owned by each country, the resulting value of national production for the resource for the current year might be ≥ *<resource>-reserves* for the country. If this is true, countries replace the estimate for their production with their leftover reserves, subsequently setting their *<resource>-reserves* for the resource to 0. Conversely, if the estimated *<resource>-production* < *<resource>-reserves* countries subtract the estimate for production to their amount of reserves hence simulating resource extraction, subsequently adding to their estimated production the stocks carried over from the previous tick resulting in the variable *<resource>-production+exports*. Finally, all the countries determine whether they are net importers or exporters of the resource by running an *ifelse* clause on the condition *<resource>-consumption* > *<resource>-production+exports*. If this clause returns *true*, countries classify as net importers and set the variables *<resource>-imports-required* and *<resource>-imports-required-before-trade* = *<resource>-consumption* - *<resource>-production*+exports. Alternatively, countries classify as net exporters for the resource and set the variable *<resource>-exports-available* = *<resource>-production+exports* - *<resource>-consumption*.

5.1.7.5. Setup-cereals-trade (Food and Food and Fuel ABMs)

This procedure is aimed at identifying countries as either net cereals exporters or importers and differs from the procedure for energy resources as cereals cannot be modelled as natural endowments for countries. During the procedure, countries with *cereal-land* < *0* are set to 0. Although this variable is not involved in any dynamic process, it was already introduced in the ABMs in case of future developments, in particular foreseeing a feedback from climate change which, when introduced, will have an impact on the quantity of land available for cereal crops. This line of code hence constitutes a check to ensure no negative values for this variable throughout the model runs. Similarly to the previous procedure for energy resources, countries with *cereal-land* = *0* are assumed not to have production of the resource by the GRO database from which data is sourced. Countries that do not possess cereal land hence move the previous tick's un-exported cereals production from the variable *cereals-stock-t-1* to *cereals-production+exports*.

Subsequently, countries with *cereal-land* > 0 calculate the current tick's (year) cereals production and multiply this number by 1,000,000 as the measurement unit used in the model is 'Kilograms', whereas the variables used to calculate production sourced from the GRO database use '1,000 Metric Tonnes'. As for the production of energy resources, cereals production for each country was calculated by fitting trend lines to data for the same time frame. However, because each trend line constitutes only an approximate fit of the data, the functions resulting were smoothed and significant production shocks were not present in these trends. These needed to be added exogenously to the model to recreate real world events where they have occurred, in particular the 2008 global food production shock. For this reason the scenario 'drought-2008' was built into the Food and Food and Fuel versions of the ABM that can be activated via a switch on the model's interface. These production shocks were derived from reported data. In particular, a significant food price shock was observed in 2008 as depicted in Figure 5.2. This approach is standard practice in the modelling of shocks, where, due to the pursuit of simplification, empirical time-series may need to be aggregated and averaged. This loss of micro-level information may hinder the dynamics that are key for the shock to realise (Filatova and Polhill, 2012). To avoid this situation, the data lost in the process was reintroduced with an exogenous shock.

The same reasoning also applies to how the shock was calculated for reintroduction in the ABMs.

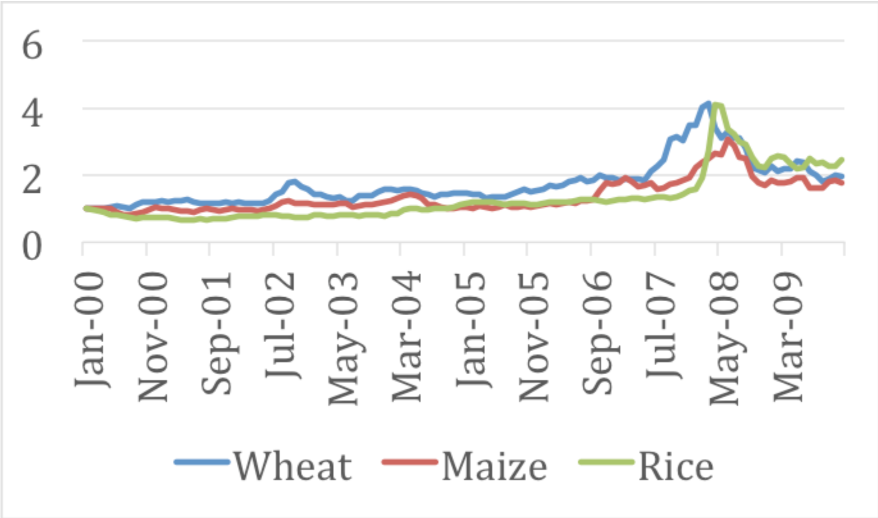

Figure 5.2 – Monthly prices for 2000-2010 for wheat, maize and rice showing significant price shocks in 2008. Prices are standardised so that price for each grain in January 2000 is 1 (Natalini, et al., 2015a).

Although several factors mainly related to weather and low stock-to-use ratios for countries (Bailey, et al., 2015) impacted food production around this time, the price shock of 2008 is widely known to have been caused by two previous major food production shock events that occurred in 2002/03 and 2006 (Headey and Fan, 2010) and by long- and short-term drivers that have been discussed in depth in Chapter 2.8. The causes of the 2008 food production shock go as far back as the 1980s, when for more than two decades, i.e. until 2000s, a long period of low real food prices led to scarce investments in the supply side of the agricultural sector. Consequently, global demand for food eventually outpaced – and for a period of time was constantly higher – than global food supply. During 2002/03 global food stocks were still at an all-time high. This was mainly due to high stock levels in China and the 2002/03 production shock happened to coincide with the time when China decided to strategically reduce its stock levels (Huang, et al., 2008; Abbott and De Battisti, 2011). Therefore, this food production shock was delayed as stocks entered international markets. Due to this early production shock and a medium-term slow growth in global food production, food stocks were already dwindling when the 2006 food production shock hit and therefore could not act as a buffer between demand and international prices, which spiked. Clearly, these price dynamics involve an intricate set of variables and feedbacks that went beyond the scope of this research. However, to be able to model the dynamics that lead to the occurrence of food riots it was critical to introduce a price shock in the ABM. To simplify, the food production shocks were collapsed in a single shock exogenously introduced in the ABMs during the tick corresponding to the year 2008. Hence, the 2008 exogenous production shock represents the average of the three production shocks occurred in 2002/03 and 2006 in the major food producing countries. The shock was introduced at the national level, i.e. one shock per country, and these figures were calculated by averaging the food production shocks per country across the three years. Although averaging the shocks resulted in a smaller overall shock due to the inevitable variation of food production between countries and years, Challinor, et al. (2015) suggest that food production seems to be anti-correlated between major producers. This means that different countries tend to experience shocks with different signs, i.e. negative and positive, within the same year. When recreating the global shock, it was hence more realistic to ‘average’ the worst three years to get a more realistic ‘shock year’ rather than take the worst of each country and recreate an over-pessimistic figure. Finally, the shock was introduced in 2008 because food stocks kept decreasing between 2006 and 2008, which was one of the drivers of the price spike in 2008. Only in 2008 the stocks were low enough for the production shock to effect prices, which is the process recreated in the ABMs. The exact dynamics of this shock(s) could be explored and included in more detail in future research.

To calculate the food production shocks in 2002/03 and 2006 best fitted lines per country were fit to cereals production data between 2000 and 2013. This was done for each of the main country producers, which represented 75% of global cereals production. These best fit lines were then subtracted from the production to remove the overall growth in production which characterised the food system. This growth matched the increase in demand from changing diets and a growing population. A percentage anomaly per year per country was then calculated away from this best fit line by dividing it by the production for that country. Table 5.2 shows these country anomalies for each year and the average for the years 2002, 2003 and 2006. These average production shocks were then summed to create the best estimate of the cumulative production shock that caused the food price shock in 2008. The sum of these production shocks represented an overall global food production shock of 8%.

Country	2000	2001	**2002**	**2003**	2004	2005	**2006**	2007	2008	2009	2010	**Average shock**
Argentina	4	1	**-3**	**-1**	0	2	**-3**	6	-3	-12	5	**-3**
Australia	4	6	**-10**	**7**	2	5	**-11**	-9	-1	-1	-1	**-5**
Bangladesh	3	0	**0**	**0**	-4	-2	**-2**	-1	1	1	2	**-1**
Brazil	0	8	**-1**	**9**	-1	-12	**-7**	1	5	-7	-5	**0**
Canada	6	-1	**-6**	**0**	2	2	**1**	-6	3	0	-5	**-2**
China	36	13	**-1**	**-40**	-13	-10	**2**	-6	4	-6	-5	**-13**
France	3	-4	**4**	**-6**	4	1	**-1**	-4	2	1	1	**-1**
Germany	0	1	**-1**	**-3**	3	1	**-1**	-2	3	2	0	**-2**
India	18	19	**-20**	**-2**	-11	-6	**-9**	2	4	-16	-7	**-10**
Indonesia	4	1	**0**	**-1**	-1	-2	**-4**	-3	-1	2	2	**-1**
Pakistan	2	0	**-2**	**-1**	-1	1	**0**	1	-2	1	0	**-1**
Russia	-11	4	**9**	**-11**	-1	1	**-2**	5	17	15	-19	**-1**
Thailand	0	1	**0**	**1**	-1	0	**-2**	0	-1	-2	0	**0**
Ukraine	0	9	**7**	**-11**	4	1	**-8**	-9	6	-3	-8	**-4**
USA	14	-13	**-46**	**-1**	32	4	**-29**	39	18	29	4	**-25**
Vietnam	1	0	**1**	**0**	1	0	**-1**	-2	0	-1	-1	**0**

Table 5.2 – Food production anomaly (percentage of overall production) away from best fit line for cereals production between 2000 and 2010 in major food producing countries. The average losses per country for the major production shock events (2002, 2003 and 2006) are shown in the final column (adapted from Natalini, et al., 2015a).

The percentage reductions of national food production for each country presented in Table 5.2 were included in the database used to initialise countries under the variable *food-scenario-parameter*. This variable equals 1 for countries that were unaffected by the food production shocks and 1 – the average shock reported in Table 5.2 otherwise. Consequently, if the switch in the ABMs' interface is 'on', i.e. the variable *2008-drought = true*, and if *ticks = 14,* i.e. the year 2008, countries multiply their current tick's *cereals-production * food-scenario-parameter*, replacing previous values for the variable *cereals-production*. Countries subsequently add the previous tick's un-exported cereals production, i.e. variable *cereals-stock-t-1*, and this tick's cereals production to the variable *cereals-production+exports*.

Finally, all the countries determine whether they are net importers or exporters of the resource by running an *ifelse* clause on the condition *cereals-consumption > cereals-production+exports*. If this clause returns *true*, countries classify as net importers and set the variables *cereals-imports-required* and *cereals-imports-required-before-trade* = cereals-*consumption* - cereals-*production*+exports. Alternatively, countries classify as net exporters for the resource and set the variable *cereals-exports-available = cereals-production+exports - cereals-consumption*.

5.1.7.6. Compute-food-price (Food and Food and Fuel ABMs)

This procedure first aggregates national values for different variables related to cereals into global variables. In particular, the global variables are called: global-cereals-production, global-cereals-consumption, global-cereals-stock-t-1 (this variable represents only the level of stocks that the current tick was initialised with), global-cereals-exports-available (cereals still available for exports before trade and after national consumption has been subtracted), global-cereals-availability (this variable represents the sum of production and exports available). Subsequently, the current tick's regime for international price of food is calculated according to the dynamics resulting from the ET presented in Section 5.2.

5.1.7.7. Compute-fuel-price (Fuel and Food and Fuel ABMs)

The same aggregation of national values into global variables is carried out for different variables related to oil: global-oil-reserves, global-oil-production, global-oil-consumption, global-oil-stock-t-1, global-oil-exports-available, global-oil-availability.

The ET implemented to calculate the current tick's regime for international price of fuel is presented in Section 5.2.

5.1.7.8. Trade-<resource> (All ABMs, all resources)

During the procedure to *trade-<resource>* importing countries try to import 10% of the total amount needed from a random country with which they share a connection and that still has exports available. This is to avoid one importing country to instantly deplete the exports available of the exporting country. However, this is still possible if the importer's *desired-imports* > *<resource>-exports-available* of the exporter or if this is the only country the importer is connected to with *<resource>-exports-available* > 0 and if *desired-imports* of the importer > *<resource>-exports-available* of the exporter. This is due to the fact that the search for new trade partners only starts when all the countries the importer has a connection with deplete their availability of exports for that resource. Therefore, the importing country sequentially imports 10% of its total imports needed from random countries it is connected with until either *desired-imports* = 0 or *<resource>-exports-available* of its current trade partners = 0. In the latter case, the importing country will randomly select a new trade partner from the pool of countries it is not yet connected with and with *<resource>-exports-available* > 0. If the criteria are not met by any of the countries, i.e. the exports available for the resource have been depleted in the whole world, the procedure terminates, otherwise a new directed link is created from the exporting country to the importer. The procedure continues until the importer's *desired-imports* = 0 or until the exports for the resource are depleted in the whole world. In addition, every successful transaction increases by one the *strength* of the link that has been used. Links 'break' after five years of consecutive not use. This figure is arbitrary and this behaviour was introduced to remove unused links.

Countries' bubbles in the ABMs' interface are coloured green if their consumption of the resource that has been selected to show are satisfied, orange otherwise. Because of the way international trade was implemented in the ABMs, if countries' bubbles turn orange signifies that the exports available for the resource have been exhausted worldwide, as importing countries will always try to (sequentially) import any exports available from any country until their national consumption is satisfied.

Countries that were constituted post-2005 and hence added during the runs of the model (Kosovo, Montenegro and South Sudan) are not assigned with any links once created, which are instead created through this procedure.

5.1.7.9. SURs (Food and Food and Fuel ABMs, only cereals)

After the first round of trade to cover consumption, countries proceed to compute their desired stocks for cereals according to the national Stock-To-Use Ratios (SURs) that they have been initialised with. This procedure and the following, i.e. to *restock-cereals*, have been introduced in the ABMs because these constitute one of the possible bases for further developments of the models. Since the 2008 global food crisis, an increasing amount of research has been dedicated to the role of food stocks in price formation. In particular, food storage has been found to greatly affect food price behaviour and that food price spikes are more likely to happen when stocks are low (Bobenrieth, et al., 2013). In addition, the work from Bobenrieth, et al. (2013) found that national SURs, coupled with prices, are good indicators of market tightness and scarcity in grain markets. This information also drove the decision to include the level of stocks in computing international prices for both food and fuel as presented in Section 5.2.

SURs are a percentage measure of a country's desire for food storage and are calculated as the ratio of stocks to consumption. In the ABMs developed as part of this work, SURs have only been calculated for cereals, as this is the only resource for which data on desired stock levels required by countries was available and, in addition, countries consciously make decisions as regards stock levels for this resource (Bobenrieth, et al., 2013). National stocks for energy resources are constituted by un-exported exports and carried over to the following tick.

National SURs have been calculated as the percentage ratio between cereals consumption and stocks for each country. Following Principle 2 of the GRO project, reported data has been used to calculate this parameter: the variable 'Food Consumption (1,000 MT) was sourced from the GRO database (GSI, 2014), whereas data for the variable 'Beginning Stocks' was sourced from the USDA database (USDA, 2015a). These two variables were used to calculate national SURs per each year for the period 1995 – 2011 and then averaged for each country to obtain a single parameter expressed as a percentage. This parameter, which, for simplicity, is kept constant throughout the simulation, is hence fed to the ABMs during their initialisation and national SURs are stored in the variable *food-SUR*.

Countries running this procedure hence calculate their SUR by executing the equation *cereals-consumption* * *food-SUR* / 100 and store the amount of food stock desired for the current tick in the variable *desired-cereals-stock*. If *desired-cereals-stock* > 0, countries with *cereals-exports-available* >= *desired-cereals-stock*, i.e. countries with cereals still available for exports after the first round of trade to cover countries' consumption, will cover their own needs for stocks with their leftover exports available, leaving the remainder in the variable *cereals-exports-available*. Conversely, countries with *cereals-exports-available* < *desired-cereals-stock* will subtract their *cereals-exports-available* from *desired-cereals-stock*.

5.1.7.10. Restock-cereals (Food and Food and Fuel ABMs, only cereals)

This procedure is only run by countries that have a preference for SURs and that could not cover their own needs for cereals stocks with their own production and previous stocks, i.e. countries with *desired-cereals-stock* > 0. The remainder of the procedure for restocking cereals is fundamentally similar to that of *trade-<resource>* and hence will not be repeated.

At the end of this procedure, the bubble of countries that could not meet their own needs for restocking turns either pink if these had also not met their needs for consumption or yellow if they did meet consumption but they did not meet their needs for restocking.

5.1.7.11. Check-network (All ABMs)

This procedure regulates the evolution of the social networks for the international trade of natural resources in the ABMs. As mentioned earlier in the text, the evolution of the networks included in the ABMs, i.e. four networks, one per each natural resource included, have emergent structures. In particular, links that have been left unused for longer than five ticks break. Two variables included in the ABMs are related to the links, which are called *strength* and *zero-time*. *Strength* increases by one unit every time natural resources are exchanged via this link, whereas *zero-time* is a counter that records the number of ticks the link has not been used.

By the time countries start running this procedure, both rounds of trade have already taken place, therefore if the link was used, its *strength* $\neq$ 0. Therefore, links whose *strength* = 0 will increase the counter *zero-time* by 1 or will set the counter to 0 if *strength* $\neq$ 0. Every five ticks, i.e. *if ticks mod* 5 = 0, links with *zero-time* ≥ 5 will *die*, whereas the other links will see their variables *strength* and *zero-time* reset to 0.

5.1.7.12. Compute-WGI (All ABMs)

As explored in depth in Chapter 3, the WGI is the measure of political fragility that has been selected and introduced in the ABMs and which significantly influences the occurrence of food and fuel riots in countries. Since this index is an aggregation of several different indices and measures (WB, 2015d), it could not be recreated endogenously and it was hence calculated for each country included in the ABMs by fitting trend lines to data sourced from the WB website (WB, 2015c). The time frame taken into account was 1996 – 2012 (as this is the first year for which data for the index is available. In addition, data for the WGI is available for every other year until 2002, after which yearly data is provided) and the polynomial functions calculated are fed into the ABMs during the initialisation of countries and stored in the variable *WGI-function*.

Countries running this procedure therefore evaluate their own WGI function with *x* = tick (year) and store the estimate for the WGI in the variable *WGI*. It is worth recalling here that the version of the WGI used in the models uses an inverted scale as compared to the original data downloadable from the WB website, i.e. high, positive estimates for the index equal to high levels of fragility and vice versa. The WGI has historically been constrained to the range {-1.94; …; 3.4}, with an increasing level of fragility as the estimate increases. This range is maintained constant in the different versions of the ABMs. In addition, to implement the findings from Chapter 4, countries needed to be divided into categories for the WGI, which were calculated as homogenous breaks using the whole range of possible estimates given by the index for the whole period: countries with a *WGI* < -0.622587779 are classified as 'low'; countries with - 0.622587779 < *WGI* < 0.69290963 are classified as 'medium-low'; countries with 0.69290963 < *WGI* < 2.008407038 and finally countries with *WGI* > 2.008407038 are classified as 'high'. The group countries belong to is stored in the variable *WGI-group*.

5.1.7.13. Food-or-fuel-fragility-first (Food and Fuel ABM)

This procedure is only present in the Food and Fuel version of the ABM, as this model includes dynamics that lead to both food and fuel riots and their mutual relationship. As presented in Chapter 4.3, the occurrence of food riots in countries increases the probabilities for the occurrence of fuel riots in the same country the same year and vice versa. Since this influence is mutual, the sequence with which the probabilities are calculated for each country is randomised. In particular, the probabilities leading to each type of riot are calculated in four different procedures grouped in two sets of two sub-procedures based on the REEM models presented in Chapter 4. According to the statistical models, the type of riot for which probabilities are calculated first will depend on both international price of the resource and national political fragility of the country, whereas the probability for the second type of riot will depend solely on whether the first type of riot occurred. The choice between which set of procedures is run, i.e. the decision determining which between food and fuel riots are calculated first, is randomised with 50% probability for each outcome. If the randomised choice results in food riots being calculated first, the first set of procedures will activate and will be run in the following order: 1. Food-fragility-first; 2. Fuel-fragility-second. Conversely, if the randomised choice results in fuel riots being calculated first, the second set of procedures will activate and will be run in the following order: 1. Fuel-fragility-first; 2. Food-fragility-second. The bubbles of countries in the ABMs' interface turn dark red if a food riot occurs or grey in case of a fuel riot.

5.1.7.14. Food-fragility-first (Food and Food and Fuel ABMs)

This procedure is included both in the Food and Food and Fuel ABMs. In this procedure, countries set to 0 a temporary variable *p*. This value will be replaced with the probability of food riot for the country according to the REEM model presented in Chapter 4.1.7.4, i.e. according to the *international-food-price* of the current tick and a country's *WGI-group*. The final probability of experiencing a food riot for each country is calculated according to Equation 5.1.

$$Pfood_{jnt} = pfood_{jnt} + i_{jt} + r_{jnt}$$

Equation 5.1 – final probability estimate for each country based on REEM model presented in Chapter 4.1.7.4 (own elaboration).

In Equation 5.1 $Pfood_{jnt}$ is the final probability of experiencing a food riot for each country n at tick t, which is the sum of each country n specific probability *pfood* given by the REEM model j according to the tick's t international food price regime and the country's WGI group, the intercept i for the REEM j and country n random-effects r for the REEM model j. Once estimated the final probability P_{jnt}, countries compare this with a *random-float* variable with value 1. If *random-float* 1 < P_{jnt}, a food riot occurs in the country running the procedure. Its variable *food-crisis* is set to *true* and the bubble of the country in the interface pane of the ABM becomes dark red.

5.1.7.15. Fuel-fragility-second (Food and Fuel ABM)

This procedure is only included in the Food and Fuel ABM. Here, a country's probability of experiencing a fuel riot solely depends on whether the same country has already experienced a food riot and the final probability is based on the REEM model presented in Chapter 4.3 and calculated according to Equation 5.2.

$$Pfuel_{mnt} = pfuel_{mnt} + i_{mt} + r_{mnt}$$

Equation 5.2 – final probability estimate for each country based on REEM model presented in Chapter 4.3 (own elaboration).

In Equation 5.2 $Pfuel_{mnt}$ is the final probability of experiencing a fuel riot for each country n at tick t, which is the sum of each country n specific probability *pfuel* given by the REEM model m according to the tick's t variable *food-crisis* for the country, the intercept i for the REEM m and country n random-effects r for the REEM m. Once estimated the final probability P_{mnt}, countries compare this with a *random-float* variable with value 1. If *random-float* 1 < P_{mnt}, a fuel riot occurs in the country running the procedure. Its variable *fuel-crisis* is set to *true* and the bubble of the country in the interface pane of the ABM becomes grey.

5.1.7.16. Fuel-fragility-first (Fuel and Food and Fuel ABMs)

This procedure is overall very similar to that presented in Section 5.1.7.14, although it is only included in the Fuel and Food and Fuel versions of the ABM and is aimed at estimating the probability for each country to experience a fuel riot based on the variable *international-fuel-price* and a country's *WGI-group*. Since the only difference between this procedure and Food-fragility-first is the REEM presented in Chapter 4.2.4 the full explanation will not be reported.

5.1.7.17. Food-fragility-second (Food and Fuel ABM)

This procedure is also very similar to that presented in Section 5.1.7.15, although it is only included in the Food and Fuel version of the ABM and is aimed at estimating the probability for each country to experience a food riot based on whether a country has already experienced a fuel riot during the same tick, i.e. variable *fuel-crisis* = *true*. Since the only difference between this procedure and Fuel-fragility-second is the REEM presented in Chapter 4.3, the full explanation will not be reported.

5.1.7.18. Update-stocks (All ABMs, all resources)

In this procedure global stocks for the natural resources included in the different versions of the ABM are calculated by aggregating national leftovers from trade, i.e. variables *<resource>-exports-available*. These aggregated values are stored in global variables called *<resource>-stock-t-1* and countries' variables *<resource>-exports-available* are set to 0.

5.1.7.19. Plots-and-monitors (All ABMs)

This procedure updates the plots and monitors present in the ABMs interface. These draw plots and update monitors that display data related to the following global variables: *global-<resource>-reserves* (only for energy resources), *global-<resource>-production*, *global-<resource>-consumption*, *global-<resource>-imports-required-before-trade*, *global-<resource>-exports-available*, *global-<resource>-availability*, *global-pop*, *global-pop-growth*. These variables are aggregates of national values for the same variables.

5.2. Calibration of the ABMs: modelling international prices for food and fuel

As presented in the previous chapter, one of the conditions that determines whether a country will experience a food or a fuel riot is the international price of each resource, which in the different versions of the ABM were modelled in two regimes: either above or below a threshold found at 140 for the FAO FPI and $93 a barrel for the EIA fuel price. International prices for food and fuel – the first included in the Food ABM, the second in the Fuel ABM and both included in the integrated Food and Fuel ABM – were the two target variables of the calibration in the models. Prices in the ABMs were calibrated using only the interaction between global demand and supply, i.e. the ratio between the two, and global stocks for each resource. Although these variables constitute only some of the factors that determine international prices of natural resources, this constitutes a good first approximation. Indeed, as discussed in Chapter 2.8, international prices of natural resources depend on complex dynamics led by different market and physical conditions, which were beyond the scope of this research. The ABMs only needed to reproduce the dynamics of price shocks – and not the exact $ amount – to recreate the conditions that lead to the occurrence of riots. The consequences of this choice will be discussed in depth in Section 5.5 and Chapter 7.

