Exploring novel techniques to assess food price shocks

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Food systems represent a significant risk to financial and political stability in a number of regions around the world. The Global Sustainability Institute at Anglia Ruskin University has been building models, gathering data and developing methods to explore the dynamics involved in civil unrest, financial instability and local responses associated with food production shocks. These include agent based modelling, systems dynamic modelling, narratives, scenario development, access to weather systems monitoring and war gaming. However, the analysis techniques applied to understanding historic food price dynamics as a result of production shocks are simple econometric tools such as regression testing. A much more sophisticated approach to data analysis could yield new insights in historic price shocks that would better inform policy and market based responses.

1. Food Production Instability

The UN Sustainable Development Goals aim to end all forms of hunger and malnutrition by 2030, ensuring all people have access to improved nutrition and food security (Organization Nation United (ONU), 2015). However, while technological advances and economic growth have improved agricultural productivity, the global food production system remains vulnerable to inherent systemic risk.

Over the last century several food production shocks have resulted in production losses to individual grains exceeding 10 percent (Lunt et al., 2016). The current food system is vulnerable to various shocks that may be exacerbated by factors such as climate change, water stress, ongoing globalisation, and intensified political instability in multiple regions. Madeddu et al. (2005), Natalini et al. (2015) note that shocks to food production may adversely and disproportionately impact developing countries with unstable political regimes, due to, among other reasons, the strong correlation between food production shocks and concomitant export/import and price shocks. Similarly, Distefano et al. (2017), Puma et al. (2015) show that the least developed countries suffer most during times of shock-induced food scarcity and systemic disruptions to 'business as usual' trade flows. Shock-induced disruptions to food production not only disturb food security in the most vulnerable populations but can also propagate outsized system-wide effects through negative feedbacks, thresholds effects and nonlinear interactions that exacerbate the unfortunate situation (Pindyck, 2013).

2. Current Modelling

Food security is often defined in relation to a combination of climatic, biological, economic and societal factors at different scales to illustrate the complicated interrelations between network elements. Due to the complexity of these networks, representative models are not always easy to comprehend and are often ambiguous for policymakers.

Technological and scientific advances, together with increasingly efficient data collection and storage, have made it possible to study a large number of factors in combination and at different scales. This enables, in principle, greater efficiency when tackling the problem of food production instability and has led to a wide range of modelling techniques within the field of global sustainability. We begin by bringing the reader up to speed with the latest developments in the modelling of food production instability at different scales, which are crudely defined by physical space coverage and the increasing level of detail in the models. Each model scale has its own advantages and limitations.

To the best of our knowledge, most of the most recent models are described in Figure 1 and include both global and regional models, as well as a model that feeds global conditions into a local land use model, i.e. MAGNET (Rutten et al., 2014). The traditional small-scale regional models include the isolated farm-level and agricultural models are unable to incorporate information relative to forecasting food price variation and stabilities. To the contrary, the global models developed under the framework of the Agricultural Model Intercomparison and Improvement Project (AgMIP combine insights from multiple food system models, and are capable of predicting food price variations with a view towards social welfare impacts. However, the model under the aforementioned framework generate heterogeneous results for the same input (von Lampe et al., 2014).

Shortridge et al. (2015) made use of multiple regression and data-mining methods to estimate the percent of a country's undernourished population (year average) with predictors including socio-economic factors, agricultural production, trade-related variables, and climate conditions. In more recent work, Bakker et al. (2018) considers a significantly shorter time-scale, i.e. monthly, to model how food access varies within a given year as well as across years, and the potential response to crop failure shocks.

Many studies have addressed the question of food insecurity, focusing on the strong association between social well-being and food access and prices. Although significant progress has been made in the recent years, the time-scale of predictions is too long for policy-relevant mitigation purposes, while the spatial-scale is at times too large due to differences and discrepancies in the data obtained from various sources. Another

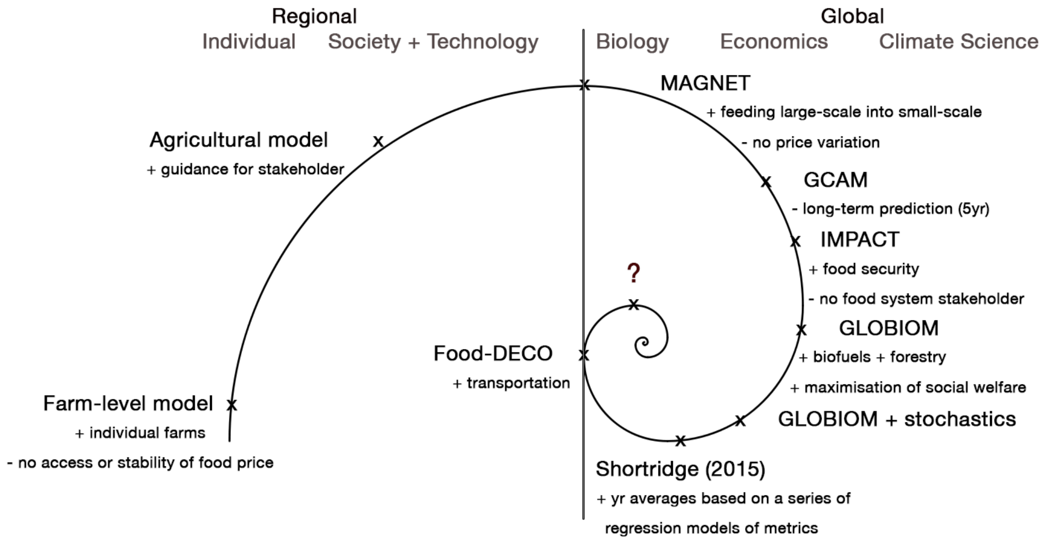

Fig. 1. Some of the current modelling approaches are summarised along the Fibonacci curve based on their spatial properties and inputs. The farm-level models have recently been reviewed by Janssen and van Ittersum (2007); Agricultural models - Jones et al. (2015); MAGNET - Rutten et al. (2014); GCAM - Calvin et al. (2013); IMPACT - Rosegrant et al. (2008); GLOBIOM - Havlík et al. (2011),Ermolieva et al. (2015); Food-DECO - Bakker et al. (2018) and Shortridge et al. (2015)