As detailed in Chapter 3.3.7, it is common practice to either use two different databases for calibration and validation of the model or split the database using a subset of observations to calibrate the model and the remaining ones to validate its results. In the case of this research, neither of these options was viable due to the short time frame considered, i.e. 2005 – 2013, and the general scarcity of data on food and fuel riots, which are still rare events. The only comprehensive databases available with records for these occurrences were those created as part of this research and the second option of splitting the database in two would have resulted in halving the number of riots for each period, which would have been detrimental to the robustness of the results from the calibration. Therefore, in the case of this work the same database was used to calibrate and validate the different versions of the ABM, although focusing each procedure on different variables. The calibration was aimed at reproducing the international price regimes for oil and food, whereas the validation of the model focused on the variables *food-* and *fuel-crisis*, i.e. food and fuel riots.

Two sets of data were tested to calibrate the ABMs, i.e. reported data for the ratio between production and consumption and stocks of the resources and data for these variables resulting from the model. To highlight the difference between these two sets of data and to justify the introduction of a food production shock in 2008, the first subsection will present a comparison. The second subsection will present findings from different experiments on reported and simulated data using different methods to recreate prices in the ABMs, i.e. ETs and the use of two free parameters. Finally, the results for each section of this chapter will be discussed and a method to introduce prices in the ABMs will be chosen. For reasons of brevity, the databases used to fit each model are provided as attachments and the ETs on reported data for food and fuel are provided in Appendix 3. The analyses were run with R (R Core Team, 2013) and ETs were built with the R package ev.tree() (Grubinger, et al., 2014).

5.2.1. *Comparing data from the model with reported data*

Conventionally, the calibration procedure uses real data to find different combinations of parameters that, once included in the computer model, allow them to match measurements as closely as possible. In other words, models are 'trained' on real data. Because the calibration of the ABMs was attempted on both reported and simulated data for these variables, it is important to compare these estimates. Even more so to justify the introduction of the 2008 food production shock in the simulated data and to speculate on why only the calibration on simulated data was successful. The simulated data for food and fuel variables was extracted from the ABMs at the end of each tick and constitutes the sum of national estimates for food/fuel production, consumption – to calculate the ratio between the two – and stocks. The national estimates for these variables result from the polynomial trend-lines discussed in the previous section and the 2008 food production shock was not activated to collect data from the Food ABM.

Reported data for production, consumption and stocks of food (cereals) was retrieved from the USDA data bank (USDA, 2015b). The data source for the variables used for the calibration was different from that used for the other analyses and for the initialisation of the ABMs, i.e. the national data for cereals production and consumption implemented in the model was derived from the GRO database, which, in turn, sourced it from Food and Agriculture Organisation Statistical Division (FAOSTAT) (Jones and Phillips, 2015), because the GRO Database did not provide world estimates for food, and FAOSTAT only provided data until 2011. In addition, national data for food stocks used to calculate several parameters implemented in the ABMs and used to initialise countries' food stocks was already sourced from USDA. The variables used were World Food Production (1,000 MT), World Food Domestic Consumption (1,000 MT) and World Stocks (1,000 MT). Although these variables are officially related to food in general, the metadata clarifies that these only capture cereals, which allows their use in combination with the FAO FPI and the variables present in the ABMs.

Table 5.3 presents the comparison between ratios and stocks relative to reported (USDA) and simulated data, extrapolated from the Food ABM.

Variable	Data source	2005	2006	2007	2008	2009	2010	2011	2012	2013
Ratio prod/cons	USDA	0.998	0.980	1.013	1.043	1.024	0.988	1.016	0.989	1.033
	Food ABM	1.027	1.018	1.021	1.017	1.006	0.994	1.002	0.995	0.988
	Ratio USDA/ABM	0.972	0.963	0.992	1.025	1.018	0.994	1.015	0.994	1.046
Food Stocks	USDA	394939	348458	371114	452058	490295	460073	466279	451577	512120
	Food ABM	350768	405156	441724	486362	523383	537250	523543	527060	514121
	Ratio USDA/ABM	1.126	0.860	0.840	0.930	0.937	0.856	0.891	0.857	0.996

Table 5.3 – Comparison between data from USDA and data from the Food ABM for the variables Ratio Food production/consumption and Food stocks. Data for stocks is expressed in 1,000 MT (own elaboration).

As shown in Table 5.3, the data for food production and consumption included in the model is generally similar to that reported by USDA. Reported data for the ratio between food production and consumption vary between -4% and +5% as compared to simulated data. As regards data for reported and simulated stocks, real international food stocks vary between -16% and +13% as compared to simulated data.

As for the comparison between reported and simulated world data for fuel, reported data was retrieved from the EIA website (US EIA, 2015a). The variables used were Total Petroleum Consumption (Millions Barrels) and Total Oil Supply (Millions Barrels) to calculate the ratio between production and consumption of oil and Total Petroleum Stocks, End of Period (Millions Barrels). Table 5.4 presents the comparison between the ratios and stocks relative to reported (EIA) and simulated data, extrapolated from the Fuel ABM.

Variable	Data source	2005	2006	2007	2008	2009	2010	2011	2012	2013
Ratio prod/cons	EIA	0.994	1.005	1.018	0.994	0.991	1.001	1.006	0.999	1.003
	Fuel ABM	1.007	1.005	1.004	1.004	1.003	0.996	0.994	0.985	0.893
	Ratio EIA/ABM	0.987	1	1.014	0.990	0.988	1.004	1.013	1.014	1.123
Oil Stocks	EIA	4075.96	4168.60	4085.52	4202.86	4206.61	4219.02	4118.68	4187.25	4126.61
	Fuel ABM	4075.96	4269.33	4388.00	4476.91	4546.14	4579.22	4381.92	4016.40	3288.26
	Ratio EIA/ABM	1	0.976	0.931	0.939	0.925	0.921	0.940	1.043	1.255

Table 5.4 – Comparison between data from EIA and data from the Fuel ABM for the variables Ratio Oil production/consumption and Oil stocks. Data for oil stocks is expressed in Million barrels (own elaboration).

The data for oil production and consumption included in the model is generally similar to that reported by EIA. Reported data for the ratio between oil production and consumption vary between -1% and +1% as compared to simulated data, with only 2013 recording a figure +12% larger than simulated data. As regards data for reported and simulated stocks, reported international fuel stocks vary between -26% and +7% as compared to simulated data.

In general, the ABMs seem to recreate quite accurately production and consumption patterns for oil, whereas the comparison of food variables shows larger variations. This is mainly explained by the use of smoothed trend lines to model these variables in the ABMs: indeed, the deterministic estimates for production and consumption – and hence stocks – of natural resources resulting from the ABMs derive from the trend lines on past data for these variables, which are introduced at the national level in the models and calculated by the agents at the beginning of each tick. Indeed, the Ratio prod/cons in the model was consistently higher than reported data in the period 2005 – 2007. This justifies the exogenous introduction of the 2008 food production shock to compensate for the higher food availability during that year in the model, as compared to reported data. It is worth noting that, although a few percentage points variations seem small, these can potentially translate in large differences when focussing on absolute estimates. Finally, data for stocks vary largely between simulated and reported data. The consequences of the difference between the variables will be subject to a critical evaluation in Section 5.5.

5.2.2. Calibration with ETs and free parameters

As explained in detail in Chapter 3.4.4, ETs are regression trees that belong to the family of Machine Learning and identify breaks in the data of a set of independent variables that lead to a specific outcome observed in the target variable. In this case, the independent variables were the ratios between world production and consumption and stocks of food and oil and the target variables were the regimes (either above or below the threshold) of the international prices of these resources.

In the first instance, the calibration was attempted on the reported data presented in the previous section. Two ETs were fit to the data, one per each resource analysing the period 2005 – 2013 to maintain consistency with previous analyses. Although ETs for both resources perfectly recreated the regimes for international price regimes, i.e.

either below or above the threshold, and identified both ratio and stocks as significant variables, the dynamics identified seemed counterintuitive and unrealistic. For instance, the models said that high levels of stocks and ratio between production and consumption correspond to high price regimes and vice versa, which are the opposite dynamics that one would expect. In addition, data for world estimates of the variables used as independent in the models presented several inconsistencies. In particular, there does not seem to be a clear relationship between stocks of the resources and supply-demand dynamics. This is particularly true for oil, where for several years, in correspondence to a surplus of production, global oil stocks decrease in the world. This suggests possible inaccuracies in the data and/or in the reporting process for these variables, which requires further investigation (see for instance Phillips, 2016). Since this went beyond the scope of this research, these variables were not used to parameterise the price dynamics in the ABMs. These models are presented in Appendix 3 for reasons of brevity, and the results will be further discussed and compared to the other ETs in Section 5.5. For all the reasons above, the models were calibrated using endogenous data from the ABMs.

The next experiment for calibration used data from the ABMs for global production, consumption and stocks of food and oil and real data for international price regimes i.e. either above or below the threshold, of the resources. The 2008 food production shock was activated to collect data from the Food ABM. Two different methods were tested: ETs and calibration using two free parameters.

As for calibration of international prices for food, an ET model was fitted to the data from the ABMs using the ratio between Global Cereals Production and Global Cereals Consumption and Global Cereals Stocks as independent variables and the real series of price regimes between 2005 and 2014 as target variable. The results from the ET model for food are presented in Figure 5.3.

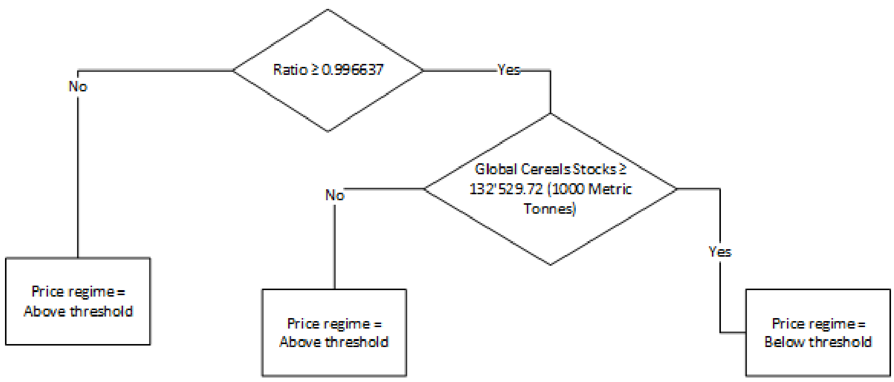

Figure 5.3 – ET model on data from the ABMs for food using ratio between 'Global Cereals Production' and 'Global Cereals Consumption' and the variable 'Global Cereals Stock' as independent variables and the variable 'Price threshold' as target variable (own elaboration).

The results from the ET for food fit to the data from the Food ABM perfectly recreate the international price regime for the period considered and show more intuitive dynamics as compared to the ET on reported food data. In particular, when the ratio between global production and consumption of cereals is smaller than 0.996637, the international price of food is above the threshold. For any ratio larger or equal to 0.996637, global stocks of cereals become significant and, in particular, when these are smaller than 132,529.72 (1,000 MT), the price climbs above the threshold, and below otherwise.

A more conventional method to calibrate models was also tested on data from the model and compared to the results from the ET for food: calibration through two free parameters, one related to the ratio between global cereals production and consumption (α) and the other related to global stocks of cereals (β). This type of calibration is usually carried out directly in NetLogo, where the emergent behaviours result in different data for each run of the model and these can be accounted for. However, since global estimates for production, consumption and stocks are deterministic in the ABMs developed in this research, data was extrapolated from the models and analysed with an R script. The script runs 100 iterations of a procedure that compares the regime price generated by each combination of the parameters α and β with the real price regime observed for the FAO FPI for each year. The range explored for the parameters are $\alpha \in \{0.909, 0.910, \cdots, 0.998\}$ and $\beta \in \{1.07e+11, 1.08e+11, \ldots, 3.51e+11\}$ and the combinations were analysed both with 'AND' and 'OR' between them. In the case with 'AND', the maximum percentage of years that the combinations could correctly predict was 80%. There were 5 combinations of parameters that led to this result and one of them presented a ratio equal to 0.9983593 whereas the parameter for stocks was 128,728 (1,000 MT). In particular these combinations were not able to capture the years 2008 and 2014, which were both predicted below the threshold. As for combinations with 'OR' 194 combinations of parameters led to a perfect recreation of the international price of food, which were not consecutive. One of these was α = 0.910088914 and β = 128,728 (1000 MT).

These two methods have also been applied to the calibration on international fuel price regimes. Firstly, an ET model was fit to the data from the models using the ratio between Global Oil Production and Global Oil Consumption and Global Oil Stocks as independent variables and the real series of price regimes between 2005 and 2014 as target variable. The results from the ET model for fuel are presented in Figure 5.4.

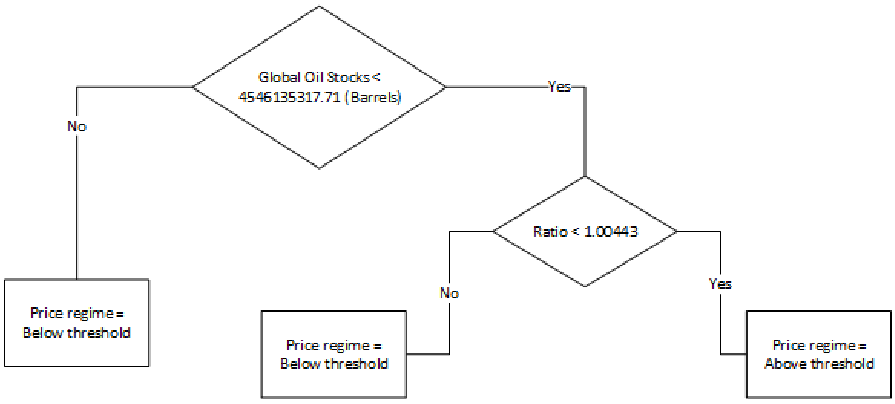

Figure 5.4 – ET model on data from the ABMs for fuel using ratio between 'Global Oil Production' and 'Global Oil Consumption' and the variable 'Global Oil Stock' as independent variables and the variable 'Price threshold' as target variable. The unit used for stocks of oil is barrels (own elaboration).

Also in the case of fuel, the results from the ET run on data from the Fuel ABM perfectly recreate the international price regime for the period considered and show more intuitive dynamics as compared to the ET on reported fuel data. In particular, when global stocks of oil are larger or equal to 4.55e+09 barrels, the international price of fuel is below the threshold. Conversely, when the stocks are smaller than 4.55e+09 barrels, the ratio between global production and consumption of oil is significant and if this is smaller than 1.00443 the international price of oil is above the threshold. For any ratio larger or equal to 1.00443, the price remains below the threshold.

The calibration of the models through the use of two free parameters, one representing the ratio between 'Global Oil Production' and 'Global Oil Consumption' (α) and the other representing 'Global Oil Stocks' (β) was also implemented in the case of oil. The range explored for the parameters was $\alpha \in \{0.871, 0.872, \cdots, 1.006\}$ and $\beta \in \{0.000, 0.001, \ldots, 4.58e+09\}$ and the combinations were analysed both with 'AND' and 'OR' between them. In the case with 'AND', 39 combinations led to correctly predict 90% of the years, not being able to predict 2008 above the threshold. One of the combinations that led to this result was ratio 0.994218549 and stocks 4.39e+09 barrels. Combinations with 'OR' achieved the same level of accuracy, as the maximum percentage of years that the combinations could correctly predict was 90%, not being able to correctly predict the price above threshold in 2008. There were 178 combinations of parameters that led to this result and one of them presented a ratio equal to 0.994218549 whereas the parameter for stocks was 4.63e+09 barrels.

Interestingly, the breaks identified with these two methods, i.e. ET and parameters, although equivalent, led to two different accuracies for the replication of international price regimes for food and fuel, probably due to the number of decimals included in the experiment with the two free parameters. ETs, overall, proved to be more accurate as compared to the calibration with two free parameters. Therefore this method was selected to simulate price regimes for food and fuel and the dynamics implemented in the different versions of the ABMs.

5.3. Validation of the ABMs

Models that aim at producing meaningful predictions for future events need to be validated, to ensure the model's ability to reproduce the dynamics that characterise the system which they aim to represent. As mentioned before, the ABMs developed as part of this research are empirically grounded, which means that reported data was used to generate the characteristics of the countries and parameters and relationships were informed on statistical tests carried out on real data from past events. This means that the ABMs are already internally validated (Squazzoni, 2012). To further test whether the dynamics included in the models were sufficient to recreate the occurrence of food and fuel riots and with what accuracy, data resulting from the models runs on the period 2005 – 2013 was analysed and compared with the real data on food and fuel riots presented in Chapter 4. As mentioned in Chapter 3, the validation of an ABM is conventionally carried out by comparing results from the model with a database different from the one used for calibration. However, due to scarcity of data it was decided to validate the different versions of the ABM on the same database used to calibrate them, although focusing on different variables to check the validity of the models' results. The country-level variables relevant to this process that have been recorded at the end of each tick in the ABM runs are *food-crisis* and *fuel-crisis*. The validation of the ABMs has been carried out separately for each version, i.e. Food, Fuel and Food and Fuel, to analyse the added value of introducing dynamics resulted from statistical models in an ABM environment and evaluate possible emergent properties. In particular, the validation evaluated the models' ability to predict four different types of information about riots: i) the total number of riots occurred when the regime of the international price of resources was either above or below the threshold; ii) the number of riots per year; iii) the countries that experienced a riot at any point during the time frame considered and iv) each specific riot occurred in each country during each year.

5.3.1. Validation of the Food ABM

In order to validate the Food ABM, 100 simulations were run and analysed. Firstly, the simulated cumulative probability of food riots to happen in the years below (2005 – 2007 and 2009) and above (2008 and 2010 – 2013) the 140 FAO FPI threshold were calculated and compared with the reported cumulative probability during those periods. The simulated probability for the below-threshold period was 0.06 whereas the real probability was 0.02. For the above-threshold period, the simulated probability was 0.17, whereas the reported probability was 0.22. Although the Food ABM overestimates countries' probability to experience a food riot when the international price of food is below the threshold and underestimates their probability when the price is high, the probabilities are remarkably similar when aggregated by price regime.

Figure 5.5 plots the number of food riots per year as they occurred in reality and as predicted by the Food ABM. The 2008 peak plotted in both lines suggests that the ABM correctly represents a higher probability of the occurrence of food riots in that year, and, although the absolute number of food riots per year is underestimated by the model, the lines follow the same pattern. Interestingly, the model failed to fully capture the second peak of food riots that occurred in 2011 and tended instead to spread the riots that occurred in 2011 over a four-year period also covering 2010, 2012 and 2013. The model also seems to overestimate non-food riot years – so the overall distribution is flatter. Overall the model seems to smoothen the real-world dynamics, which suggests the lack of some important positive feedback mechanism (something to include in future versions).

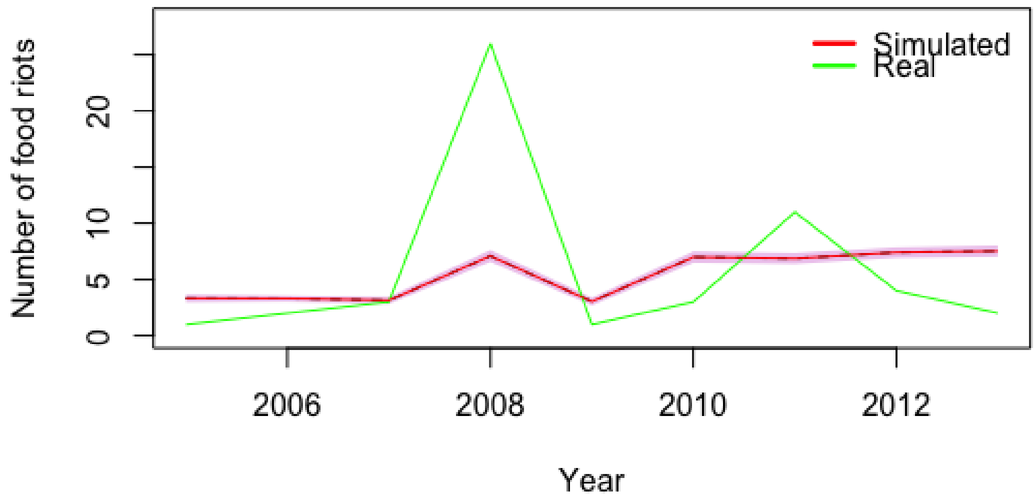

Figure 5.5 - Number of food riots per year as they were reported and as predicted by the Food ABM. The pink shaded area represents the 95% confidence interval in the model's results (own elaboration).

To further investigate the results from the Food ABM, the list of countries with the highest likelihood of food riots throughout the whole period as simulated in the model and the database of food riots presented in Chapter 4.1.7.1 were compared to evaluate the accuracy of the Food ABM at predicting which countries experienced food riots in the time frame considered. The simulated probabilities ranged between 0% and 9% with the lowest probability assigned to Australia and the highest to India. In particular, 70% of the countries that fell within the top 10 countries most at risk of experiencing a food riot as calculated by the Food ABM experienced a food riot. This percentage remains unvaried for the top 20 countries most at risk and 63% for the top 40.

The accuracy of the Food ABM was investigated further by evaluating the predictions for both year and country for each food riot resulting from the ABM simulations. To do this, an R script calculating the percentage match between the variable food-crisis extrapolated for each country for each year from the results of the Food ABM and the variable Food Riot from the dataset was run. The script first calculated the overall accuracy of the model, i.e. at predicting both countries that did experience a food riot during a given year and countries that did not, the percentage of correctly predicted food riots in each country for each year, and, finally, the percentage of false food riots predicted, i.e. food riots predicted by the model in a certain country during a given year that did not occur in reality. This was done for each of the 100 runs of the Food ABM and the average results are presented in Table 5.5.

Variables	**Percentages predicted**
Food.all	95.13%
Food.true	6.86%
Food.false	2.44%

Table 5.5 – Summary of the averaged results for the predictions from the 100 runs of the Food ABM, where Food.all is the overall accuracy of the model at predicting both countries that did and did not experience a food riot in reality, Food.true the percentage of correctly predicted food riots in each country for each year and Food.false is the percentage of false food riots predicted (own elaboration).

Table 5.5 shows that the Food ABM correctly predicts only around 7% of the specific food riots reported (both country and year), although maintaining a high overall accuracy (95%) due to the low number of false positives predicted, i.e. around 2%. The low accuracy at predicting specific food riots clearly highlights the lack of important dynamics and factors in the ABM. It is in fact highly likely that the international price regimes and national political fragility are only some of the drivers of food riots.

5.3.2. Validation of the Fuel ABM

Similarly to the Food ABM, the Fuel version was run 100 times and the results analysed. The simulated cumulative probability of fuel riots to happen in the years below (2005 – 2007 and 2009 – 2010) and above (2008 and 2011 – 2013) the $93 per barrel threshold for the EIA fuel price were calculated and compared with the reported cumulative probability during those periods. The simulated probability for the below-threshold period was 0.07 whereas the reported probability was 0.04. For the above-threshold period, the simulated probability was 0.12, whereas the reported probability was 0.15. Although, similarly to the Food ABM, the Fuel version overestimates countries' probability to experience a fuel riot when the international price of fuel is below the threshold and underestimates their probability when the price is high, the probabilities are remarkably similar when aggregated by price regime.

Now comparing the predicted number of riots per year and the number of events occurred, Figure 5.6 plots the results for reported and simulated riots. As for the validation of the Food ABM, also for Fuel the 2008 peak plotted in both lines suggests that the ABM correctly represents a higher probability of the occurrence of fuel riots in that year, and in general the fit seems somewhat better than for food. Indeed, differently from the analysis for the Food ABM, the Fuel version captures the second peak of riots occurred in 2011, although the probability of riots remains almost constant for the following years. This results in the ABM's failure to capture the fall and subsequent rise in the probability of fuel riots for the years 2012 and 2013.

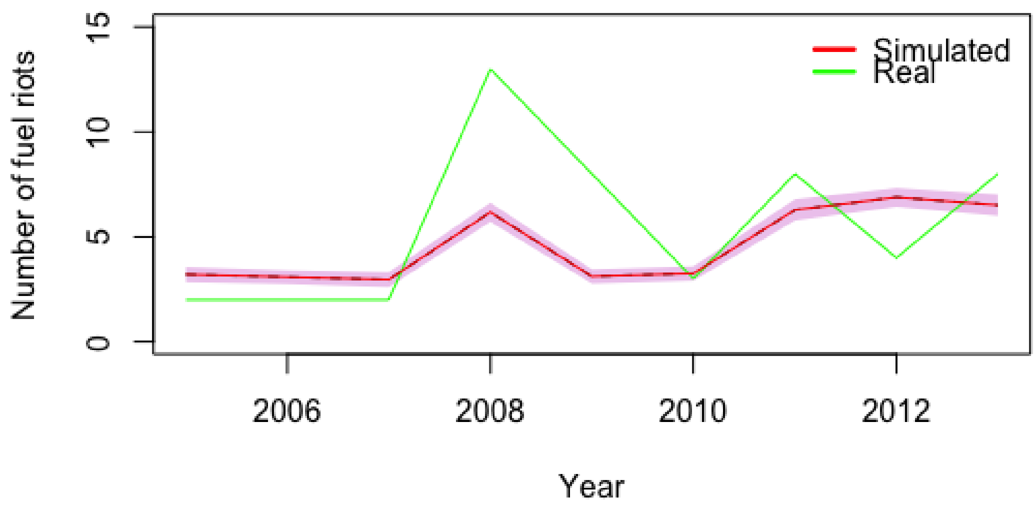

Figure 5.6 - Number of fuel riots per year as they were reported and as predicted by the Fuel ABM. The pink shaded area represents the 95% confidence interval in the model's results (own elaboration).

Now investigating the accuracy of the Fuel ABM at predicting the countries that, throughout the whole period considered, experienced fuel riots, the list of countries with the highest likelihood of fuel riots throughout the whole period as simulated in the model and the database of fuel riots presented in Chapter 4.2.1 were compared. The simulated probabilities ranged between 0% and 25% with the lowest probability assigned to Bahrain and the highest to India. 100% of the countries that fell within the top 10 countries most at risk of experiencing a fuel riot as calculated by the Fuel ABM effectively experienced a fuel riot. This percentage equals 95% for the top 20 countries most at risk and all the countries that experienced a fuel riot, i.e. 32 countries, were ranked in the top 43 countries most at risk.

The accuracy of the Fuel ABM was investigated further by calculating the percentage of fuel riots occurred in each country during each year correctly predicted by the model. This was tested by adapting the same R script implemented for the validation of the Food ABM. The averaged results from the 100 runs of the Fuel ABM are presented in Table 5.6.

Variables	**Percentages predicted**
Fuel.all	96.07%
Fuel.true	10.24%
Fuel.false	2.00%

Table 5.6 – Summary of the averaged results for the predictions from the 100 runs of the Fuel ABM, where Fuel.all is the overall accuracy of the model at predicting both countries that did and did not experience a fuel riot in reality, Fuel.true the percentage of correctly predicted fuel riots in each country for each year and Fuel.false is the percentage of false fuel riots predicted (own elaboration).

The Fuel ABM performed better than the Food ABM (around 10%) at predicting the year and country when (fuel) riots occurred, although its accuracy remains low. Remarkably, also the Fuel ABM had a low percentage of false positive of around 2%, which resulted in a high overall performance of more than 96% of observations correctly predicted. Even in this case the results show the ABM's lack of specific dynamics that would allow it to predict specific fuel riots, i.e. the country and the year when these occurred.

5.3.3. Validation of the Food and Fuel ABM

Finally, the integrated Food and Fuel ABM was validated implementing the same methodology as the previous sections. Since this version of the model includes dynamics that lead to both food and fuel riots and their interaction (see Chapter 4.3), its predictions have been validated for both types of event.

The simulated cumulative probability of food riots to happen in the years below (2005 – 2007 and 2009) and above (2008 and 2010 – 2013) the 140 threshold for the FAO

FPI were calculated and compared with the reported cumulative probability during those periods. The simulated probability for the below-threshold period was 0.08 whereas the reported probability was 0.02. For the above-threshold period, the simulated probability was 0.16, whereas the reported probability was 0.22. These results are in all similar to those from the Food ABM, and the minimal differences are likely to be due to the stochasticity built into the models.

Focusing now on fuel riots, the simulated cumulative probability of fuel riots to happen in the years below (2005 – 2007 and 2009 – 2010) and above (2008 and 2011 – 2013) the $93 per barrel threshold for the EIA fuel price were calculated and compared with the reported cumulative probability during those periods. The simulated probability for the below-threshold period was 0.09 whereas the reported probability was 0.04. For the above-threshold period, the simulated probability was 0.11, whereas the reported probability was 0.15. Even in the case for fuel riots, the inclusion of dynamics between food and fuel riots does not increase the predictive power of the ABM as far as the cumulated probability of riots per price regime.

Now comparing the predicted number of riots per year and the number of events occurred, Figure 5.7 plots the results for reported and simulated food riots. The plot is nearly identical to the one presented in Section 5.3.1, highlighting that the analysis does not gain any predictive power when focusing on the total number of food riots per year.

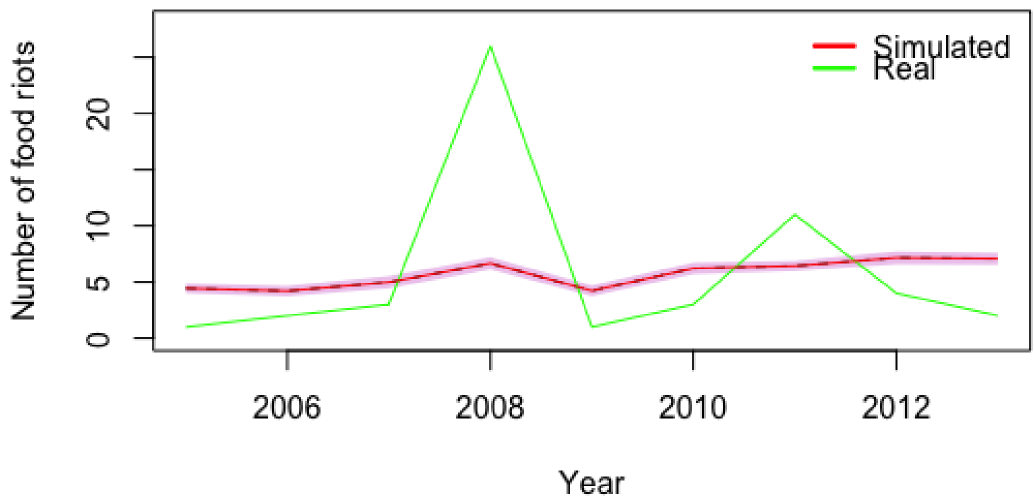

Figure 5.7 - Number of food riots per year as they were reported and as predicted by the Food and Fuel ABM. The pink shaded area represents the 95% confidence interval in the model's results (own elaboration).

Figure 5.8, instead represents the comparison between the yearly number of fuel riots as predicted by the Food and Fuel ABM and those reported, which even in this case is nearly identical to that produced for the results from the Fuel ABM, presented in Section 5.3.2. The only noticeable difference between the two figures is that in Figure 5.8 the small peak of fuel riots that can be found in Figure 5.6 is missing, resulting in a pattern that resembles reality more closely.

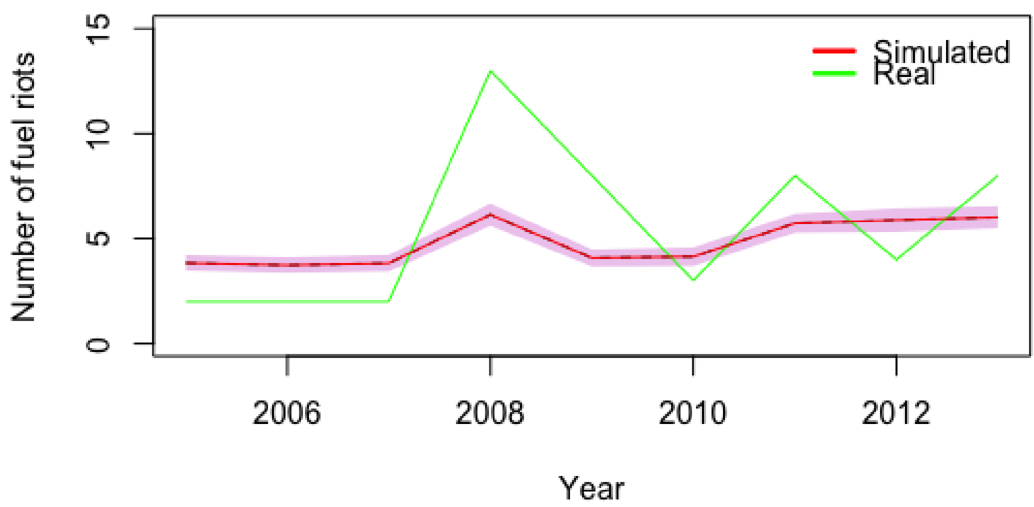

Figure 5.8 - Number of fuel riots per year as they were reported and as predicted by the Food and Fuel ABM. The pink shaded area represents the 95% confidence interval in the model's results (own elaboration).

Now focussing on the countries that experienced a food riot at any point during the time frame considered, the accuracy of the predictions from the Food and Fuel ABM was evaluated. The simulated probabilities ranged between 0% and 8% with the lowest probability assigned to Tanzania and the highest to India. 41.90% of the countries that fell within the top 10 countries most at risk of experiencing a food riot as calculated by the Food and Fuel ABM experienced a food riot. This percentage is equal to 85% for the top 20 countries most at risk and 73% for the top 40. These percentages show a clear improvement from the predictions for single countries' probability to experience a food riot as resulting from the Food ABM.

The same analysis was applied to fuel riots. The simulated probabilities for fuel riots resulting from the Food and Fuel ABM ranged between 0% and 27% with the lowest probability assigned to Tunisia and the highest to India. The total number of countries that experienced a fuel riot during the time frame considered in this analysis was 32, which all fell within the top 33 countries most at risk of experiencing a fuel riot as calculated by the Food and Fuel ABM. In this case the model's accuracy at predicting which country will experience a fuel riot during the time frame considered is exceptional and also constitutes a remarkable improvement from the predictions resulting from the Fuel ABM.

The accuracy of the Food and Fuel ABM was investigated further by calculating the percentage of food and fuel riots occurred in each country during each year correctly predicted by the model. The averaged results from the 100 runs of the Food and Fuel ABM are presented in Table 5.7.

Variables	Food	Fuel
All	94.99%	95.99%
True	6.86%	10.76%
False	2.58%	2.09%

Table 5.7 – Summary of the averaged results for the predictions from the 100 runs of the Food and Fuel ABM, where the variable 'All' is the overall accuracy of the model at predicting both countries that did and did not experience a riot in reality, 'True' the percentage of correctly predicted riots in each country for each year and 'False' is the percentage of false fuel riots predicted (own elaboration).

The comparison between the results presented in Table 5.7 and Tables 5.5 and 5.6, clearly show that the inclusion in the ABM of mutual influence between food and fuel riots does not add any predictive power to the model when focusing on both countries and years for each type of riot.

5.4. Future forecasts for the year 2017

One of the possible uses of computer models is to provide insights about possible futures. These future projections are commonly highly arbitrary, being produced by taking into account only the specific dynamics and assumptions implemented in the computer model. In order to provide insights about the future of food and fuel riots, 100 simulations of each version of the ABM were run and the results for food and fuel riots for the year 2017 were analysed. These consider the Business As Usual (BAU) dynamics included in each of the versions of the ABM. 2017 was selected because it is the first year in the future at the time of writing this thesis, i.e. March 2016, and, in addition, the different versions of the ABM were built to provide short term forecasts for the 5 – 10 years after the last year used to calibrate the models, which in this case was 2013.

The results from the ABMs for the international price regimes suggest that both food and fuel price are likely to be above the threshold in 2017, thus increasing the probability of the occurrence of food and fuel riots during this year. However, the predictions for the international price regime need to be taken with reservations as explained in depth in the Discussion Section of this chapter.

First the results for the forecast from the Food ABM were analysed. Out of all the years considered, 2017 had one of the highest probability for a random country to experience a food riot, which was around 4% as compared to 1% in 2005 (the year with the simulated lowest probability of food riots) and 3% in 2008 (the year that registered the largest number of food riots reported). The probabilities of food riots for countries for the year 2017 ranged between 0% and 17%, with the highest probability assigned to Turkey. In the top 10 countries most at risk we find Turkey, Afghanistan, Cameroon, Congo Democratic Republic, Iran, Lao, Thailand, Algeria Mauritania and Nigeria, with probabilities spanning between 17% and 13%. 30 countries were assigned with the lowest probability, amongst these we find Austria, Belgium and Iceland. For a better visualisation, the results from the food riots forecast for 2017 from the Food ABM are presented in Figure 5.9.

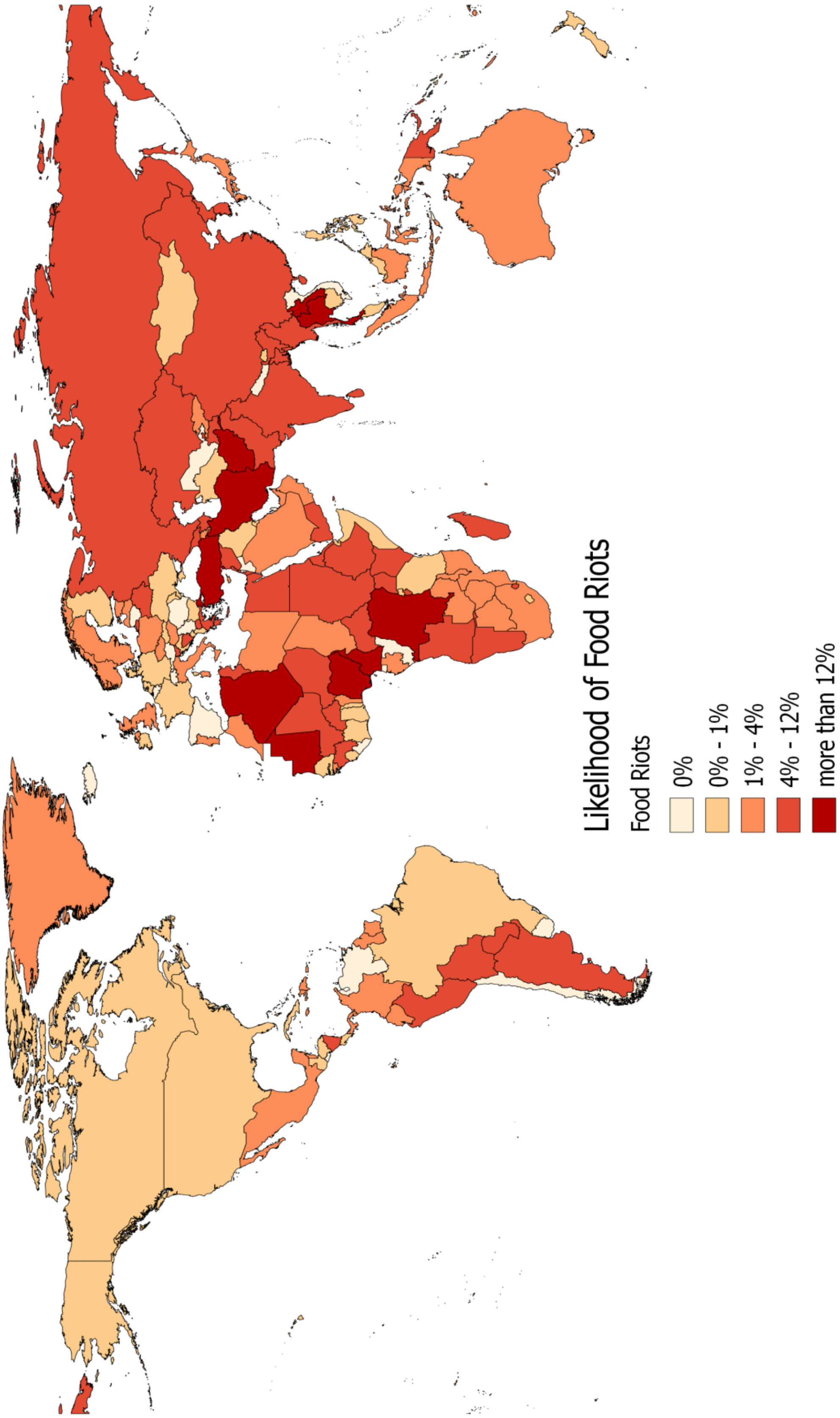

Figure 5.9 – Probability of food riots for countries based on the forecast for 2017 from the Food ABM (own elaboration).

Subsequently, the results for the forecast from the Fuel ABM were analysed. Similarly to the forecast from the Food ABM, out of all the years considered 2017 was the second year with the highest probability for fuel riots, which was around 4% as compared to 1% for 2006, which was the year with the lowest simulated probability of fuel riots and 3% in 2008, the year with the largest number of fuel riots reported. The probabilities of fuel riots for countries for the year 2017 ranged between 0% and 32%, with the highest probability assigned to India. At the top of the list of countries most at risk we find India, China, Bolivia, Greece, Yemen, Italy, Korea Democratic Republic, Pakistan and Nicaragua, with probabilities spanning between 32% and 13%. 68 countries were assigned with the lowest probability, amongst these we find Côte d'Ivoire, Japan and Haiti. For a better visualisation, the results from the fuel riots forecast for 2017 from the Fuel ABM are presented in Figure 5.10.

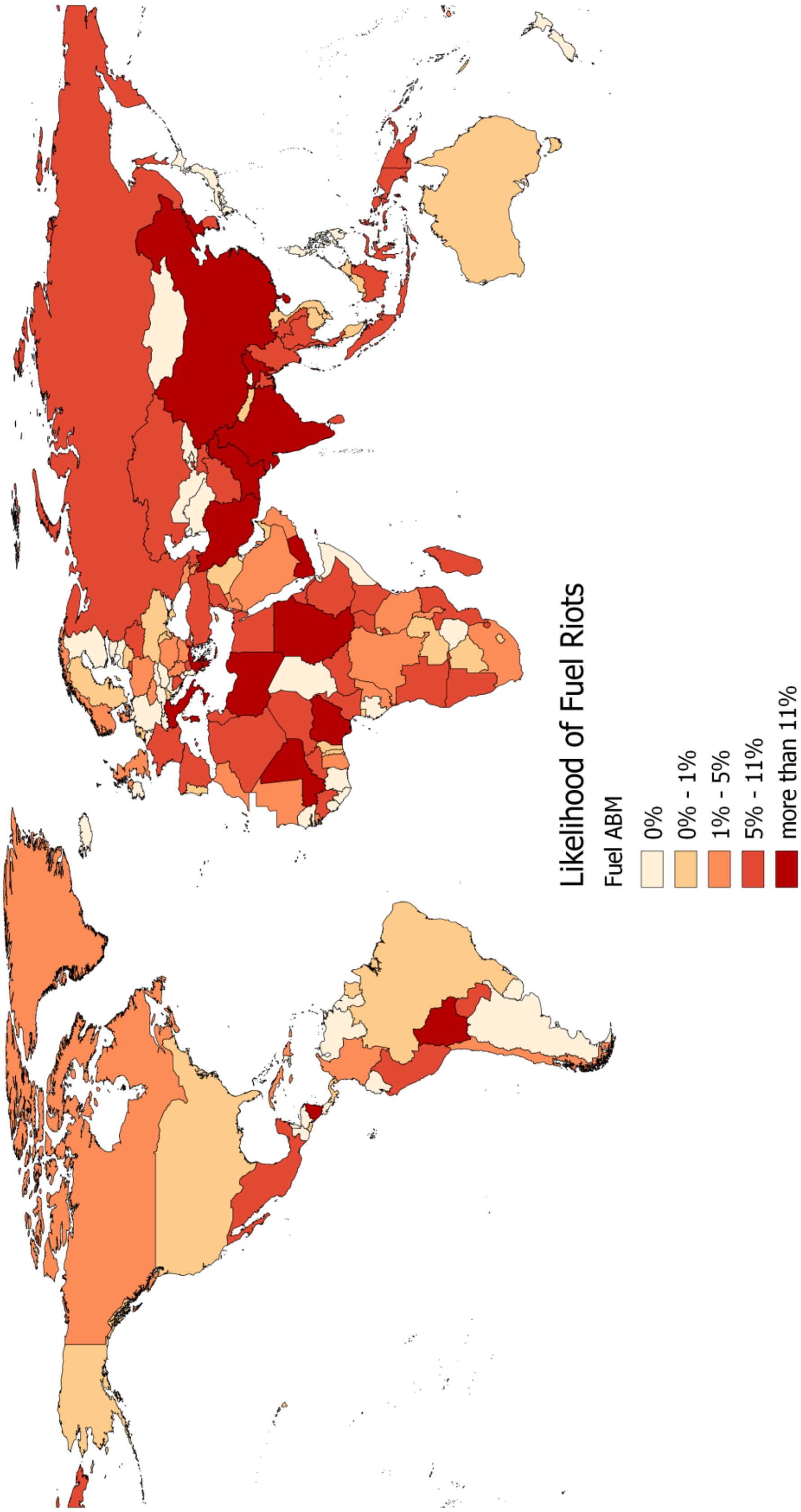

Figure 5.10 – Probability of fuel riots for countries based on the forecast for 2017 from the Fuel ABM (own elaboration).

Finally, the predictions for both food and fuel riots from the Food and Fuel ABM were analysed. As for food riots, out of all the years considered 2017 was the second year with the highest probability for food riots, which was around 4% as compared to 2% in 2005 (the year with the lowest simulated probability of food riots) and 3% in 2008 (the year with the largest number of food riots reported). The probabilities of food riots for countries for the year 2017 ranged between 0% and 13%, with the highest probability assigned to Kenya and Sudan. At the top of the list of countries most at risk we find Kenya, Sudan, Kazakhstan, Egypt, Tunisia, Congo Democratic Republic, Cameroon, India, Myanmar and Sri Lanka, with probabilities spanning between 13% and 11%. 23 countries were assigned with the lowest probability, amongst these we find Congo Republic, Ukraine and Zimbabwe. For a better visualisation, the results from the fuel riots forecast for 2017 from the probabilities of food riots for the Food and Fuel ABM are presented in Figure 5.11.

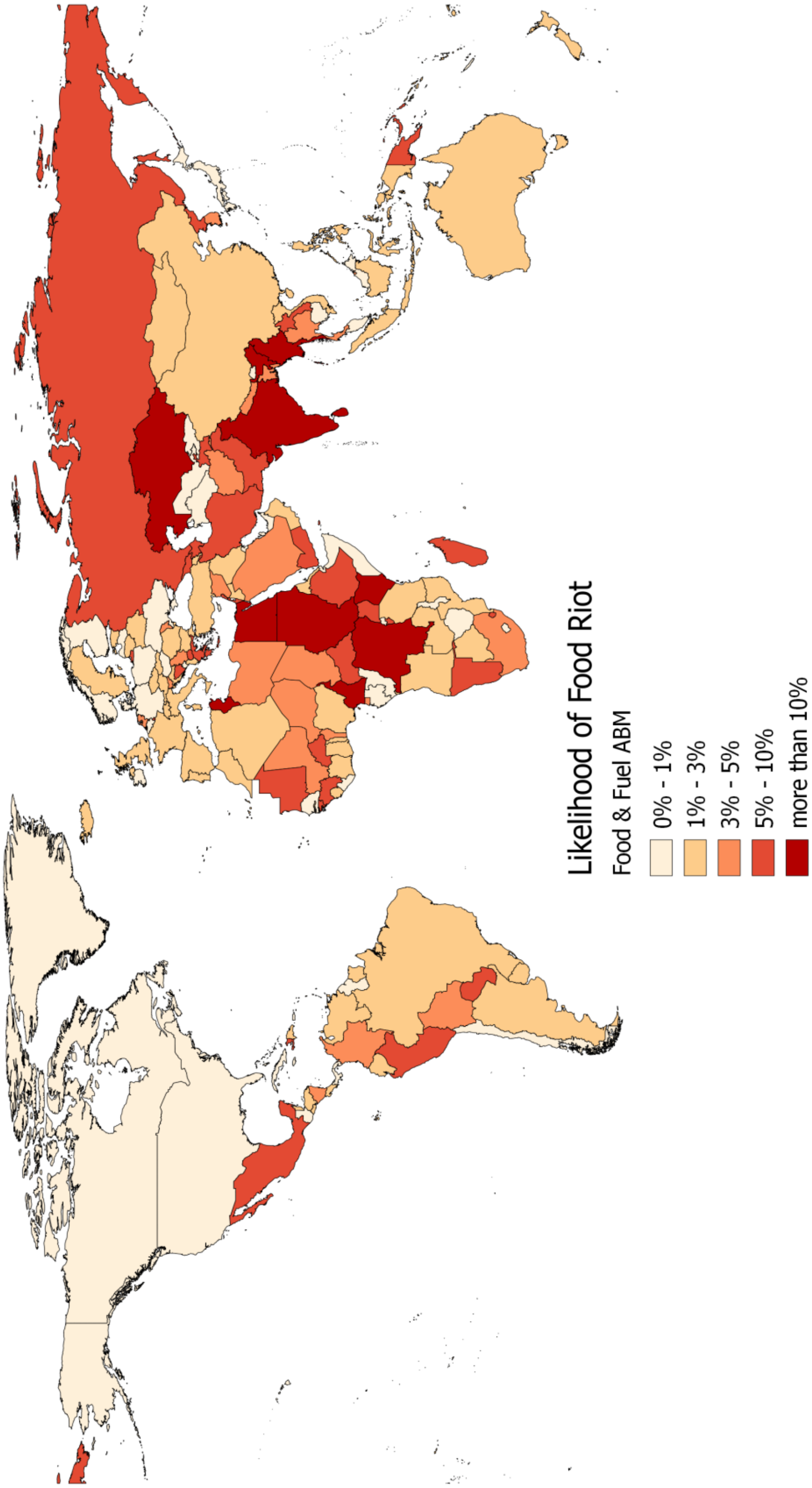

Figure 5.11 – Probability of food riots for countries based on the forecast for 2017 from the Food and Fuel ABM (own elaboration).