important issue was raised by Pindyck (2013), who warns of large economic impacts that would arise from catastrophic temperature change this century, which Weitzman (2009) poses as a plausible scenario given parameter uncertainties that may lead to a fat-tailed distribution for climate sensitivity.

3. What Can We Learn from Other Fields?

In order to improve our understanding of the dynamics of highly nonlinear systems, adequately predict food instability periods and identify the underlying patterns and potential drivers of these instabilities, we need to employ new techniques.

In this paper, we propose to combine methods from global sustainability with methods from mathematics and physics to describe the food production system as a dynamical system with many degrees of freedom. In particular, we have extensively reviewed a full range of potentially relevant methodological applications in other disciplines, determining preliminarily that the most relevant are contained in financial mathematics and geophysical sciences.

A. Financial Mathematics. In the financial industry, advances in computing power and data analytics are changing the face of asset management, leading to computer-driven decision making. In financial mathematics, predictions of shocks to stock prices are foundational and form the core of profit-making strategies; the machine learning techniques used to aid in shock predictions (Guresen et al., 2011) (both aggregated and isolated) appear directly applicable to the prediction of food production price shocks, especially since many of the 'pre-shock' predictors are human-related or market-induced, and relate to political systems more broadly. The data generating process for shocks to food prices is likely to have similar properties, albeit with a different set of predictors.

The field of econophysics, with its emphasis on assessing mathematical patterns that capture the 'fat tails' of market fluctuations, has helped to change the direction of much economics research. Similarly, its insights may help establish a financial market-esque framework for forecasting changes to food production markets, and a power law to describe the probability of large food market movements, whether positive or negative.

In a recent study, Abis (2017) explores quantitative investment modelling using machine learning techniques. The model in consideration is based on price prediction of multiple assets subject to common aggregate and individual idiosyncratic shocks. The model assumes that during a recession that is viewed as a period of greater risk aversion, i.e. the period of high volatility arising from an aggregate shock, the focus is on learning from the aggregate shock rather than idiosyncratic shocks. The latter are more important in periods of expansion. Predictions of price movements of stock portfolios are based on, among other variables, a number of risk factors, learning capacity, and shock volatility prior distributions using the random forest algorithm. Greenwood and Thesmar (2011) also noted that stock connectivity and fragility affect the amount of exposure to non-fundamental risk - i.e. correlated liquidity shocks - information that was used in the analysis in Abis (2017).

Using the concept of aggregate and individual idiosyncratic shocks as well as the external and endogenous shocks, food price volatility response functions may be predicted similarly to methods used in (Sornette et al., 2002), who validated the theory empirically on data from a hierarchy of volatility shocks, major crashes, and major external disturbances, identifying specific signatures and characteristic precursors for the endogenous class of shocks.

Due to the underlying stochastic nature of food production pricing and its exposure to international markets and other external pressures, the decision making techniques in financial institutions are directly applicable and may be used to derive short-term predictions as well as long-term forecasts.

B. Tectonophysics. The field of earthquake prediction has faced significant challenges for many years due to the shear complexity and nonlinearity of the dynamical system we all live in (Tiampo and Shcherbakov, 2012). Like the cascade effects of food production shortfalls, impacts from earthquakes may be catastrophic and socially detrimental. Both types of events previously seemed intrinsically unpredictable and for years attention was directed towards collecting vast amounts of data associated with the underlying processes. However, recent developments suggest that both short-term earthquake forecasting (days to weeks) and longer-term forecasting (five to ten years) are now more realistic than ever before.

Over the last decade, data mining techniques have been utilised in the estimation of large earthquake event occurrences, including but not limited to the work of Adeli and Panakkat (2009), Alexandridis et al. (2014), Martínez-Álvarez et al.. The studies deal with such issues as limited training data, removal of after-shocks, and inferences from regional versus global data. The authors typically adopt widely-used regression models for benchmarking as well as backtesting the results, which provide fresh pattern discovery before an earthquake takes place.

The results derived using data mining techniques pose new challenges to the earthquake prediction community. In particular, there is a need to make use of all available and relevant information collected over many years and develop new predictors to improve the current state of modelling. The field of global sustainability has a lot to learn from the young but promising field of AI-inspired prediction of earth system processes.

4. Conclusion

In our era of unprecedented data mining and dynamical modelling capabilities, the field of global food sustainability has the potential to move beyond the limits of conventional regression techniques and significantly improve forecasting capabilities. It is now possible to build prediction engines that incorporate insights from the wealth of historical observational data pertaining to past food production shocks, while using data mining algorithms frequently utilised in the fields of mathematical finance and tectonophysics. Building such a prediction engine could help produce more reliable, policy-relevant insights about the combination and sequence of common or idiosyncratic factors that more accurately signal the arrival time of food system shocks via a feature selection process. Shock identification can be improved by the use of transforms that provide predictors that are more sensitive to signal changes and can be useful for transient detection.

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