Looking now at the predictions for fuel riots from the Food and Fuel ABM, out of all the years considered 2017 was the year with the highest probability for fuel riots, which was around 3% as compared to 2% in 2010 (the year with the lowest simulated probability of fuel riots) and 3% in 2008 (the year with the largest number of fuel riots reported). The probabilities of fuel riots for countries for the year 2017 ranged between 0% and 27%, with the highest probability assigned to India. At the top of the list of countries most at risk we find India, Cameroon, Italy, Yemen, Myanmar, Guinea, China, and Indonesia, with probabilities spanning between 27% and 13%. 41 countries were assigned with the lowest probability, amongst these we find Côte d'Ivoire, Senegal, Somalia and United States. For a better visualisation, the results from the probabilities of fuel riots for the Food and Fuel ABM are presented in Figure 5.12.

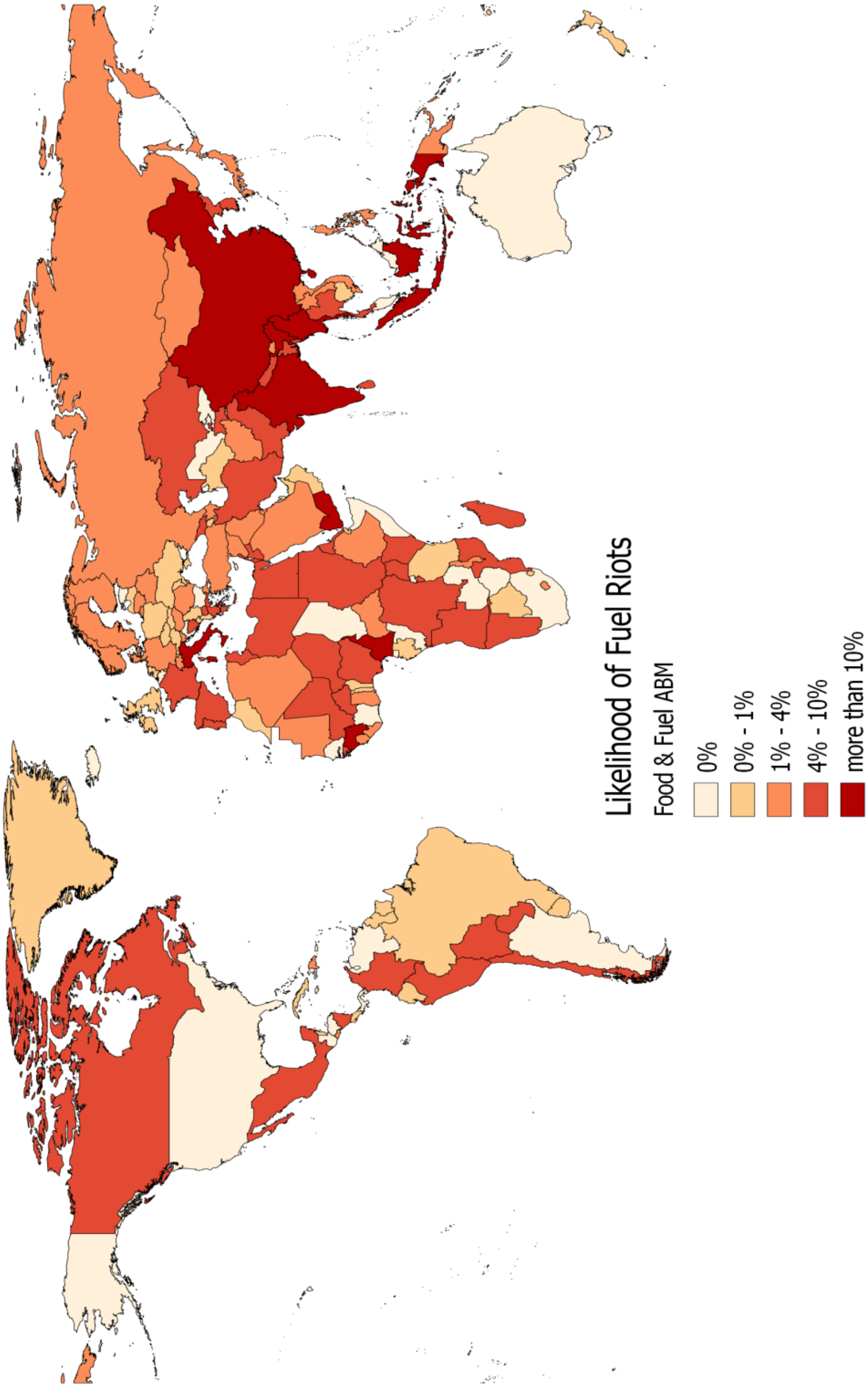

Figure 5.12 – Probability of fuel riots for countries based on the forecast for 2017 from the Food and Fuel ABM (own elaboration).

5.5. Sensitivity analysis of the Food, Fuel and Food and Fuel ABMs

As shown in Figures 5.4 – 5.7 in the previous section, the uncertainty related to the ABMs' results (in this case represented by the confidence interval in the probability of riots resulting from the ABMs) is small. However, as highlighted in Chapter 3 of this thesis, it is also important to evaluate the sensitivity of the dynamics represented in the ABMs to some key conditions. Because some of the critical parameters implemented in the ABMs and that drive some of the key dynamics simulated have been estimated outside of the ABMs, the common approach to sensitivity analysis could not be implemented in this case. In an ideal situation, some of the key parameters would be varied within certain ranges, both singularly and in combination, evaluating the sensitivity of the ABMs to changes in these values. In this case these would be the thresholds for the international prices of food and fuel, the combinations of ratio and stock of the resources leading to a price either above or below the threshold and the categories of the WGI. All these cut-offs were estimated with RE, ET and REEM models, respectively. In the ABMs, the force driving all the different dynamics that lead to the occurrence or absence of riots is the availability of food and oil, which is in turn driven by the production and consumption of the resources. For this reason, the sensitivity analysis of the ABMs was run by exogenously introducing positive and negative shocks to the production of the resources in each ABM. In particular, a positive and a negative shock was introduced in the Food and Fuel ABMs on the single resources and, for simplicity, only a positive shock on food and a negative shock on oil in the Food and Fuel ABM. The shocks were introduced in 2014, i.e. the first year not supported by data in the models, and the global probability of food and fuel riots was compared with the baseline projections presented in the previous section for the year 2017. The year 2017 was selected to allow the shock to produce short-term effects in the system and to allow the comparison with the forecasts presented in the previous section.

The size of the food shock was hypothesised as an increase or a decrease in the global food production by 10% in the year 2014. This figure is consistent with the other food shocks implemented and tested in the model, i.e. the 2008 food shock and the El Niño scenario (see Chapter 6). For simplicity, the shock was redistributed amongst the top ten cereals producers, proportionally to their national contribution to the global production. This was implemented in the Food and Food and Fuel ABMs.

As for the oil shock, this was imagined to be around 15% of the global total, and was also implemented at the national level. The negative oil shock hypothesised the ‘switch off’ of the top oil producer, Saudi Arabia in 2014, whose production amounted to 15% of the total. This method for the implementation of the shock was selected for simplicity, although it is not inconceivable for a country to officially stop trading a resource in case, for example, of the seize of oil wells from rebel movements (e.g. Ahmed, 2017). The positive shock was hypothesised as a doubling in the production of oil from the second and third largest oil producers, whose 2014 production corresponded to 17% of the global total. These were Russia and Iraq, whose production was 11.3% and 5.7% of the total, respectively. Once again this constitutes a simplification, although it is not impossible for a country to increase its production by, for example, implementing measures to increase productivity, or the discovery of new oil wells, or the sale of national stocks.

For the sensitivity analysis of the Food ABM, the model was run 100 times with both shocks. The results from the runs with the negative shock showed a price above the threshold for the year 2017. 2017 had one of the highest probability for a random country to experience a food riot, which was around 4% as compared to 1% in 2006 (the year with the simulated lowest probability of food riots) and 3% in 2008 (the year that registered the largest number of food riots reported). These results are very similar to the baseline projections for the Food ABM for the same year presented in the previous section. The reason being that the ‘normal’ runs of the Food ABM already show a price above the threshold, which, as explained in the previous sections, is the main driver of the increased probability of a random country to experience a food riot. Now looking at the results from the sensitivity analysis with the introduction of a positive food shock, 2017 recorded a price below the threshold. The positive shock caused the price to fall and remain below the threshold in 2014 and the following years, due to the build up of national food stocks, which is another important variable in the determination of international prices in the ABMs. The probability for a random country to experience a food riot in 2017 was around 2% as compared to around 4% in 2013 (the year with the simulated highest probability of food riots) and around 3% in 2008.

Now looking at the sensitivity analysis for the Fuel ABM, the results from the runs with the negative shock show a price above the threshold for the year 2017. The probability for a random country to experience a fuel riot in 2017 was around 4% as compared to around 1% in 2007 (the year with the simulated lowest probability of fuel riots) and around 3% in 2008. Once again, these results closely resembled those from the baseline projections from the Fuel ABM, since even in the case of oil the price ‘normally’ showed a regime above the threshold for this year. The results from the runs with a positive oil shock showed a price above the threshold for 2017, with the highest probability of fuel riots for this year, i.e. about 4%. 2010 registered the lowest probability for the period, i.e. about 1%, and this was 3% in 2008. The similarity with the results from the introduction of a negative shock can be explained by the oil demand and supply dynamics simulated in the model. Although the price showed a regime below the threshold in 2014, i.e. the year the production was exogenously increased, hence producing lower probabilities of riots during that year, a global demand larger than supply did not allow the build up of national stocks, thus bringing the price above the threshold for the following years and causing increased probabilities of fuel riots.

The sensitivity analysis for the Food and Fuel ABM implemented a combination of positive and negative shocks on the resources. The results from the runs with a negative shock on food and a positive shock on oil showed both prices above the threshold in the year 2017. This was the year with the highest probability of food riots out of all the years considered, i.e. around 3%. Similar results were found for fuel riots, whose probability was around 3% for the same year, although 2017 was the third year in order of fuel riots probabilities. Similarly to the sensitivity analyses on the single-resource ABMs, due to a high-price regime for both resources the results were very similar to the baseline projections for the year 2017, which showed a 4% probability of food riots and a 3% probability of fuel riots for this year. The results from the sensitivity analysis with the introduction of a positive shock on food and a negative shock on fuel showed a price of food below the threshold and a price of fuel above the threshold for the year 2017. This resulted in a probability of food riots of around 2% and a probability of fuel riots of around 3% for 2017. This year was the eighth year in order of probability of food riots and the second in order of fuel riots. The results for food riots show the same dynamics as the introduction of a positive shock in the Food ABM, and the results for fuel riots are instead similar to the baseline projections for this type of event from the Food and Fuel ABM.

In conclusion, the sensitivity analysis of the models showed that the ABMs responded differently to the introduction of positive and negative shocks, or a combination of these. Neither the Food nor the Fuel ABMs were sensitive to the introduction of a negative shock on either resource, showing probabilities that closely resembled those for the baseline projections. This was due to the unvaried effects on the price regimes, which showed a regime above the threshold in the ‘normal’ runs of the models. The Food ABM was sensitive to a positive food production shock, with a decreased probability of food riots for 2014 that lasted for the following years. The Fuel ABM was instead only partially sensitive to a positive oil shock as 2014 showed a price below the threshold with a lower probability of fuel riots, which however didn’t last as the price returned above the threshold from 2015 on. The combination of a negative food shock and a positive fuel shock in the Food and Fuel ABM showed that this model was not sensitive to the first type of shock and only partially sensitive to the second, showing similar responses as the single-resource ABMs. As for the combination of a positive food shock and a negative fuel shock, the Food and Fuel ABM was sensitive to the former type of shock and not sensitive to the second type of shock, once again showing similar responses as the single-resource ABMs. Finally, the sensitivity analysis on the Food and Fuel ABM where food and fuel riots influence the probability of one another and where shocks with opposite signs are introduced in combination did not produce results different from the single-resource ABMs.

5.6. Discussion

Section 5.1 of this chapter presented an in-depth description of dynamics included in the Food, Fuel and Food and Fuel versions of the ABM by providing the ODD for the models. This protocol is aimed at facilitating the understanding and possible replication of ABMs by drawing out the fundamental assumptions and characteristic properties of the models, such as emergent properties.

Section 5.2 focussed on the calibration of food and fuel prices for the ABMs, briefly introducing an experiment on reported data and analysing more in depth the experiment on simulated data. The analyses between resources were very similar. It was possible to make a statistical fit to prices in both cases, although only simulated data seem to fit with an intuitive view of how supply, demand and stocks are likely to affect prices and is more likely to produce results that are consistent with the internal operation of the model. For this reason the calibration on simulated data was preferred. For this two different approaches were tested: ETs and via two free parameters, with the former outperforming the latter in terms of accuracy for the prediction of price regimes for both resources. For this reason ETs on simulated data were chosen as the preferred method. It is worth remembering here that, although the dynamics captured by the calibration procedure run on data from the ABMs, are more intuitive and logical as compared to those resulting from the ETs run on reported data for food and oil, the data stemming from the ABMs does not perfectly recreate reality. Arguably, neither does reported data, as observed in a study on the GRO database (Phillips, 2016). Data from the models is not that dissimilar from reported data as can be seen from Section 5.2.1, however, the dynamics between ratio and stocks levels and international prices are reversed when compared to those resulting from the model. In particular, reported data seem to suggest that international prices of resources are high for high levels of stocks and ratio for the resource, whereas calibration on data extrapolated from the ABMs show opposite dynamics. The inability of Ets to reproduce the dynamics of price regimes when fitted to reported data for ratio and stocks of natural resources has two possible explanations: either supply and demand dynamics are not sufficient to recreate international prices and/or the data gathered for the variables is not accurate.

As highlighted in this chapter, key dynamics that in reality influence and shape consumption and supply of natural resources have not been included in the current versions of the ABM, causing the estimates for consumption and production of natural resources for countries to be inaccurate. In particular, two key feedbacks have not been included in the ABMs: the change in trends for consumption and production of natural resources. The former depends on factors such as increased population levels (which are present in the ABMs but not currently used) and change in diets, whereas the latter depends on complex dynamics between prices, land availability, climate change, productivity of the factors involved and several other factors. Because the national levels for production and consumption of natural resources have been modelled by calculating estimates based on past trends between 1995 and 2012, the values for these variables calculated in the ABMs only capture long-term trends in these variables and fail to model sudden changes that might affect either production or consumption in the short-term, which anyway are largely unpredictable. This inaccuracy is acceptable in a very short time frame, as the dynamics that affect either positively or negatively production and consumption of natural resources such as an increased population or new technologies that increase productivity, take time to come online. This characteristic of the ABMs was in line with Principle 1 of the GRO project, which shaped the conceptual framework of this work. The inaccurate estimation of production and consumption of natural resources affects international price regimes only from the year after the end of the calibration, i.e. 2014. As regards cereals, due to the introduction of an exogenous shock on cereals production in 2008 to correct the availability of cereals in the system – which was inaccurate due to its estimation on past trend lines that smoothed the shocks that occurred during the time frame considered – global stocks of cereals are more than halved: these are reduced from 330,688 MT in 2008 (estimate before trade), to 132,530 MT in 2009 (estimate before trade). Since in the ABMs the ratio between global cereals production and consumption constantly remains below 1 until 2017, global stocks of cereals are continuously reduced, year on year, causing international price of food to remain constantly above the threshold from 2010 onwards. Running the Food ABM beyond the time frame it was developed for, i.e. 5 years from the last year that was calibrated, shows that the ratio between global cereals production and consumption goes above 1 from 2017 and global stocks of cereals hence start building up. The international price of food only falls below the threshold from the year 2023, when enough stocks have been accumulated in the system.

The same argument applies to the versions of the ABM that include dynamics for fuel. The Fuel and Food and Fuel versions of the ABM perfectly recreate the international fuel price regime trends until 2013. Global oil consumption overtakes production from the year 2010 and, running the ABMs beyond the time frame they were developed for, the ratio between the two variables is consistently below 1 until 2029, causing global oil stocks to be exhausted in 2014. Stocks only start building up again in the year 2033. Because of these dynamics, the international fuel price regime predicted by the model is constantly above the threshold between 2011 and 2029.

At the time of writing this thesis, i.e. March 2016, the last year for which the deflated version of the FAO FPI and the EIA fuel price as calculated in Chapter 4 are available is 2015, which recorded a real price regime below the 140 threshold for the FAO FPI and below the $93 per barrel for the EIA fuel price. The predictions from the ABMs for international food prices for 2015 diverge from the observed data and this poses questions about the validity of how international prices of both food and fuel have been modelled in the ABMs. Although the consequences of these inaccuracies will be further explored in Chapter 7 and possible solutions will be suggested in Chapter 6, it is worth remembering here that the aim of this research was never to investigate and model the formation of international prices, rather to model some of the dynamics that lead to the occurrence of food and fuel riots. Although the presence of an international price for the natural resources is essential in the ABMs at their current stage of development, the dynamics of price formation are not. Potential improvements to the ABMs as relates to international prices and their feedback on the occurrence of food and fuel riots will be further discussed in Chapter 6.

Now commenting on the validation of the models, the results show that the ABMs are remarkably accurate at predicting general probabilities both for food and fuel riots and for both price regimes, i.e. below and above the threshold for international prices of natural resources, although slightly overestimating the probability of riots below-threshold and slightly underestimating it in the opposite case.

When analysing the number of riots per year predicted by the ABMs as compared to those occurred, although the trends predicted by the models generally follow reported trends, the results vary according to the type of riot predicted. For food riots, the Food and Food and Fuel versions of the ABM capture the increased probability of riots for the year 2008 – although underestimating the number of riots – but fail to capture the other peak in number of food riots occurred in 2011, rather spreading the number of riots throughout the second period when the regime for the FAO FPI was above the threshold. The predictions from the Fuel and Food and Fuel versions of the ABM for fuel riots show better fits. Both models capture the 2008 peak in fuel riots – although underestimating its height – but also capture a successive increase in the numbers of fuel riots in 2011. However, these models fail to capture the fall and subsequent rise in the number of fuel riots in 2012 and 2013, respectively, rather keeping the number of fuel riots constant at the levels predicted for 2011. These behaviours are due to the fact that one of the main factors that influence the probability of riots in the ABMs is the international price regime, which is modelled as a binary variable. This means that the current version of the models will predict a roughly similar amount of riots for years that recorded an international price regime above/below the threshold. One of the other factors that influences the total amount of riots in the ABMs is the WGI group of countries. If in a given year more countries are classified with high levels of political fragility according to the estimates for their WGI as calculated in the ABMs, the resulting number of riots for that year is likely to be higher, even more so if in correspondence with an international price regime above the threshold. In reality, the years 2010, 2012 and 2013 for food and 2012 for fuel, although registered an international price regime above the threshold, did not see a number of riots comparable to those occurred in 2008 and 2011, highlighting the possibility that the conditions of the food and fuel systems for these years were different and raising interesting research questions for possible future developments of the ABMs. These smoothed dynamics resulting from the ABMs may represent a limit of the capacity of the models to simulate self-reinforcing effects that are likely to occur in the real world and represents an opportunity for further refinements.

One finding that was partially unexpected was the ABMs' accuracy at predicting which countries were most at risk of experiencing a riot at any point during the time frame considered. Predictions from the ABMs based on single resources, i.e. the Food ABM and the Fuel ABM, already resulted in a high degree of accuracy at ranking the countries in order of risk of riots. This accuracy increases even further when the results from the integrated Food and Fuel ABM are taken into account. Probabilities for individual countries to experience a riot are mainly driven by the country's WGI group and the country-specific RE calculated with REEM. The random effects assigned to each country by each REEM model increase individual countries' probability of experiencing a riot according to the countries' own previous experience, i.e. countries that have experienced multiple riots are more likely to experience a riot in the future. Likely, the RE for each country play a role in producing this emergent property in the ABMs, hence proving the benefits of implementing an ABM approach to this research.

When estimating the ABMs' accuracy at predicting both country and year for riots, the models show their shortcomings: only 7% of the food riots that occurred during the time frame considered in the analysis were correctly predicted by the Food and Food and Fuel ABMs. The number of false positives, however, is remarkably low, and the overall level of accuracy of the model reaches 95%. Similarly, the Fuel and Food and Fuel ABM's accuracy at predicting both country and year for fuel riots reaches 10%, although keeping the percentage of false positives low and registering an overall accuracy of 96%.

As for the Food and Fuel model more specifically, adding the interaction between food and fuel riots to the predictions of the ABMs does not seem to add any predictive power to the results from the resource-specific ABMs as far as the probability of food and fuel riots per price regime and the prediction of specific riots are concerned. However, the interaction seems to positively influence the model's predictions as relates to the specific countries that will experience a food or a fuel riot during the time frame considered.

The predictions for food and fuel riots for 2017 provided by each version of the ABM were compared, finding the predictions for food riots fundamentally similar between the different ABMs, i.e. Food and Food and Fuel ABMs, in terms of probabilities of riots for each year considered in the analyses, whereas the probabilities for annual fuel riots were slightly different according to the ABM used, i.e. Fuel and Food and Fuel ABMs. As per the national probability of both food and fuel riots, the ranges of probabilities forecasted by the different ABMs, although different, remain comparable. The specific countries forecasted as most and least likely to experience a food or a fuel riot in 2017 differ greatly between the lists produced by the ABMs. This is mainly due to the stochasticity embedded in the models, which is standard practice in the field of computer modelling. Indeed, due to the unpredictability of future scenarios and situations, it is standard practice to build variability into the code of the models and aggregate results from multiple runs to account for this variability.

Finally, a note on the sensitivity analysis run on the different versions of the ABM. This was implemented by introducing positive and negative shocks to the production of resources in the models, both singularly (in the Food and in the Fuel ABMs) and in combination (in the Food and Fuel ABM). None of the ABMs resulted sensitive to negative shocks on either resource, as opposed to positive shocks, which the models were sensitive to, although to different degrees. Both the Food and Food and Fuel ABMs were highly sensitive to positive shocks on food, with the price falling below the threshold from 2014 (the year of the introduction of the shocks) and remaining below the threshold until 2017 (and beyond). Conversely, the Fuel and Food and Fuel ABMs were only partially sensitive to positive oil shocks, as the oil price fell below the threshold for the year 2014, and climbed up (and remained) above the threshold from the following year.

6. Next steps

As it is common in research, the findings from this PhD brought about further interesting research questions and possible future developments of the ABMs that can improve the predictions of food and fuel riots in countries.

In general, the main issues related to the current versions of the ABM are associated with the way national production and consumption of natural resources and their international prices are currently estimated in the models. National estimates for production and consumption of natural resources were calculated based on trend lines fitted to reported data, which was sourced from the GRO Database (GSI, 2015). This choice was made to allow this research to comply with Principle 2 of the GRO Project, which required the models developed as part of the project to be fully data-led. As a result, national estimates for production and consumption of natural resources are deterministic in the different versions of the ABMs, i.e. they do not vary between different runs of the models, unless a scenario different from BAU is being run. If these variables were not exogenously imposed, but rather endogenously calculated via the dynamics included in the models, the ABMs would be generate emergent properties, also providing useful insights about the relationships between these variables and the occurrence of food and fuel riots. In particular, the quantity and distribution of oil and cereals stocks could have an impact on countries' food and energy security and on the probability of riots via international prices.

Future versions of the models could generate endogenous estimates for consumption of natural resources by introducing a more realistic population model and linking this to national consumption. Better estimates for production could be achieved by introducing physical limitations to the availability of the resources (e.g. land and ores), their productivity and production costs. Another further development could relate to the introduction of a measure of countries' level of economic development. This could be linked to several feedbacks, for instance, on national consumption of resources, as developed countries have higher per capita consumption. However, these dynamics, which are found in the current configuration of the world, will possibly change due to policies aimed at mitigating climate change and, in general, a higher awareness, which may lead populations to shift to more healthy and sustainable lifestyles and diets, and a more sustainable use of land which can in turn have a positive impact on life expectancy and reduce levels of consumption. In addition, policies will likely drive technological improvements in every sector, hence helping reduce emissions and increase productivity, and the diffusion of renewable resources.

Possible extensions may include different types of conflict, such as civil and international wars. This research ignores important alternative measures of conflict such as its length, escalation and intensity, which could be explored in association with the framework and results yielded by this research. Future versions of the model could also include some of the 'planetary boundaries' (Rockstrom, et al., 2009), or new systems and natural resources, such as the inclusion of water hence allowing to explore the link between water[15] scarcity and conflict and the inclusion of climate change, with a feedback between levels of pollution and impacts on availability of resources, extreme climatic events and, ultimately, human conflict. Although the field of climate and environmental security, which is where this work fits, has only recently been formally instituted (at least in the UK academic landscape), research in this field is plentiful and new data on these issues is being measured as I write. This makes me confident about future developments of the ABM to include these dynamics.

Now exploring improvements to the ABMs that involve specific dynamics already included in the models, the experiments that will be presented in the next few sections were developed during the course of my PhD. However, these could not be included in the main findings from the research due to several issues that will be explained in detail. All these further developments of the ABMs are somewhat related to how international prices are estimated in the current versions of the models. The next section will focus on an alternative to the thresholds calculated on the absolute values of international prices. The following section will present three what-if scenarios: firstly, a future scenario implemented in the Food and Fuel ABM investigating the impact of the implementation of export bans on cereals and the subsequent impact on international prices and hence on the occurrence of food and fuel riots. Two additional scenarios involving likely future production shocks, one for food and another for fuel, will be presented in the following two sub-sections. These were developed and

[15] Water was not included as a natural resource in these versions of the models due to lack and inaccuracy of data.

implemented in the Food ABM and in the Fuel ABM, respectively, to demonstrate possible applications of the models as early warning assessment tools for the evaluation of possible future threats to countries' security in terms of food and fuel riots due to negative shocks to the production of either resource.

6.1. Thresholds on price variation

As demonstrated in Section 5.3 of the previous chapter, the different versions of the ABM show acceptable levels of accuracy at predicting food and fuel riots, as the models capture important information with their predictions, such as the list of countries most likely to experience a riot at any point during the period considered. However, different experiments to evaluate the influence of international prices on the occurrence of food and fuel riots were run in an attempt to improve their predictions. In particular, as mentioned in Chapter 2, previous literature highlighted that it is the volatility in food prices rather than absolute values that cause most of the problems on international markets (e.g. Kharas, 2011; Tadesse, et al., 2014; Bazzi and Blattman, 2014; Cuesta, et al., 2014; Lagi, et al., 2015), with a few discordant voices (e.g. Bellemare, 2014). To investigate this further and provide insights about this relationship for fuel variables as well, I ran new analyses recalculating the price thresholds on price variations rather than on absolute price levels. The reasoning behind this is fundamentally similar to the analyses presented in the previous chapters, i.e. the threshold calculated on the variation of the international price divides the price fluctuations in two regimes, either above or below the threshold. Whenever the price variation is above the threshold, countries' probability to experience a riot increases, and vice versa. The following sub-section presents the results from two RE models fit to the data for food and fuel, followed by a REEM model for each resource also evaluating the model's accuracy at generating predictions for riots and, finally, a summary of the results from different ET models predicting price fluctuations to allow the implementation in the ABMs (the models can be found alongside a brief description in Appendix 4 for reasons of brevity). A conclusive sub-section will comment on the results.

6.1.1. Calculation of threshold on price variation for the FAO FPI and EIA fuel price

Two RE models were fit to the data for the period 2005 – 2013, one focusing on food riots and the other on fuel riots. The dependent variable expressed the number of riots occurred during the time frame selected, whereas the independent variables represented the volatility in the international prices of either food or fuel, testing the one- and two-year variation in prices, i.e. $P_{t-t\text{-}1}$ and $P_{t-t\text{-}2}$.

For the analysis on food riots, both price variations had a positive, significant effect on the occurrence of food riots when run singularly, whereas the one-year price variation sign became negative and lost significance when both variables were introduced in the same model. This result indicates that the two-year variation in prices is a better predictor and includes the effect of the one-year variation on the occurrence of food riots. For this reason the two-year price variation was selected as predictor and further analysed. The results for the RE model for FAO $P_{t-t\text{-}2}$ are presented in Table 6.1.

	Estimate	**SE**	***t*-value**	***p*-value**
(Intercept)	-5.769	0.484	-11.908	< $2e^{-16}$***
FAO $P_{t-t\text{-}2}$	0.069	0.010	6.602	$4.07e^{-11}$***
σ	1.72	0.421	4.071	$4.69e^{-05}$***
Log-Likelihood	-201.8843			

Table 6.1 – Results for RE model with the variable Food Riot used as dependent variable and one- and two-year variation in prices as independent to predict the occurrence of food riots (own elaboration). Sig. codes: 0 '***'; 0.001 '**'; 0.01 '*'; 0.05 '.'; 0.1 ' '.

As for the previous analyses, the 1% probability threshold for the price variation was calculated and found at 17.1. In other words, the results from the model say that whenever the two-year variation in food prices is greater than 17.1, the probability of food riots is expected to increase significantly. Comparing these results with real price variation, we find that the years that saw an international food price volatility above the threshold were 2007, 2008 and 2011, already showing that this model captures with more accuracy the years with the largest number of food riots.

The variable was hence transformed in a discrete binary form, classifying each year as either above (1) or below (0) the threshold and included as an independent variable alongside the discrete version of the variable WGI group in an REEM model to operationalise the models' prediction for food riots. The results are presented in Figure 6.1.

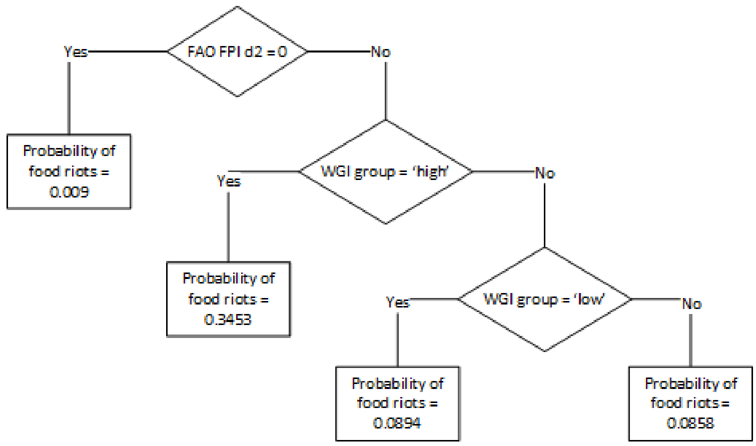

Figure 6.1 – REEMtree model testing the effect of two-year price volatility and WGI group on the occurrence of food riots (own elaboration). Notes: n = 1904; intercept = 0.001469882; Estimated variance of errors = 0.0194768047140661; Log likelihood = 986.414684322138.

The accuracy for the REEM model was further tested by generating 1000 predictions accounting for country-specific RE and comparing the results with reported food riots occurred during the period 2005 – 2013. The averaged results are presented in Table 6.2 and compared with those from the REEM with RE calculated on the threshold on the absolute price of food.

Models	**Food riots predicted**	**Total correct**
REEMre VOL	11.11%	95.04%
REEMre ABS	6.39%	94.83%

Table 6.2 – Results of the accuracy test for the REEM models on 2-year price volatility (REEMre VOL) and on the absolute value (REEMre ABS) evaluated in this analysis. The second column reports the mean of the percentage of food riots correctly predicted by each model throughout the 1000 iterations, whereas the third column reports the mean of the percentage of any record (food riot 0s and 1s) correctly predicted by each model throughout the 1000 iterations (own elaboration).

Table 6.2 shows a clear improvement in the prediction of food riots for the REEM model presented above as compared to that presented in Chapter 5. Looking at these results in association with the years above the threshold on the price variation, i.e. 2007 – 2008 and 2011, this is a clear indication that populations of fragile countries are more likely to respond with grievances to large changes in the international price of food rather than to its absolute value.

To implement these findings in the Food ABM, the dynamics already included needed to be adapted to predict the regimes for the price fluctuations. To do this, two ETs were fit to the data using the two-year price variation as target variable and either reported or simulated data for the ratio between world production and consumption of cereals and stocks as predictors. Both models correctly predicted the regimes of price fluctuation for each year, although once again the conditions identified showed counterintuitive dynamics for both reported and simulated data, which suggests that the variables included in the models are not sufficient to predict two-year fluctuations for the FAO FPI.

Another experiment replaced the absolute values of the independent variables with their two-year variations, which resulted in counterintuitive dynamics once again, which are commented in detail in Appendix 4. These dynamics could not be implemented in the ABMs to generate price fluctuations for food, but raised interesting questions about the drivers of food price volatility that require further research.

Moving onto the analysis on fuel riots, the influence of the one- and two-year variation in the EIA international fuel price on the occurrence of fuel riots was tested by implementing different RE models. Both variables have a positive, significant (at the 10% level) effect on the occurrence of fuel riots when evaluated in isolation, whereas when introduced jointly as predictors, only the one-year variation remains significant and positive at the 1% level. This finding seems to highlight that it is only the one-year variation in prices that is influential and the significance of the result for the two-year variation when evaluated in isolation is due to the fact that this already includes the one-year variation in prices. For this reason the one-year price variation was selected as predictor and further analysed. The results for the RE model for EIA P_{t-t-1} are presented in Table 6.3.

	Estimate	**SE**	***t*-value**	***p*-value**
(Intercept)	-5.297	0.457	-11.597	$< 2e^{-16}$***
EIA P_{t-t-1}	0.048	0.016	3.098	0.00195**
σ	-2.039	0.417	-4.892	$1e^{-06}$***
Log-Likelihood	-186.0501			

Table 6.3 – Results for RE model with the variable Fuel Riot used as dependent variable and one- and two-year variation in prices as independent to predict the occurrence of food riots (own elaboration). Sig. codes: 0 '***'; 0.001 '**'; 0.01 '*'; 0.05 '.'; 0.1 ' '.

The 1% threshold calculated on the one-year price variation for the EIA international fuel price corresponded to $14.6 per barrel, which indicates that any annual variation of the price larger than this amount is likely to trigger an increased probability of fuel riots around the world.

The threshold was used to transform the variable EIA international fuel price from continuous to discrete version, identifying each year's price fluctuation as either above (1) or below (0) the threshold. The variable was used alongside the groups for the WGI in a REEM model aimed at predicting fuel riots. The results of the model (not presented for reasons of brevity) show that the only variable that significantly affects the occurrence of fuel riots is countries' WGI group, hence contradicting the results from the RE model presented above. The variable representing the yearly price fluctuations is only significant when introduced in isolation in the REEM model. This result seems to suggest that the WGI already includes the part of information relative to the contribution of international fuel prices to the increase of social unrest. Indeed, as mentioned before in the text the WGI is an index that aggregates several variables gathered from various sources (WB, 2015d), many of which are likely to be highly correlated with increases in fuel prices. To further explore this finding, another experiment was run fitting an RE model to data for fuel riots using the discrete variables for the one-year fuel price variation and the groups for the WGI. The results from this RE model showed a positive effect for both variables on the occurrence of fuel riots, which were mutually significantly different. The results from the REEM and RE models were discordant and clearly indicate that further research is required to investigate how fluctuations in the international price of fuel affect the occurrence of fuel riots, if at all. For this reason the analysis on the threshold for fuel price variation terminated here.

6.1.2. Conclusions on the analyses on international price variations

The dynamics resulting from the analysis presented in this section, raised interesting questions on what drives prices of natural resources on international markets and the relationship between these and the occurrence of resource-related social unrest. In particular, statistical tests run on the relationship between the international prices of food and fuel and the occurrence of food and fuel riots showed that populations seem to be more responsive to volatility in prices for the first type of events and to absolute values of the price of oil, although mixed evidence showed a potential relationship between fuel price volatility and the occurrence of fuel riots as well. Populations seem to be more likely to react with the use of violence to sudden changes in the price of food, where the two-year increase in prices seems to be what causes unrest, rather than annual variations as for oil prices. Interestingly, initial findings suggest a different tolerance towards price increases for food and fuel resources, i.e. two years for food and one year for fuel. Social responses to prices of different resources are worth exploring with future research.

The relationship found between volatility in food prices and the occurrence of riots, agrees with the main literature (e.g. Kharas, 2011; Arezki and Bruckner, 2011; Brinkman and Hendrix, 2011; Crawley, et al., 2012; Berazneva and Lee, 2013; Smith, 2014; Raleigh, et al., 2015) that believes that the changes in prices of food are the main issue and found positive relationships between variation in prices and the occurrence of social unrest. To the best of my knowledge, the only study that compared the effect of both the absolute value of prices and their volatility on the occurrence of food riots was Bellemare (2014), who found that food price volatility decreases, rather than increases, the probability of riots. The author finds that it is the absolute value of the international prices that populations react to with unrest. Although the findings presented in this section seem to disagree with this study, the findings presented in Chapter 4 fit with the results from Bellemare (2014). Two possible reasons for this disagreement are that the author uses a more general definition of food riots, which does not restrict these events to the use of violence, hence resulting in a larger (and likely substantially different) database. In addition, Bellemare (2014) uses a coefficient of variation and monthly data to evaluate the relationship between food price volatility and the occurrence of food riots, which, once again, can lead to different results. It is also worth noting that the results of the analysis undertaken by this author may not be reproducible due to the use of LexisNexis news database (LexisNexis, 2016) to collect data for food riots, where the media outlets included can vary with time, possibly leading to a different number of records for searches carried out at different times.

Now commenting on the relationship between volatility in the international price of fuel and the occurrence of fuel riots, further research is required to disentangle these complex dynamics. The RE model highlighted a significant, positive effect of one-year volatility in fuel prices and the occurrence of fuel riots, although when the variable was translated in a discrete form and tested alongside the WGI groups of countries in an REEM model, its significance disappeared. However, when both variables were introduced in an RE model, both resulted in a positive, significant effect on fuel riots. Their effect on the dependent variable is also mutually, significantly different. These mixed findings raise new exciting questions on the relationship between fuel price volatility on international markets and the occurrence of fuel riots, a topic that, to the best of my knowledge, remains completely unexplored in academic literature. Future research should focus on evaluating this relationship alongside different measures of political fragility, possibly less aggregated ones. As for the ABMs, further developments could endogenise countries' political fragility to eliminate the potential correlation between fuel prices and the WGI.

The results from this section highlighted another clear direction for possible future developments of the ABMs. The results from the ETs fit to the data for the FAO FPI fluctuations not only showed that the interaction between reported global availability of food and the interaction between global demand and supply are not sufficient to recreate food price volatility, but also data from the model was unable to recreate price fluctuations. Literature supports this finding: Lagi, et al. (2015) found that the trend in the FAO FPI is explained by supply-demand model until 2000 and that the underlying increase trend is explained by biofuel dynamics, whereas the peaks are due to speculation. One of the possible further developments of the model is to implement Lagi, et al. (2015) equation to introduce accurate price dynamics in the ABMs. To do this, the model will need to be extended to include the international market of biofuels alongside its national and global production and demand. In particular, the ABM could simulate the dynamics that revolve around production, consumption and trade of the main cereals (wheat, maize, rice and soybean) separately, hence allowing to model the competing demand for maize driven by demand for food consumption and policies around conversion to biofuels. This would potentially allow the ABM to recreate the underlying upward trend in prices seen post-2000, although to be able to simulate price spikes similar to those registered in 2008 and 2011, the model will need to be able to incorporate dynamics related to prices of food futures, which is a highly complicated topic that draws on concepts such as buyers' behaviour on markets, future price expectations and climate change, just to name a few. Although critical for the study of food riots, these dynamics lay outside the scope of my research questions, and, as mentioned above, the current versions of the models will need to be re-adapted to include these findings. Therefore, these constitute a starting point for future studies and developments of the ABMs. However, the findings from this research on the relationship between the variation in food prices and its influence on food riots were informative and remarkably promising in their own right, and add to the current debate on whether food price fluctuations impact food riots and food security more in general.

The analysis on fuel prices was halted before trying to predict and implement in the models international prices volatility due to the mixed findings presented above. Literature on fuel price formation is relatively scarce as compared to that presented for international food prices. However, most of the authors highlight the complexity of trying to disentangle the different factors that lead to the international price of fuel and its volatility. Hamilton (2009) found that the real price of oil seems to follow a random path, hence making it almost impossible to predict. Supply and demand dynamics play a role, but it is difficult to discern to what extent. This author and other relevant literature in the field (e.g. Kilian, 2009) mainly attribute the 2008 fuel price shock to the increased oil demand from the developing world, accompanied by a failure of global oil production to increase accordingly and unstable political situations in key oil-producing regions (Yu, et al., 2008). Hamilton (2009) argues that the lack of responsiveness from the production side is consistent with the hypothesis of global peak oil, although this does not explain the sudden fall in prices after the 2008 peak. Yu, et al. (2008) used a less descriptive approach and implemented an empirical mode decomposition based neural network ensemble learning paradigm to identify the main underlying trends in oil prices and forecast them. The study showed promising results, although the authors neglected to associate these decomposed variables with real world dynamics, hence not furthering the understanding of what are the drivers of international fuel prices. From this overview of studies on international fuel prices, it is clear that the picture is not yet complete and more research will need to be devoted to understand the complex relationship between the different variables that drive fuel price fluctuations and in particular shocks, in order to be able to simulate them in the ABM.

6.2. Future scenarios analysis

One of the possible applications of the ABMs developed during this work is scenario analysis. ABMs, as other computer modelling paradigms, support the implementation of scenarios with different aims, e.g. the fomalisation of a new theory, the generalisation of an extant one or the *ex-ante* analysis of the possible consequences of a policy, before its implementation. In general, scenarios constitute a deviation from the BAU dynamics included in the model and can be implemented by simply introducing a switch on the model's interface, which activates a new or different series of procedures and conditions written in the code of the model. The first sub-section reports the results from a scenario analysing the impacts of the implementation of cereal export bans on national cereal stocks and on the occurrence of food and fuel riots. This scenario was built as part of the UK – US task force on Food Security on the Impact of Extreme Weather on US/UK Food Security, which was a project in collaboration with the UK Foreign Commonwealth Office amongst other partners and institutions. This scenario has been developed during my role as a Research Assistant on the project between April and June 2015 and its results partly informed the publications Lloyd's (2015) and King, et al. (2015). This scenario was later updated to be included in this thesis.

The following two sections will present development and findings from two what-if scenarios that have been implemented in the current versions of the ABM for the year 2016. The aim of both scenarios is to evaluate the risk for countries in terms of food and fuel riots in case of a future production shock for food and oil resources. The first scenario focusses on a strong El Niño event that is likely to have a negative impact on food production around the world. This scenario was published in Natalini, et al. (2015a). The following section will present a similar scenario (still unpublished) for an oil production shock that was developed following the example of the El Niño scenario.

6.2.1. The Cereals Export Bans scenario

As highlighted in Chapter 2.8, one of the factors that worsened and accelerated the global food crisis in 2008 were the panic behaviours that governments of countries around the world implemented to ensure a safe and cheap food supply for their populations (King, et al., 2015; Puma, et al., 2015). One type of policy that governments implemented were aimed at restricting trade, particularly banning or restricting exports of food to prevent precious cereals from leaving national borders. Importing countries implement this policy to try to isolate their internal markets from international prices: by not exporting nationally-grown food, these countries hope to reduce the quantity of food imported from abroad. Exporting countries are instead subject to conflicting interests: similarly to net importers, these countries tend to prevent precious cereals from leaving national borders. However, the prospect of high revenues from selling their production and stocks of food on the international market for a high price are tempting. Policies aimed at restricting international trade, because of the high interconnectedness of the global food system, increase its vulnerability to sudden reversals in connectivity, although simultaneously increasing countries' resilience towards local shocks (King, et al., 2015). The authors King et al. (2015) are the first to call for the development of 'greater understanding of how responses may amplify, or mitigate, how production shocks impact prices (King, et al., 2015, p. 117).

As a first attempt to address this gap in knowledge and to provide insights from the emergent behaviours generated in the Food and Fuel ABM, a scenario involving restrictions to the international trade of cereals was developed. This was aimed at trying to understand the influence of national trade-restrictive policies for cereals – and more in particular of export bans – on the international price of food and hence on the probability of food riots. Because the scenario was implemented in the integrated version of the ABM, its effects on the occurrence of fuel riots were also analysed and reported. The scenario is implemented in the year 2016 and starts affecting the model's dynamics from 2017. For this reason, the results and findings from the scenario will be presented for 2017 only.

Although trade restrictions are widely believed to affect prices of all the natural resources, this type of scenario was only implemented on cereals because of the lack of a database of policy changes as comprehensive as the one used for this analysis on cereals. Indeed, once again this scenario could only be developed thanks to data gathered and published by the WB in the Policy Monitor Dataset that listed the national policy changes for the international trade of food-related commodities between 2007 and 2014 (WB, 2015b). In particular, the database is aimed ‘to provide an integrated and comprehensive “one-stop shop” to monitor price- and commodity-related policies that may affect, or that may be affected by, food price crises’ (Barbet-Gros, 2014). In the database each record corresponds to information for one policy change. The attributes of each record identify the country that implemented the policy change and its date, it defines the direction of the change, i.e. policy introduction/removal, the commodities affected, the policy instrument used (e.g. tariff, trade restriction, export ban) and a brief description[16]. This database was analysed to gather information about which countries are likely to implement trade-restrictive measures in case of an international food price spike and to evaluate the length of the ban. This information was then introduced in the Food and Fuel ABM and the results analysed to infer whether these measures have an impact on the occurrence of food and fuel riots around the world.

The database contains information for policy changes related to food commodities (including meat, dairy, etc.), therefore to maintain consistency with the analyses presented in the previous chapters of this work and the natural resources included in the ABM only policy changes related to cereal commodities were selected. In particular, only the records whose attribute ‘commodity’ equalled to: ‘wheat’, ‘rice’, ‘maize’ or ‘cereals’ were taken into account for the development of this scenario. In addition, following the example of similar analyses (e.g. Puma, et al., 2015), to simplify the implementation of this scenario in the Food and Fuel ABM this analysis only focused on full export bans, ignoring other policy changes such as export tariffs, import bans, import tariffs, etc. This decision was also led by the fact that this type of policy is most likely the one that affects prices the most and sends the strongest signal to international markets. As a consequence, it is important to notice that for the purposes of this analysis export bans implemented on single grains were accounted for as export bans on cereals more in general. The time frame used was consistent

[16] For further information refer to the document that accompanies the database that can be found at this link http://www.worldbank.org/content/dam/Worldbank/document/Poverty%20documents/Introduction%20Guide%20for%20the%20Policy%20Monitor.pdf.

with the analyses presented in the previous chapters, i.e. 2005 – 2013. In order to infer the typical length of export bans, the data was analysed to trace each export ban and subsequently extrapolate the date of its implementation and removal. Export bans whose date of either implementation or removal could not be traced or inferred, were not taken into account.

The final list of countries that implemented an export ban on single grains or cereals as a whole and whose start and end date could be inferred contained 26 entries. The length of the export bans on cereals spanned between 2 months and 4.5 years, with an average length of 1.6 years. In the ABM, countries that implemented an export ban on cereals in the past were assumed to repeat this behaviour when the international price of food surpassed the 140 threshold for the FAO FPI calculated in Chapter 4 and were assumed to keep them in place for at least one year (tick). Countries re-evaluate their decision once a year when the international price of food falls below the threshold according to a cumulated probability calculated on the data that was extrapolated from World Bank (2015b). In particular, countries remove export bans on cereals according to the probability function expressed in terms of time (years) presented in Equation 6.1.

$$y = 0.2482\ln(x) + 0.5424$$

Equation 6.1 – Equation that expresses the probability for countries to decide to remove the export ban, based on the cumulated probability calculated from WB (2015b) (own elaboration).

The scenario is introduced in the model through a switch in the model's interface which is connected to a categorical variable *export-ban-switch* which equals *true* when the switch is on and *false* otherwise. Countries are initialised with a categorical variable *cereal-export-bans* which equals *true* if the country is included in the list of countries likely to implement an export ban or *false* otherwise. Data for this variable can be found in the database that initialises the variables for the agents provided as attachment. A new procedure called *to export-bans* was included in the ABM and run after the procedure *to compute-fuel-price* and before the procedure *to trade-<resource>* listed in Chapter 5.1.3, i.e. by when countries need to decide whether to implement an export ban, the international price of food will already have been formed, whereas international trade will not have taken place yet. In this procedure, if *export-ban-switch = true* countries calculate their SUR (which in the BAU presented in Chapter 5.1.7.9 is calculated in the procedure *to SUR*) and save the value in the variable *desired-cereals-stock*. Subsequently, if *international-food-price = 1*, i.e. if the international price of food is above the 140 threshold, countries with the variable *cereal-export-bans = true* set their variable *cereal-banned = true* and the variable *length-cereal-export-ban = 0*. Every year below the threshold after a price spike, if *international-food-price = 0*, countries create a temporary variable called *prob-ban-off* which stores the probability to remove the export ban, which is based on Equation 6.1. *prob-ban-off* is hence equal to *(0.2482 * ln(length-cereal-export-ban) + 0.5424) * 100*. The result from this equation is compared to another temporary variable called *prob*, whose value is a randomly generated number between 0 and 100. If *prob < prob-ban-off*, countries set *cereal-banned = false*, i.e. removing the national export ban on cereals, and set the variable *length-cereal-export-ban* to 0. All the countries with *cereal-banned = true* after these controls, move their exports available for cereals to national stocks by setting the variable *cereals-stock-t = cereals-exports-available* and setting the variable *cereals-exports-available = 0*, taking their stocks of cereals off the international market. Finally, these countries will check whether their current *cereals-stock-t > desired-cereals-stock*. If this control returns *true*, countries will set the variable *desired-cereals-stock* to 0 or its value will equal *desired-cereals-stock* - *cereals-stock-t*. The model's simulation subsequently resumes normally and all the remaining procedures listed in Chapter 5.1.3 are run.

The scenario was run 100 times until the year 2021 and the results were averaged and analysed. At the global level, the main effect of the implementation of the export ban by some countries is the emergence of unexpected behaviours. When the scenario is activated, the distribution of international price of food ceases being deterministic, with different runs potentially generating different price regimes for the years beyond 2017 and hence different probabilities for food and fuel riots. Throughout the 100 runs, the only year whose distribution was different from the BAU scenario was 2020, where one of the runs returned a food price below the threshold for this year. These results seem to partly disagree with the current literature in the field. Although literature on the effect of trade restrictions on prices has increased after the 2008 global food crises, the size and directions of these effects are still subject of research. Tadesse, et al. (2014) and King, et al. (2015), for instance, believe in the negative effect of these measures on prices level and volatility, with Puma, et al. (2015) highlighting the potential multiplier effect of panic behaviours on markets. Other authors simply acknowledge the effect on prices, without specifying its direction (e.g. Kharas, 2011; Cuesta, et al., 2014). The negative relationship between the implementation of trade restrictions and the food price regime witnessed in the results from the ABM is due to the dynamics that were implemented to determine the price regimes of resources: the global variables that determine whether the international price regime of food (and fuel) is above or below the threshold are the global ratio between production and consumption of food (or fuel) and the global stocks of the resource. These variables consist in the sum of the national production, consumption and stocks of the resource, before the international trade takes place in the model. The Export Ban Scenario influences the level of national stocks of food, allowing countries to take these off the international market. However, in the ABM these stocks still concur to create global stocks of food, which influence the international price. As a consequence, when the scenario is activated countries will limit their exports, resulting in some countries being unable to cover their own consumption or desire for stocks of food via imports and ultimately positively affecting the size of global food stocks that concurs to determine the international price, which can hence be pushed below the threshold. As mentioned in the introduction to this chapter, this scenario was developed as part of a larger framework to evaluate food production shocks (Jones and Hiller, 2015) which found that it is the global level of food stocks that influence the international food price regime, independently from their tradability, which partly led the dynamics implemented in the model to estimate international food price regime. It is worth noting that in the current version of the ABM, a country not being able to meet its own need for consumption of food and other resources does not trigger any consequence. As presented in Chapter 4, the relationship between national food security (net food production of countries was used as a proxy) and the occurrence of food riots, was not found to be significant. For this reason this feedback was not introduced in the current ABMs, although it is realistic to believe that the use of different variables that capture the state of food security of a country could lead to different results. Therefore, this constitutes another possible future development of the ABM, alongside further research on the effect and direction of trade restriction on prices and ultimately on the occurrence of riots.

The analysis of national food stocks for countries that implement trade restrictions led to less disputable results. Table 6.4 presents the comparison between the stocks of cereals successfully sourced by countries under the export ban scenario and under the BAU scenario. The stocks gathered by countries are presented as a percentage of the stocks of cereals required by countries, i.e. their SUR. As expected, the results show that when countries implement export bans, the percentages of stocks successfully acquired out of those required is higher, in some cases meeting the desired stock defined by their own SUR. In addition, Figure 6.2 presents the same information in the form of quantity of cereals owned by countries as inventories. These results show that countries that implement export bans avoid exporting cereals abroad, successfully protecting their internal markets from high international prices, or at least reducing the countries' imports for the resource.

Country	**Percentage stocks met with scenario**	**Percentage stocks met without scenario**
Bangladesh	39.03%	1.29%
Bolivia	3%	0%
Cambodia	8%	1%
Ecuador	6%	0.12%
Egypt Arab Rep.	3%	0.05%
Ethiopia	5%	1.63%
India	2.95%	0.60%
Indonesia	6.11%	0%
Iran Islamic Rep.	6.92%	0%
Kazakhstan	100%	1.16%
Kenya	4%	0%
Madagascar	8%	1%
Malawi	5%	0%
Moldova	100%	2.27%
Myanmar	100%	1.54%
Nepal	6%	0%
Pakistan	100%	2.76%
Russian Federation	100%	1.24%
Serbia	100%	1.92%
Sierra Leone	100%	1%
Sri Lanka	5.54%	0%
Tanzania	5%	0%

Thailand	100%	0.08%
Ukraine	89.35%	0%
Vietnam	3.23%	0%
Zambia	100%	1%

Table 6.4 – Comparison of cereals stocks for countries that implement export bans under the export ban scenario and under the BAU scenario. The stocks gathered by countries are presented as a percentage of stocks of cereals required by countries, i.e. their SUR (own elaboration).

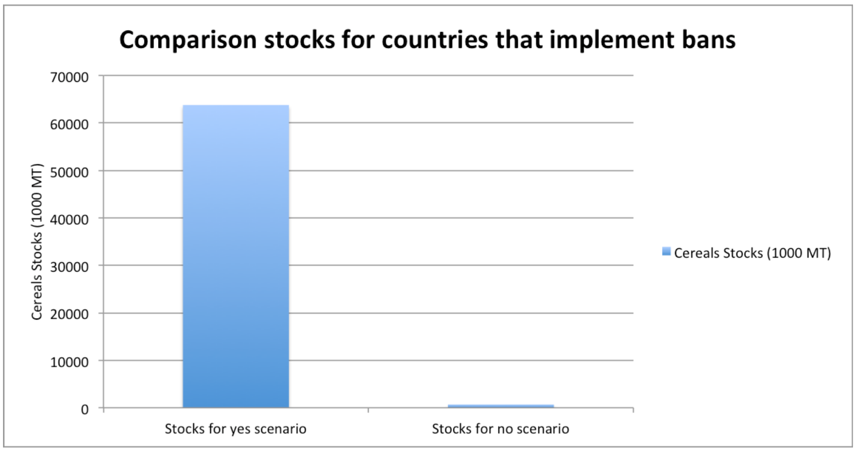

Figure 6.2 – Comparison of cereals stocks for countries that implement export bans on cereals under the Export Ban Scenario and under the BAU scenario (own elaboration).

Figure 6.3 presents another important result from the implementation of the scenario. Countries that restrict trade on cereals achieve comparatively higher stocks than countries that do not regulate their exports under the Export Ban Scenario.

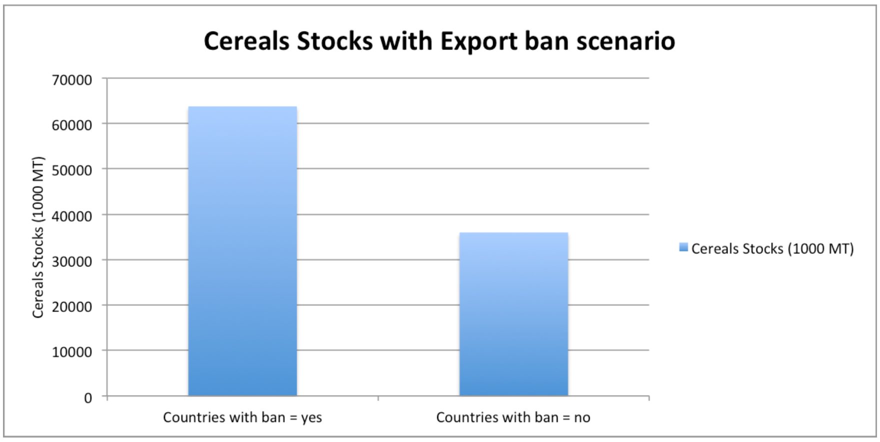

Figure 6.3 – Comparison of stocks of cereals for countries that implement export bans and those that do not regulate trade under the Export Ban Scenario (own elaboration).

Finally, the predictions for food and fuel riots from the Food and Fuel ABM under the Export Ban Scenario were analysed and compared with those from the simple forecasts for the same year presented in the previous chapter. As for food riots, out of all the years considered 2017 was the third year with the highest probability for food riots, which was around 3% as compared to 4% resulting from the simple forecast under the BAU scenario. The probabilities of food riots for countries for 2017 ranged between 0% and 18%, as compared to the probabilities assigned to countries in the BAU scenario that only reached a maximum of 13%. At the top of the list of countries most at risk we find Egypt, Madagascar, Yemen, Burkina Faso, India, Ethiopia, Kosovo and Peru with probabilities spanning between 18% and 10%. 25 countries were assigned with the lowest probability, amongst these we find Congo Republic, Ukraine and Germany. Although the probability of a general country to experience a food riot is comparatively slightly lower under the Export Ban scenario as compared to the BAU scenario, the probability distribution for countries differs and some countries report higher probabilities for food riots under this scenario. For a better visualisation, the results from the Export Ban scenario for food riots in 2017 are presented in Figure 6.4.

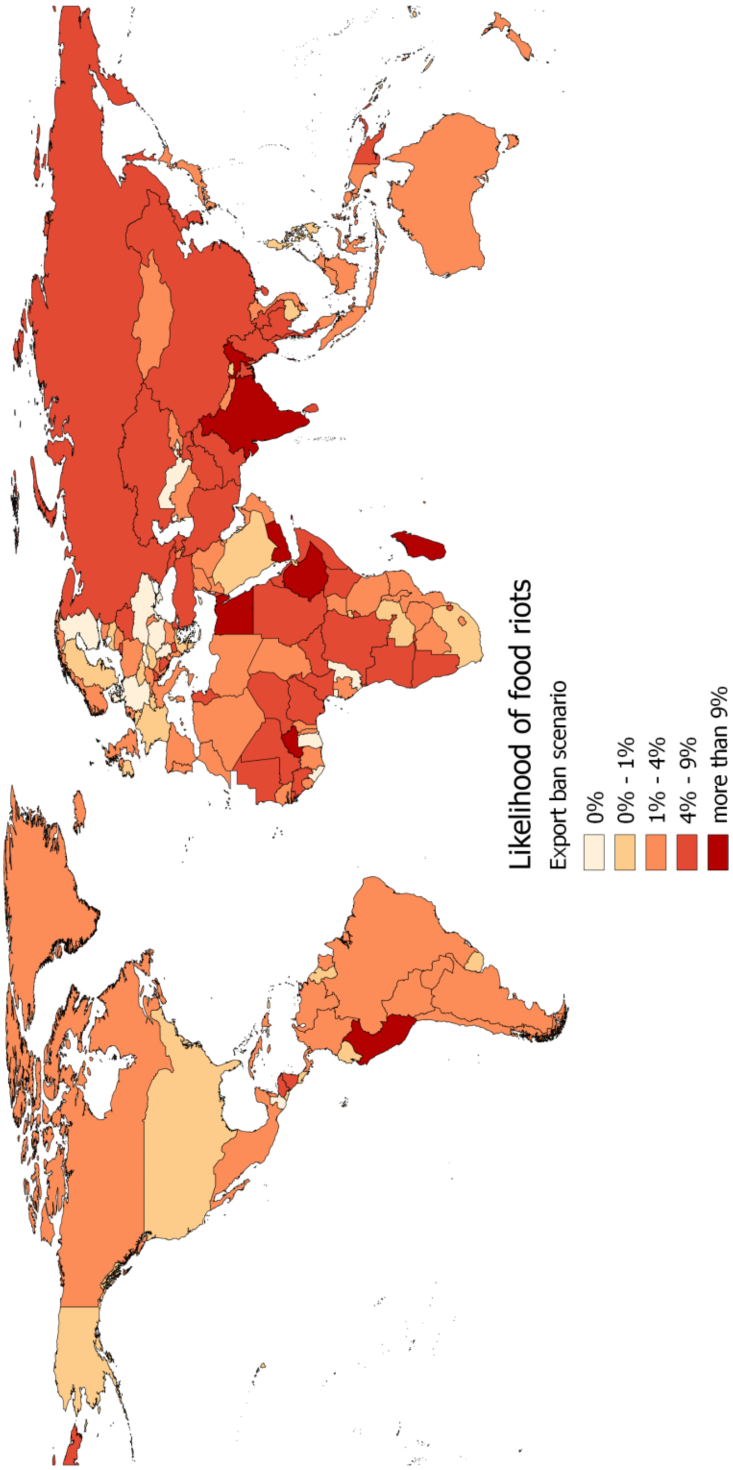

Figure 6.4 – Probability of food riots for countries based on the year 2017 for the Export ban scenario (own elaboration).

Looking now at the predictions for fuel riots, 2017 was the year with the highest probability for fuel riots, which was around 3% as for the BAU scenario. At the top of the list of countries most at risk we find India, Cameroon, Bolivia, Indonesia, Nigeria, and Italy, with probabilities spanning between 30% and 13%. India's probability of experiencing a fuel riot increases by 3% under the Export Ban scenario as compared to BAU. 49 countries were assigned with the lowest probability, amongst these we find Côte d'Ivoire, Senegal, Somalia and United States. The list of countries ordered by decreasing probability of fuel riot under this scenario is remarkably similar to that resulted from the simple forecast under the BAU scenario. For a better visualisation, the results from the probabilities of fuel riots for the Food and Fuel ABM under the Export Ban scenario are presented in Figure 6.5.

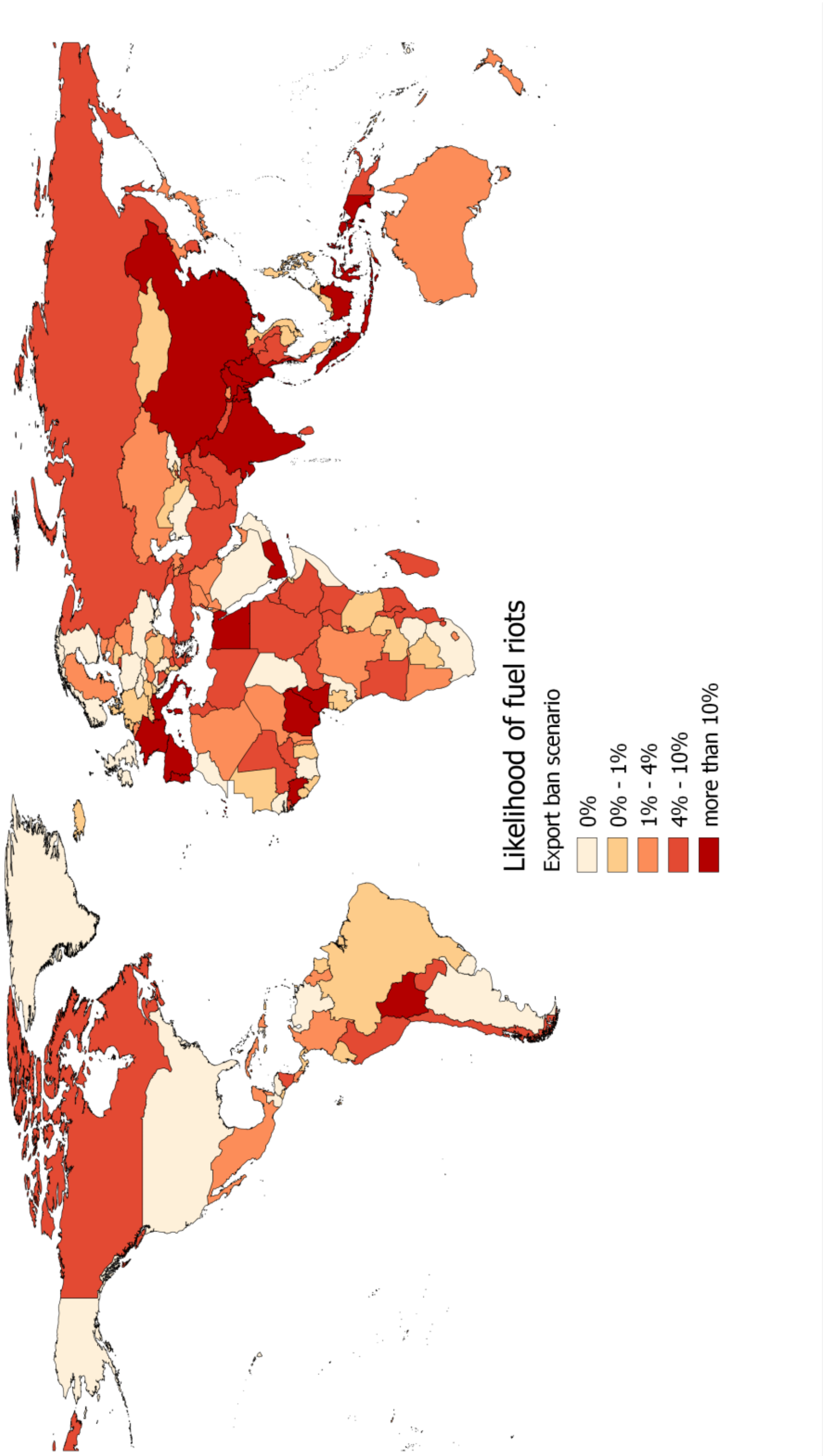

Figure 6.5 – Probability of fuel riots for countries based on the year 2017 for the Export ban scenario (own elaboration).

The results from this scenario were mainly positive and provided a good exploratory analysis of the effects of trade restrictions on international prices and ultimately on the occurrence of riots. However, questions remain as relates to the direction of the effect trade-restricting policies on prices, which is why this scenario was not introduced in the main findings from this work. In this scenario these are shown to negatively affect prices, hence disagreeing with the main literature in the field, although the implementation of the scenario was guided by findings from Jones and Hiller (2015). Future versions of the model may implement different dynamics to generate prices, hence leading to possible different outcomes as relates the effect of trade-restrictive policies.

6.2.2. El Niño scenario and food riots

To provide a first example of application of the Food ABM, a what-if scenario hypothesising a shock on the production of cereals caused by a strong El Niño in 2016 was implemented in the model. This climatic event was chosen as it is forecasted to cause major disruptions around the world and it is considered as plausible (Lloyd's, 2015). The implementation of this scenario in the Food ABM is based on the analysis recently published in a report by Lloyd's of London (Lloyd's, 2015). This report tries to quantify and qualitatively model the development and the possible impacts of a similar scenario. In particular, the authors elaborated that a strong El Niño event and spread of disease could result in the following percentage reduction in global production of food commodities: maize 10%; soybean 11%; wheat 7%; rice 7%. Since the food system in the Food ABM is simulated at the country level, and does not diversify between the different food commodities, but rather cereals are considered as a single category, the first step to implement this food production shock was to aggregate the reductions for each commodity as a more general 'cereal shock' and then translate the global shock at the national level. To do so data from FAOSTAT (FAOSTAT, 2015) was used. Since the data included in the model was originally sourced from the GRO Database, which, in turn, sourced it from FAO balance sheets for cereals, the model does not include data for soybeans. The shock on this commodity could not thus be modelled in this scenario. The first step to create a global 'cereal shock' was to find the average proportion of wheat, maize and rice on the more general cereal category for the last two years for which data was available (2012 and 2013). Subsequently the absolute value of cereal losses after the shock struck were calculated, which resulted in a total cereal loss of 7.3%. The scenario reported by Lloyd's (2015) already provided national reductions for some of the commodities, however these were not comprehensive and did not add up to the percentages reductions mentioned above. Those national reductions that were reported were therefore summed and compared with the reported global reductions for each commodity. The remainder of the global loss was then redistributed between the remaining countries producing wheat, maize or rice that were not already mentioned in the report. This accounts for ≈1% loss of the total loss of wheat, maize or rice and was spread across producing countries not mentioned in the scenario. The percentage reductions for each country due to the El Niño and disease shock are provided in the database that initialises countries provided as attachment. It is worth noting that the estimation of total losses due to the shock was slightly underestimated for two reasons: i) soybeans were excluded from the shock in this analysis; ii) data downloaded from FAOSTAT for total cereals production did not align when summing from different datasets.

The shock was implemented in the year 2016, as when it was developed (July 2015) it was aimed at trying to provide insights about possible future scenarios. In addition, a strong El Niño has been forecast to have major food production impacts for this year (Oxfam, 2015). 100 simulations of the Food ABM were run between 2005 and 2017 and the results were aggregated. The results from the model suggest that the shock as developed by Lloyd's (2015) is significant enough to bring the FAO FPI over the 140 threshold, hence significantly increasing the probability of food riots to occur around the world. Out of all the years considered, 2016 had one of the highest probability for a random country to experience a food riot, which was around 4% as compared to 1% in 2005 and 3% in 2008. The probability for single countries to experience a food riot ranged between 0% and 17%, with the top ten countries in terms of risk being Somalia, Cameroon, Mali, Eritrea, Russian Federation, Angola, Bosnia and Herzegovina, Maldives, Papua New Guinea and Thailand, all with more than 10% probability of experiencing a food riot that year. At the bottom of the list with a probability equal to 0% we find Solomon Islands, South Africa, St. Lucia, Timor-Leste, Tonga, Tuvalu, United Kingdom, Uzbekistan, Virgin Islands (U.S.) and Zimbabwe. For a clearer visualisation, the probabilities of food riots for each country are summarised in Figure 6.6.

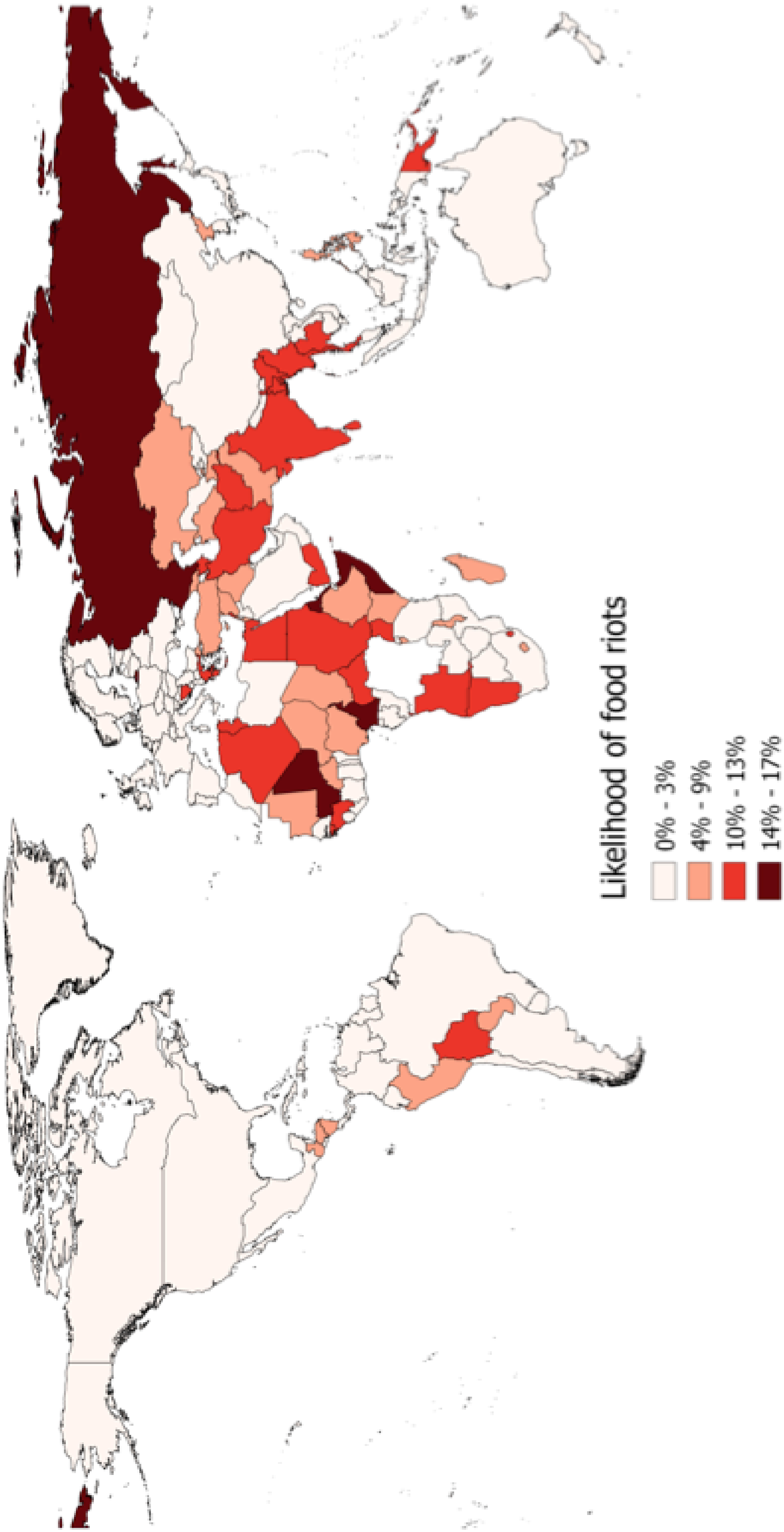

Figure 6.6 – Probability of food riots for countries based on the 2016 El Niño scenario (Natalini, et al., 2015a).

Although the findings from this scenario seem plausible and were presented at an international conference on food security (Natalini, 2015), I decided not to include this in the main text of the thesis, but rather to present this as a possible future development of the Food ABM and one of its possible applications. This decision was led by the fact that the aim of this scenario is to evaluate whether a food production shock of the size presented in the text is large enough to cause the international price of food to spike, hence resulting in a higher probability of food riots in countries for the year 2016. As it was highlighted in Chapter 5.5, the BAU runs for the Food ABM show a regime for international price of food above the threshold for the year 2016, hence posing reservations about the validity of the results presented above.

However, in reality the year 2015 registered food prices below the threshold. If the model were able to capture this drop, the implementation of this scenario would provide meaningful results. In particular, the model would be able to tell if the production shock is large enough to bring the price above the threshold. As previously highlighted, the introduction of more realistic price dynamics in the ABMs is a priority for further developments.

Independently from whether the predictions of the Food ABM from the El Niño scenario will turn out to be true, this experiment shows the potential of the Food ABM as an early warning assessment tool, which will prove to be useful to highlight increased risk of food riots in countries in case of a food production shock once a more accurate estimation of the prices will be introduced in the model.

6.2.3. Fuel production shock scenario and fuel riots

A what-if scenario similar to that presented in the previous section was developed and implemented in the Fuel ABM to evaluate consequences of a possible fuel production shock in terms of fuel riots. Following the example of Kumhof and Muir (2013), this scenario was developed hypothesising a 2% reduction in global oil supply based on a review of several different future forecasts based on Sorrell, et al. (2010). Differently from the first authors, the scenario implemented in the Fuel ABM simulated a one-off shock for the year 2017, rather than an annual 2% decrease in the extraction of oil.

Since the oil production shock is a prediction of a future event, data for national and global oil production for 2016 was not available and its quantification had to rely on previous data. Reported data for oil supply was sought from the GRO Database (GSI, 2015). The last year for which complete data for this variable was available was 2012. Global daily oil supply for that year amounted to 89,878.47 Thousand barrels per day. A global loss in the daily oil supply would thus be quantifiable as 1,797.57 Thousand barrels per day.

Saudi Arabia was the largest oil producer in 2012 and since then data shows a decline in its daily oil production. In fact, Saudi Arabia's oil production is forecasted to soon begin its descent, due to its peak oil approaching fast, possibly before the end of the next decade (Ebrahimi and Ghasabani, 2015). Therefore, the reduction in oil supply modelled with this scenario was allocated to Saudi Arabia alone.

The 2% shock on global oil production needed to be translated in a national loss for Saudi Arabia's oil production in 2016. According to the estimates calculated by fitting trend lines to countries' production of natural resources, Saudi Arabia's oil production in 2016 is forecasted to amount to 12,694.98 Thousand barrels per day. A production loss of 1,797.57 for Saudi Arabia corresponds to a 14.16% loss in oil production for the country in 2016.

The scenario was hence introduced in the Fuel ABM and 100 simulations were run between 2005 and 2017 and the results aggregated. The results from the model suggest that the shock is significant enough to bring the EIA fuel price over the $93 per barrel threshold, hence significantly increasing the probability of fuel riots to occur around the world. Out of all the years considered, 2016 had the highest probability for a random country to experience a fuel riot, which was around 4% as compared to 2% in 2009 and 3% in 2008. The probability for single countries to experience a fuel riot ranged between 0% and 18%, with the top ten countries in terms of risk being Indonesia, India, Libya, France, Chad, Uganda, Bahrain, Cameroon, Egypt and Iran, all with more than 13% probability of experiencing a fuel riot that year. At the bottom of the list with a probability equal to 0% we find 60 countries, amongst which are Côte d'Ivoire, Denmark, Morocco, United States, Haiti and Zimbabwe. For a clearer visualisation, the probabilities of fuel riots for each country are summarised in Figure 6.7.

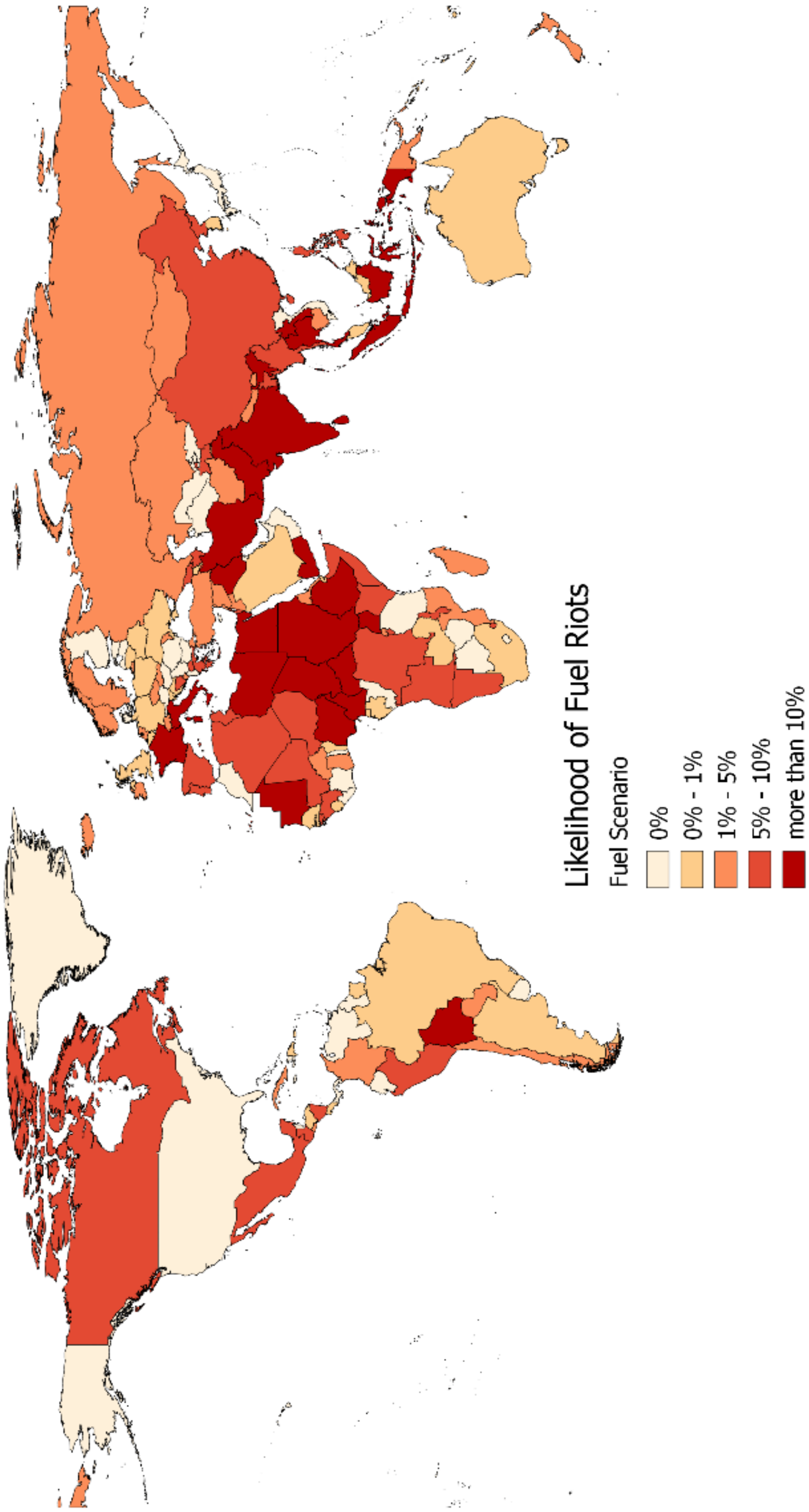

Figure 6.7 – Probability of fuel riots for countries based on the 2016 fuel production shock scenario (own elaboration).

This scenario was also included in this section because, as highlighted in Chapter 5.5, the BAU runs for the Fuel ABM show a regime for international price of fuel above the threshold for the year 2016, even without the introduction of the fuel shock forecast by the scenario, hence posing reservations about the validity of the results presented above. In reality, international fuel prices have dropped below the threshold in 2015 due to a low increase in demand coupled with increased production (especially from US) and the failure of OPEC countries to reach an agreement on national quotas for production, which remained high (European Commission, 2016). This dynamic is not currently reflected in the ABM. However, once a more accurate estimation of prices is introduced, this scenario would acquire validity, as it would be fairly realistic to see Saudi Arabia restrict its oil production by 14% due to terrorism, civil unrest or even politics.

7. Conclusions

The research presented in the previous chapters is highly interdisciplinary and aimed at advancing knowledge in several different academic fields: environmental security, global food and energy security, international economics, political science and computer modelling.

The contributions of this research to the current literature are multiple: i) definition of threshold for the international prices of food and fuel (both on their absolute values and volatility) that can trigger increased social unrest, ii) novel insights on food and fuel riots, iii) open up a novel stream of research on fuel riots, iv) development of fully data-led ABMs, and, finally, v) the provision of an ABM that can constitute a starting point for further developments.

Referring back to the description and characteristics of computer models provided in Chapter 3.1, the models developed as part of this research only constitute a simplification of reality. As it is standard practice in modelling literature, part of the research provided involved the formulation of a clear research question, which led to the identification of key dynamics that have been explored quantitatively and introduced in ABMs to model them and provide predictions of possible future states of the system. Finally, the models have been used to test the effect of different scenarios and policies.

Although a discussion section was provided to comment on the findings from the most interesting sections, the next section will answer the research questions underlying this research, also providing general comments on the findings. The following section will discuss the policy relevance of the research and, finally a summary of the contributions to literature of this research will be provided.

7.1. General Statement and answers to research questions

The challenges ahead of humanity are multiple and complex. Environmental dynamics such as climate change and scarcity of natural resources play together with social structures such as prices and governments to exacerbate increased insecurities and political fragilities. The 2008 global multisystem crisis is testimony of the interconnectedness of different SESs and the potential for conflict driven by underlying environmental trends. These conditions are expected to worsen in the future, with increased incidence of conflict and in particular of environmentally driven riots. For these reasons, the topic of environmental security is worth being explored.

7.1.1 Research question 1 – Is there a linked environmental causal factor in the triggering of civil unrest in different countries around the world?

Sub-research questions:

- Do international prices have an impact on the occurrence of food and fuel riots? What has the biggest effect, absolute prices or volatility? Is there a threshold for prices over which food and fuel riots are more likely to happen?
- How does availability of food and oil impact the occurrence of riots?
- Does national political fragility have an impact on the occurrence of food and fuel riots?
- Are food and fuel riots characterised by the same dynamics? Do they have an impact on the occurrence of one another?
- What is the probability of food and fuel riots to occur according to these variables?

A review of the current literature on environmental conflict presented in Chapter 2 highlighted a history of mixed findings on the connection between environmental processes and conflict, although there seems to be an agreement on the role of environmental pressures as catalyst for conflict, in particular riots. Food riots have widely been studied since the 2008 global multisystem crisis that saw a sharp increase in the occurrence of these events, highlighting the role of international food prices and scarcity of food as main drivers. Newspaper articles also identified the occurrence of similar events, although connected to fuel, which are known as fuel riots. This topic is still unexplored by academic research.

This research implemented a quantitative approach to explore the answers to these questions. Databases with observations for food and fuel riots were compiled by collecting data from online newspapers that reported occurrences of violent uprisings due to scarcity and/or price of food and fuel. To the best of my knowledge, this produced the largest and most accurate database of violent food riots and the first on fuel riots. Some of the records specifically mentioned the terms ‘food’ or ‘fuel riot’, whereas others reported a more general discontent towards the country’s economic/social situation and in particular towards government’s policies that also regarded one or both these resources. Most of the riots were concentrated in 2008 and 2011, years that corresponded to the Arab Spring and, more generally, to the multisystem crisis. It is hence possible to speculate on the fact that food and fuel riots were the beginning of a more generalised crisis, which was first exacerbated by environmental issues. This is in line with the definition of SF (Homer-Dixon, et al., 2015), i.e. the idea that the 2008 crisis had environmental roots and that these develop within different SESs, which then start interacting and synchronise, giving life to a generalised crisis and widespread political fragility. This is also in line with the argument that environmental issues are catalysts of conflict rather than direct contributors, which is also supported by the non-significant relationships found between national availability of food and fuel and riots.

Chapter 4 found that the absolute level of international prices for both resources has a positive and significant effect on the occurrence of food and fuel riots. In particular, the hypothesis of the existence of thresholds for the international price of food and fuel was found to be true and were identified at 140 for the FAO FPI and $93 per barrel for food and fuel. The effect of price volatility was tested in Chapter 6, where RE models showed a positive, significant relationship between volatility in international food prices and the occurrence of food riots, and mixed findings for the relationship between international fuel prices and fuel riots. For fuel riots an RE model found a positive, significant relationship between the 1-year variation in international fuel prices and the occurrence of fuel riots, also identifying a threshold at $4.6 per barrel. However, a REEM model did not find this relationship significant. Food riots were found to be more likely to occur when the 2-year price variation is greater than 17.1 of the FAO FPI. These preliminary findings show that, although there seems to be a tolerance for increases in food prices, this is not the case for fuel prices, which seems to suggest a lack of oil stocks or their unavailability. Globally, scarcity of oil stocks does not show in data, however their availability may be concentrated in specific countries, or, more simply, the data on oil stocks is inaccurate. A more in-depth analysis of the effect of national stocks of resources on the occurrence of food and fuel riots is hence required.

A comparison of the accuracy at predicting food riots between two REEM models, one on the absolute price regimes and another on regimes in price variation found the latter the most accurate. The model with price variation correctly predicted 11.11% of food riots, as compared to 6.39% of the model with the absolute price. This finding partly disagrees with Bellemare (2014), who found an inverse relationship between the two variables, i.e. food price fluctuations decrease the probability of social unrest. The author justifies his findings with the argument that, historically, food producers have been the main actor in social upheavals related to food prices. Price volatility has a positive effect for these actors as price spikes increase their revenue, hence resulting in lower probability of unrest from this category (Bellemare, 2014). The main difference between this research and Bellemare's was the definition of food riots, with Bellemare's database also including non-violent events. Speculating on this difference, one could argue that food price volatility does not affect non-violent protests, as opposed to violent food riots. As for fuel riots, future research should further explore their relationship with fuel price variability. As presented in Chapter 4, the international price of fuel was modelled as the simple average between two spot prices, which may have concealed key differences between different parts of the world and hence caused the mixed results. Different measures of international price of fuel should be tested.

Findings presented in Chapter 4 showed that the national availability of food and fuel, modelled as net production, does not significantly affect the occurrence of food and fuel riots. This finding is highly controversial, although agrees with the main literature (e.g. Buhaug, et al., 2015). These variables were modelled as net production as this thesis was testing the hypothesis that when a country relies on imports of a resource to cover national demand, it is exposed to the international price of that resource. By running the HZ models only on the months when the price of those resources was above the threshold, the model was testing whether a country's exposure to high international prices influences its probability of experiencing a riot. Although these findings suggest that the connection is not significant at the national level, food and fuel availability indirectly affects – alongside other factors – the probability of riots at the international level by acting on the prices of these resources, which in turn have a positive and significant effect on riots. More research should hence be devoted to better understand the relationship between national food and fuel security and the occurrence of riots, testing different variables that capture the national availability or access to these resources, such as the percentage of income spent on food and energy, or the effectiveness of their redistribution. Legwegoh, et al. (2015) also found that diets are an important variable in the willingness to riot. Country-specific studies focussing on the availability of cereals central to their diet could lead to different results.

Chapter 4 also tested the accuracy of different measures of political fragility at capturing the national exposure to food riots. The most accurate index was the WGI. The contribution of national political fragility to the probability of a country to experience a food or a fuel riot was hence tested. The results show that countries that are more politically fragile are also more likely to experience a food or a fuel riot. This finding is in line with the wider literature on food riots (e.g. Brinkman and Hendrix, 2011). In addition, REEM models for both food and fuel riots highlighted that international prices for both resources are only relevant for classes with high political fragility. Politically fragile countries tend to be the poorest and located in the global south, which supports the hypothesis that high prices impact poor countries more. As we have seen in Chapter 2, countries heavily subsidise the prices of natural resources and poor countries do not seem to be able to afford them when prices are high, hence leading to their removal, which leads to unrest.

In general, this research highlighted that food and fuel riots are driven by the same dynamics. In fact, the symmetry between the analyses on food and fuel riots – apart from the mixed findings on price volatility – show a clear connection between these two events and, more generally, between the food and fuel system. Indeed, the study on the interaction between food and fuel riots found a mutual, positive relationship between the two types of riot: a country that has experienced a food riot is more likely to experience a fuel riot and vice versa. This finding is in line with the idea of SF, where different SESs – in this case the food and energy systems – are linked and become synchronised, resulting in a generalised crisis. More research should be devoted to explore the variables that permit these interactions. This research suggests that a key factor is prices of natural resources, which transmit shocks from the availability of one resource to its price and the price of other resources, eventually leading to violent riots.

The accuracies of RE and REEM models at predicting food and fuel riots were compared, first using only the international price regime and WGI as predictors and then using the other type of riot as independent variable. REEM models were eventually selected as preferred method to evaluate the probability of riots under different conditions because of their overall better performance (when including countries' RE) and the return of probabilities that can readily be implemented.

Finally, the probabilities of riots in countries under different conditions are presented in Tables 4.18, 4.26, 4.29, 4.30 and 6.2.

7.1.2 *Research question 2 – Which is the optimal method that can be used as a policy tool that can simulate these dynamics using a data-led approach?*

Sub-research questions:

- Does adopting a fully data-led approach in developing an ABM generate a 'good' model?
- Does the introduction of stochasticity and interaction between the agents and the feedback between food and fuel riots result in more accurate predictions than the underlying statistical extrapolation?

System pressures such as climate change, food and energy insecurity, globalisation and synchronisation between different SESs and their consequences for social systems make these connections worth exploring with a system approach. Chapter 3 presented different modelling approaches that can and have been implemented to study similar topics. Computer simulation was preferred to other modelling techniques due to the possibility to introduce dynamic feedbacks between different variables and, in particular, ABM was selected because they allow to model heterogeneous agents and capture emergent properties through the simulation of interaction between agents. Recommendations on when ABMs are most effective perfectly suited this research and this method provided the most potential in answering the research questions.

Three ABMs were developed: the Food ABM (including dynamics for food riots), the Fuel ABM (including dynamics for fuel riots) and the Food and Fuel ABM (including both types of riots). Following Principle 2 of the GRO project, which this research was part of, the models developed ought to be fully data-led. Both the input data and the parameters of the ABMs were estimated on reported data. In particular, the results from the studies presented above informed some of the key dynamics included in the models, i.e. the relationships between prices, national political fragility and the occurrence of riots and the influence between different types of riot. In addition, reported data from UN Comtrade (2014) was used to develop the social networks representing international trade in the models and production and consumption of the natural resources and national political fragility were estimated by applying trend-lines on data from the GRO database (GSI, 2015). By introducing these parameters in an ABM environment, one would expect the ABMs to be more accurate than the underlying statistical models that inform them.

The validation of the ABMs presented in Chapter 5 contradicts this expectation and highlighted the first limitation of the combination fully data-led and ABM approach. Table 7.1 presents the comparison of the accuracy of the REEM models presented in Chapter 4 and of the Food and Fuel ABM at predicting food and fuel riots, which shows that the introduction of these dynamics in an ABM does not add to the accuracy of its predictions.

Variables	Food	Fuel
Food and Fuel ABM	6.86%	10.76%
REEMre (food)	6.39%	-
REEMfoodre	7.77%	-
REEMre (fuel)	-	11.29%
REEMfuelre	-	12.10%

Table 7.1 – Comparison of the accuracy between the Food and Fuel ABM, and models REEMre (food), REEMre (fuel), both including the two price regimes and the four groups of fragility for the WGI as predictors and REEMfoodre and REEMfuelre, which include the mutual influence between food and fuel riots (own elaboration).

Indeed, the accuracy of the underlying models on relationships between international prices and political fragility and the occurrence of riots (models REEMfoodre and REEMfuelre) correctly predict 6% and 11% of food and fuel riots, respectively. These percentages are very similar to the accuracy of the Food and Fuel ABM, which correctly predicts 7% and 11% of food and fuel riots, respectively. This is a clear signal that the fully data-led approach used to develop the ABMs resulted in models that are just as accurate as the underlying statistics and that the introduction of dynamic behaviours and interaction through a social network are not sufficient to improve the models' predictions. Surprisingly, not even the introduction of the mutual influence between food and fuel riots estimated by the models REEMfoodre and REEMfuelre was beneficial. Indeed, the percentages of riots correctly predicted by these models added to the other REEM models would amount to a respectable percentage of accuracy for an ABM. However, the accuracy of the different REEM models do not sum when their interaction is implemented in the ABM, but rather the overall accuracy of the model remains unvaried. This is due to the fact that, although four different REEM models were created to analyse different possible causes that lead to each type of riot, i.e. i) international price regimes and WGI group and ii) the occurrence of the other type of riot, the variables included in each model are likely to be highly cross-correlated between models, hence nullifying the potential increase in accuracy that could have been gained by including the mutual influence between the two types of riots. Indeed, fuel is one of the primary factors employed in agriculture, therefore its international price is likely to have a positive effect on the occurrence of food riots. Likewise, food crops are increasingly being utilised for the production of biofuels, which can affect the international price of oil and which in turn has an impact on the occurrence of fuel riots.

Despite the inability of a data-led ABM approach to increase the understanding of the drivers of food and fuel riots, this does not make of the ABMs developed 'bad' models. The models are indeed at least as accurate at predicting riots as the statistics that underlie their dynamics, which suggests no coding errors. This allows the use of the models as platforms for further developments by zooming into specific issues highlighted by this research. In addition, the development of fully data-led ABMs contributed to the field of computer simulation, as this was never attempted before.

It is worth noting here that the ABMs developed as part of this work, similarly to any other computer model, is not aimed at giving (cannot provide) precise predictions about which country will experience a riot and when, which is the information being tested in the table above. Rather, the ABMs are aimed at giving an indication about which countries are at risk of social upheavals due to multiple factors, amongst which we find a high international price of natural resources and their political fragility. Indeed, the different versions of the ABM can still provide invaluable information: the results of the models constitute an indication for situations of stress induced by a high international price of food and/or high political fragility that need further investigation and expert field analysis.

Indeed, the validation of the ABMs also highlighted positive results. The cumulative probability of riots by price regime is remarkably close to reality, although the models slightly underestimate the probability of riots for years above the threshold and slightly overestimate it when the price is low. Surprisingly, the ABMs are incredibly accurate at predicting which country will experience each type of riot throughout the period considered. In this case, the Food and Fuel ABM performed better than the ABMs on single resources, showing the advantages of using the integrated model. Care should be taken in the evaluation of these results, as they may partly be due to the inclusion of country-level RE in the calculation of their probability of riots. It is worth noting that using the REs to improve predictions constitutes an acknowledgement of our ignorance on some of the drivers of riots, as these are empirically estimated but represent 'black boxes' that do not explain why riots occur. The REs, which are provided in the database used to initialise countries attached to the thesis, are however very small as compared to the other factors, hence a potential strong effect is dubious.

To partly solve these issues, future developments of the models should relax the fully data-led limitation, in particular countries' decision making as relates to production and consumption of natural resources and national political fragility, which should all be endogenised in the models.

7.1.3 Research question 3 – Can these models be used to predict future riots?

The three versions of the ABM include some of the dynamics that explain the occurrence of resource-related riots, but are not yet able to provide future forecasts. As presented and discussed in Chapter 5, although the ABMs perfectly recreate the price regime trends between 2005 and 2013, the dynamics included in the models predict prices above the threshold for around a decade. In reality, international prices of food and fuel registered a regime below the threshold in 2015, hence questioning the method used to calibrate the prices in the ABMs. Once again, this is partly due to the inaccurate estimates for production and consumption of natural resources, which were based on trend lines calculated on reported data, as explained in Chapter 5.5. In addition, the calibration on reported data presented in Chapters 5 on absolute prices and 6 on price volatility, showed that interaction between supply and demand and levels of stocks are not sufficient to recreate prices. When calibrated on reported data, the ET models produced counterintuitive dynamics, with prices above the threshold when the availability of resources is high and vice versa. This finding adds to the literature on drivers of international food prices, which does not find food availability, i.e. production, consumption and stock dynamics, as significant factors for recent prices. Lagi, et al. (2015) found that the supply-demand model only explains the trend in the FAO FPI up until 2000. After that year, the predictions of the model are inconsistent with the real trend observed in international food prices. The authors provided evidence that the underlying upward trend for the FAO FPI post-2000 can be explained by increasing demand from ethanol conversion and that the 2008 and 2011 spikes in the FAO FPI are only related to speculation on the food futures market. As can be recalled from Chapter 4, the years 2008 and 2011 saw the largest number of food riots, which in that chapter were explained by the absolute price of food going beyond a critical threshold, or in Chapter 6 by the two-year food price fluctuation surpassing a critical threshold. If what argued by Lagi, et al. (2015) were true, the direct driver of those peaks would be speculation, hence also being the indirect driver of most of the food riots occurred during those years. As for the food riots occurred in different years, it would hence be possible to speculate that these were driven by forces different than financial speculation, such as demand for biofuels and, therefore, scarcity of food due to competing uses of the resource. In addition, the two different thresholds, i.e. on absolute prices and on price variation, capture different years as more 'at risk': the former sees 2007-2008 and 2010-2013 above the threshold, whereas the latter identifies 2007-2008 and 2011 as above the threshold. The threshold on food price variations clearly identifies the years with the highest occurrence of food riots, strengthening the hypothesis of a difference between food riots in these years and the others. This reasoning would hence allow to differentiate between at least two types of food riots: those due to speculation and those due to scarcity. A similar classification was used by Cuesta (2014) which in its Food Riots radar distinguishes between food riots of type 1 and 2. The former are mainly caused by inflation in food prices and directed against the government of the country, whereas type 2 are smaller and more localised and usually have weaker political motivations, as typically caused by scarcity of food in localised regions (Barbet-Gros and Cuesta, 2014). However, to the best of my knowledge, this research and classification was never published in a peer reviewed journal, which leaves many unresolved questions and potential for further research. In addition, some authors cite the prospected or successful removal of subsidies as the main cause of the 2008 food riots (Brinkman and Hendrix, 2011), and this was also found during the collection of data for food and fuel riots occurrences carried out in this research. This could potentially constitute another category of riots. Further research could hence focus on the different drivers of food riots, producing a categorisation, also in light of the findings presented above.

When able to provide realistic price regimes, the ABMs can be used to evaluate different scenarios such as those presented in Chapter 6. Several authors call for models able to evaluate the impact of production shocks on prices (e.g. King, et al., 2015) and the scenarios presented here are proof that the ABMs will be able to fulfil this aim. In particular, the dynamics already included in the models, i.e. international trade of natural resources, the connection prices, national political fragility and riots and the connection between food and fuel riots, make of the Food and Fuel ABM the perfect starting point to develop a more realistic and comprehensive ABM that could be used for different aims: i) as an early warning assessment tool, to highlight the beginning of a food or fuel crisis as in Cuesta, et al. (2014), ii) the consequences of future production shocks as in Lloyd's (2015), or iii) capture the development of global multisystem crises such as SF as in Homer-Dixon, et al. (2015).

Now commenting on the 'Cereal Export Bans scenario', the results from the simulations raised interesting questions for further research on the role of trade restrictions, and panic behaviours in general, in the formation of price spikes. Indeed, although the price regimes are not accurately simulated in the model, the dynamics for international trade and the accumulation of stocks are valid. The aim of the scenario was to simulate the consequences of the implementation of export restrictions when prices are high and provide evidence of potential of the emergent properties that characterise ABMs. The results of the scenario shows that countries that implement export bans successfully achieve their aim of shielding national markets from the high international prices, which supports the view expressed in the current literature. Surprisingly, the accumulation of food stocks in countries resulted in a medium-term reduction of international food prices, which disagrees with current literature, as presented in Chapter 6. Despite the limitation of the ABM, this finding echoes King, et al. (2015) call for further research on how national responses affect prices, and once adjusted its price dynamics this ABM will be able to achieve this aim.

Finally, a note of caution on the REs included in the ABMs. REs were calculated on data between 2005 and 2013, on conditions that are likely to evolve in the future, such as countries' political fragility. Their introduction in the models as constants deteriorates the long-term predicting power of the models, i.e. their predictions will only be accurate for the short-term future. In the case of this research this was not concerning, since the models were only required to provide predictions for the near future (5 years ahead) (Principle 1 of the GRO Project).

7.2. Policy relevance

Findings from the quantitative analyses on the drivers of food and fuel riots will prove critical in shaping future policies that can address and prevent these events. Although the ABMs were first envisioned as a tool to provide policy-makers with precious and actionable information and forecasts on food and fuel riots, in their current state are unable to provide this information with confidence. However, future versions of the models will potentially be critical in the definition of policies to tackle price spikes and food and fuel riots in relation to food and energy crises. Throughout my PhD I engaged with different policy makers and stakeholders to ensure the policy relevance of my research. From the conversations, I gathered a clear interest for accessible and transparent computer models that can capture the development of shocks to production of natural resources and their consequences, which is perfectly in line with the main aim of the ABMs that were presented.

The potential uses of the models are multiple. For instance, these could be used as support to multi-stakeholder engagement activities such as 'Serious Games', or, most importantly, as support to policy evaluation. The development of tools able to help evaluate policies *ex-ante* is indeed critical in times of austerity and limited funds. Policies are often tested on a small basis on a small sample of participants to evaluate their positive and negative effects, for their subsequent implementation on a larger scale in case of positive results. However, due to globalisation and the interconnectedness of the system we live in, this task is becoming more difficult as the policies, when implemented, can have repercussions on other sectors and distant places. Computer models such as the Food and Fuel ABM can provide the 'virtual lab' where policies can be trialled on a virtual population. For instance, Global Food Security (2015) suggested the institution of international food stocks to strategically release when prices are high or when a production shock strikes to act as a buffer, and help control prices. It is easy to see how the 'Cereal Export Bans scenario' presented in Chapter 6 could be adapted to test this policy and explore its consequences.

7.3 Summary of contributions to literature

The research presented in this thesis produced several contributions to literature, especially in the fields of environmental security, global food and energy security, international economics, political science and computer modelling.

The first contribution to literature of this research is constituted by a robust quantitative assessment of the relationship between scarcity of food and fuel, their international prices, national political fragility and the occurrence of food and fuel riots. This research contributed to the current literature on drivers of food riots, identifying international food prices and national political fragility as significant drivers, as opposed to national food availability. In addition, this research opened a new stream of research on fuel riots, finding symmetry between the analyses on food and fuel riots and a positive, reinforcing feedback between the two types of event. Related to this, this research also contributed two databases recording the occurrence of violent food and fuel riots between 2005 and 2013.

The second main contribution to literature relates to the identification of thresholds for the prices of food and fuel over which food and fuel riots are more likely to occur in countries. These were identified for both absolute prices and volatility for food, whereas only a threshold on absolute prices for fuel was identified. In addition, the research on prices and riots highlighted that the effect of volatility in food prices on food riots is larger than the effect of absolute food prices, as opposed to fuel riots, where fuel price volatility does not seem to be significant.

The third contribution to literature regards the development of three novel ABMs, one for each type of event considered and another including both types of event and their interrelationships. The development of these models followed a fully data-led approach, which constitutes another novelty in the field of ABMs. This research found that the fully data-led approach used to develop the ABMs resulted in models does not add predictive power to their underlying statistics: the introduction of dynamic behaviours and interaction through a social network are not sufficient to improve the models' predictions. However, this does not make of the ABMs developed ‘bad’ models, which are indeed at least as accurate at predicting riots as the statistics that underlie their dynamics, which suggests no coding errors. This allows the use of the models as platforms for further developments.

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Appendices

Appendix 1 – Final database for food riots

Country	2005	2007	2008	2009	2010	2011	2012	2013
Burundi	April (BBC News, 2005)							
Somalia		June (USA TODAY, 2007)	May (NBC News, 2008)			August (Pflanz, 2011)		
India		October (Majumdar, 2007)	August (Mukherjee, et al., 2008)		**September** (WB, 2015a)			
Mauritania		November (Mail and Guardian, 2007)						
Cameroon			February (Healy and Munckton, 2008)					
Burkina Faso			February (Healy and Munckton, 2008)					
Senegal			February (Healy and Munckton, 2008)					
Ethiopia			February (Healy and Munckton, 2008)					
Cote d'Ivoire			April (BBC News, 2008b)					
Haiti			April (Christie, et al., 2008)				**October** (Morrison, 2012)	
Yemen			March (Worth, 2008)					
Morocco			February (Worth, 2008)					
Lebanon			February (Worth, 2008)					
Egypt			April (BBC News, 2008a)			January (Rianovosti, 2011)		
Tunisia			June			January		

			(Schneider, 2008)			(Aburawa, 2011)		
Sudan			August (Sanders, 2008)			January (McDoom, 2011)		
Mozambique			**February** (Schneider, 2008)		September (Mangwiro, 2010)			
Algeria						January (The Daily Telegraph, 2011)		
Oman						February (Aljazeera, 2011)		
Iraq						February (Al-Salhy, 2011)		
Uganda						April (Kron, 2011)		
Syria						September (Asian Correspondent, 2013)		
Bangladesh			February (The Times of India, 2008)					
Guinea			June (Schneider, 2008)					
Kenya			May (Schoen, 2011)					
Afghanistan			**April** (IRIN News, 2008)					
Chad			**September** (Scoop, 2008)					
Honduras			**April** (WB, 2015a)					
Madagascar			**April** (Schneider, 2008)					
Peru			**April and July** (Schneider, 2008)					
Trinidad and Tobago			**April** (Schneider, 2008)					
Zambia			**May** (WB, 2015a)					
Zimbabwe			**April**					

			(Schneider, 2008)					
Pakistan				**September** (Reese, 2014)	**August** (The Times Of India Delhi, 2010)			
Malawi						**January** (Joy, 2012)		
Maldives						**April** (BBC News, 2011)		
Argentina							**December** (Daily Mail UK, 2012)	
Iran							**October** (Bozorgmehr, et al., 2012)	
South Africa							**August** (Technology Review, 2013)	
Colombia								**August** (The Associated Press, 2013)
Venezuela								**September** (Vega, 2013)

Table 1 – Database of food riots from Natalini, et al. (2015a). Each cell contains the month(s) during which each country experienced a food riot during the year listed in each column. The months in **bold** constitute the update from the database of food riots originally published in Natalini, et al. (2015b).

Appendix 2 – Database for fuel riots

Country	2005	2006	2007	2008	2010	2011	2012	2013
Yemen	July (IRIN, 2005)					July (Raghavan, 2011)		
Canada	August (Menzies, 2005)							
Iraq		January (Gupta, 2006)						

India		June (The Times of India, 2006)		June (Alter, 2008)	June (Hindustan Times, 2010); July (Timmons and Kumar, 2010)	September (The Hindu, 2011)		February (Banerji, 2013)
Iran			June (Blair, 2007)					
Myanmar			August (Thomson Reuters Foundation News, 2012)					
Mozambique				February (The Khilafah, 2008)				
Cameroon				February (IRIN, 2008a)				
Burkina Faso				February (IRIN, 2008b)				
Indonesia				June (The Jakarta Post, 2009)			March (Express, 2012)	June (Weisenthal, 2013); August (SBS, 2013)
Nepal				June (Alter, 2008)				
France				June (Siddique, 2008; The Daily Mail, 2008)	October (Allen, 2010)			
Italy				June (Siddique, 2008)				December (RT, 2013)
Spain				June (Siddique, 2008; The Daily Mail, 2008)				
Portugal				June (Siddique, 2008; The Daily Mail, 2008)				
Thailand				June (The Daily Mail, 2008)				

China				October (Graham-Harrison, 2008)		April (White, 2011)		
Guinea				November (Topix, 2008)				
Bolivia					December (Kraul, 2011)			
Chile						January (Russell, 2011)		
Libya						February (Epoch Times, 2011)		
Uganda						April (RNW, 2011)		
Malawi						July (Industriall Union, 2011)		
Pakistan						December (Dawn, 2011)		
Nigeria							January (The Tripoli Post, 2012)	
Sri Lanka							February (DBSJEY ARAJ, 2012)	
Jordan							November (Luck, 2013)	
Banglades h								January (Naim-Ul-Karim, 2013)
Greece								February (Euronews, 2013)
Egypt								March (Haaretz, 2013)
Colombia								August (Wills, 2013)
Sudan								September (BBC News, 2013)

Table 2 – Database of fuel riots. Each cell contains the month(s) during which each country experienced a fuel riot during the year listed in each column (own elaboration).

Appendix 3 – ET models on the absolute value of prices for reported data for food and fuel

As for the ET on international prices of food, real data for production, consumption and stocks of food (cereals) was retrieved from the USDA data bank (USDA, 2015b). As in the previous analyses, the FAO FPI was used as a proxy for international prices of food, which was sourced from the FAO website (FAO, 2015). The ET was hence built using the world ratio between the two variables 'World Food Production' and 'World Food Consumption' and the variable 'World Stocks' as independent variables and the variable 'Price threshold' which equals 0 when the FAO FPI is below the 140 threshold calculated in the Chapter 4 and 1 otherwise as dependent variable. The results of the ET on real data for food are presented in Figure 8.1.

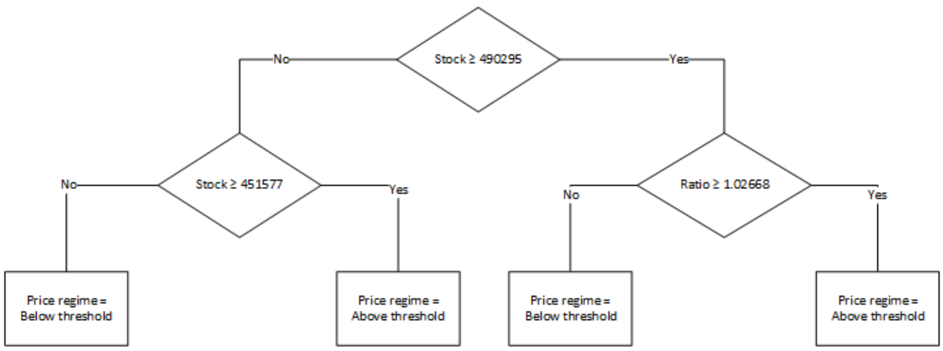
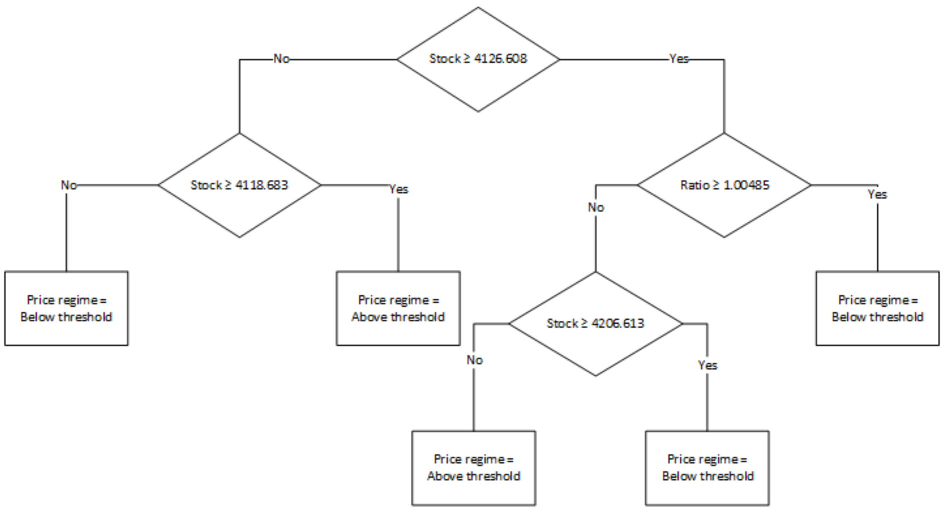


Figure 8.1 – ET model on real world data for food using ratio between 'World Food Production' and 'World Food Consumption' and the variable 'World Stocks' as independent variables and the variable 'Price threshold' as target variable (own elaboration).

The results from the ET for food presented in Figure 8.1 show that both variables, i.e. ratio and stocks, significantly affect the international food price regime and the dynamics perfectly recreate the international price regime for the period considered. However its dynamics are counterintuitive: when the world stocks of food are below 451,577 (MT), the price is below the threshold, whereas when these are between 451,577 (MT) and 490,295 (MT) we have a price spike. For world food stocks equal or larger than 490,295 (MT), the world ratio between food production and consumption becomes significant as well: when this is lower than 1.02668, the international price of food is below the threshold and above for higher ratios. Intuitively speaking, it is to expect high international food prices for low stock levels and ratios below 1, i.e. when world consumption of food is larger than production, and low prices otherwise. The results from the food ET suggest the exact opposite, adding proof to the argument that international prices of natural resources are only minimally governed by demand-supply dynamics, and rather depend on several different variables (see for example Lagi, et al., 2015) and/or that the data is inaccurate.

Another ET was developed for the international price of fuel. Similarly to the previous ET, the statistical model used data for world production, consumption and stocks of oil to identify breaks in the values for these variables that lead to the two different regimes presented in Chapter 4 for the international price of fuel. The model used as independent variables the ratio between Total Petroleum Consumption (Millions Barrels) and Total Oil Supply (Millions Barrels) and Total Petroleum Stocks, End of Period (Millions Barrels). Data for these variables was sourced from the EIA website (US EIA, 2015a). The target variable of the model was the EIA fuel price[17] recoded in two regimes: the variable equalled 0 when the price was below the 93$ per barrel threshold, as calculated in Chapter 4, and 1 otherwise. The results of the statistical model are presented in Figure 8.2.



[17] For an in-depth explanation of how the EIA fuel price was calculated throughout this work refer to Chapter 4.

Figure 8.2 – ET model on real world data for fuel using ratio between Total Petroleum Consumption (Millions Barrels) and Total Oil Supply (Millions Barrels) and Total Petroleum Stocks, End of Period (Millions Barrels) as independent variables and the variable EIA fuel price as target variable (own elaboration).

Similarly to the ET for the international price of food, although the results presented in Figure 8.2 show that the dynamics perfectly recreate the international price regime for the period considered, these also show counterintuitive dynamics between availability, supply and demand interaction and international price of fuel. When world oil stocks are below 4118.683 (Million Barrels), the international price of oil is below the threshold. This climbs above the threshold when world oil stocks are between 4118.683 (Million Barrels) and 4126.608 (Million Barrels). For any value of stocks equal or larger than 4126.608, the ratio between world oil production and consumption becomes significant: when the ratio is below 1.00485 and stocks are below 4206.613 (Million Barrels), the international oil price is above the threshold, whereas when the ratio is low and stocks are larger or equal to 4206.613 (Million Barrels) the price is below the threshold. Conversely, when stocks are high, i.e. larger or equal to 4126.608 (Million Barrels), and the ratio is high, i.e. larger or equal to 1.00485, the price climbs above the threshold.

Although both statistical models perfectly recreate the trend in the international price regimes for both food and fuel during the time frame considered, the conditions they identify are counterintuitive and unrealistic. In addition, the data for world estimates of the variables used as independent in the models presented several inconsistencies. In particular, there does not seem to be a clear relationship between stocks of the resources and supply-demand dynamics. This is particularly true for oil, where for several years, in correspondence to a surplus of production, global oil stocks decrease in the world. Although this could be justified by a global redistribution of stocks of resources and countries preferring to use their own stocks rather than buying the resource on the international market, these variables were not suitable to parameterise the price dynamics in the ABMs. For these reasons, the model was calibrated using endogenous data for production, consumption and stocks of the resources and the results are presented in the following section.

Appendix 4 – ET models on food price variations

These ET models were fit to data to predict two regimes for the FAO FPI variation, i.e. either above or below the threshold calculated in Chapter 6. The first model in Figure 9.1 uses the two-year FAO FPI variation as target variable and USDA data for the ratio between food production and consumption and for stocks as predictors.

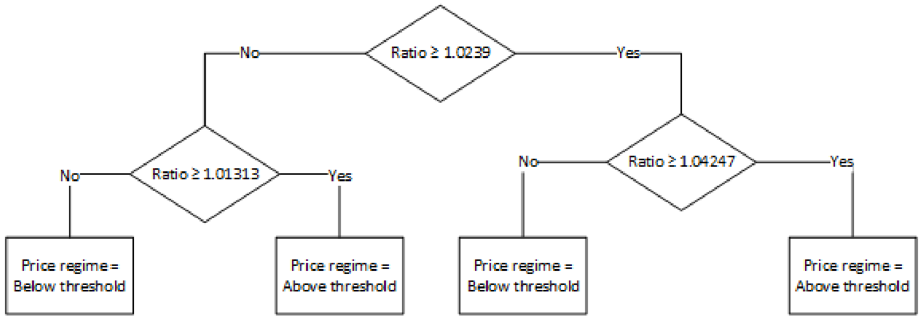


Figure 9.1 – ET model fit to reported USDA data for the period 2005 – 2013 using the two-year FAO FPI price variation and ratio between world food production and consumption of cereals and world stocks as predictors (own elaboration).

Figure 9.1 shows that the variable for the stocks is not significant in the prediction of the two-year price variation and found counterintuitive dynamics for the ratio between food production and consumption. In particular, the model predicts a price above the threshold for high (ratio > 1.04247) and mid (1.01313 < ratio < 1.0239) estimates for the ratio, and a regime below the threshold for mid (1.0239 < ratio < 1.04247) and low (ratio < 1.01313) estimates. These dynamics are counterintuitive as one would expect high increases in prices when food availability is low and vice versa.

The second ET used the same variables, although this was fit to data from the model. Results are presented in Figure 9.2 and show the same counterintuitive dynamics, also including stocks.

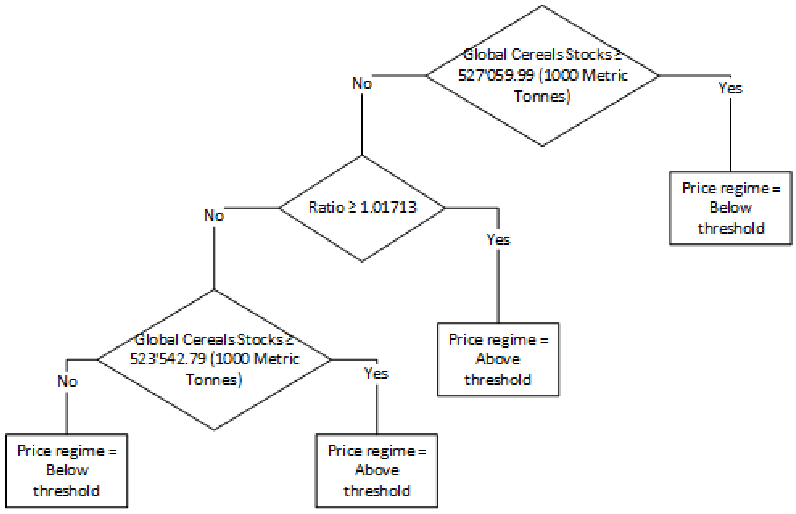


Figure 9.2 – ET model fit to data from the Food ABM for the period 2005 – 2013 using the two-year FAO FPI price variation and ratio between global food production and consumption of cereals and global stocks as predictors (own elaboration).

Another experiment involved the development of two more ETs, replacing the absolute values of the independent variables with their two-year variations. Figure 9.3 presents the results from the ET fit to data from USDA.

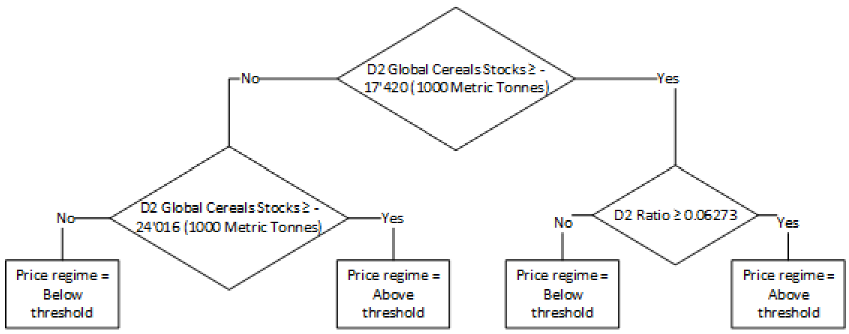


Figure 9.3 – ET model fit to reported USDA data for the period 2005 – 2013 using the two-year FAO FPI price variation and two-year variation in the ratio between world food production and consumption of cereals and two-year variation in world stocks as predictors (own elaboration).

The model in Figure 9.3 shows a more complex set of conditions that can lead to wither price regime. In particular, when the variation in stocks is positive and larger than -17,420 MT and the variation in the ratio is larger than 0.06273, the FAO FPI variation is above the threshold, whereas for lower estimates of variation in the ratio the price variation is below the threshold. When the variation is stocks is between --24,016 MT and -17,420 MT, the price variation is again above the threshold and below for any negative variation of the stock below 24,016. Once again, the dynamics resulting from the model appear counterintuitive, although in this instance it is possible to speculate on some of the conditions, especially when we reverse the causality in the model, i.e. when we think of how a high variation in prices can trigger a variation in the other variables. The two ‘yes’ branches starting from the root node on stocks could represent a situation where a large positive variation in prices has triggered large investments in food production, which in turn increases as well. A combination of ‘Yes’ and ‘No’ from the root node leaves the prices unaffected, which may show a level of tolerance towards a small decrease in food stocks and small ratios between production and consumption. When the loss of stocks is relatively large (combination of ‘No’ and ‘Yes’ from the root node), the price variation is above the threshold, whereas for large losses of food stocks the price variation is below the threshold. This last dynamic is highly counterintuitive and even speculation does not come in aid. However intuitive, these dynamics clearly require further research in the light of the findings presented above, which highlighted either inaccuracy of reported data on food production, consumption and stocks or complex dynamics.

The ET was fit to data from the Food ABM and its results are presented in Figure 9.4. Once again the dynamics were counterintuitive, which led to the choice of presenting these findings as work in progress and implement the threshold on the absolute value of the FAO FPI in the Food version of the ABM.

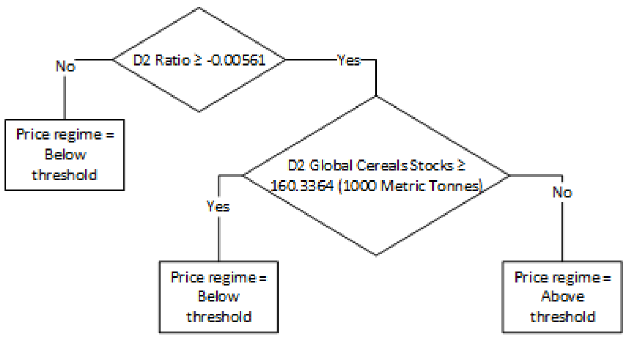


Figure 9.4 – ET model fit to data from the Food ABM for the period 2005 – 2013 using the two-year FAO FPI price variation and the two-year variation in the ratio between global food production and consumption of cereals and two-year variation in global stocks as predictors (own elaboration).