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MODELING THE RELATIONSHIP BETWEEN FOOD AND CIVIL CONFLICT

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ABSTRACT

We built a system of systems model to better understand the relationship between the agricultural sector, other economic factors, and changes in the expected value of conflict. Our model integrates multiple factors, including food production, food trade, population, and civil conflict, and determines their interdependencies based on shared inputs or outputs. We find that severe food price shocks, precipitated by multiple breadbasket failures, can severely impact a country's GDP and its ability to purchase and consume a sufficient amount of food, resulting in an increase in civil conflict and related casualties. A sharp population increase, as potentially caused by an immigration surge, was found to have a similar impact, though not as strong.

1 INTRODUCTION

The world's systems are highly interdependent, exhibiting cascading effects when a shock occurs within even one single system. The global food system, which includes relationships between production, trade, and distribution, is particularly complex. As the world experiences climate change, as well as disrupting geoeconomical and geopolitical events, the food system is susceptible to more frequent shocks from extreme weather events, and the risk of multiple breadbasket failure grows (Janetos et al. 2017). Food insecurity can cause additional pressures in an already fragile state, leading to increased conflict (The United Nations Interagency Framework Team for Preventive Action 2012), for instance in Yemen (Werrell and Femia 2016) during the Arab Spring. Accordingly, one of the more effective ways to motivate preventative or adaptive investments in response to climate change is to understand its potential economic and security impacts (Bazilian et al. 2011). In this paper, we demonstrate that a system of systems approach can provide better understanding of the potential economic- and conflict-based implications of food insecurity. In addition, we use a flexible model integration framework and leverage pre-existing models to build a larger system model, which can be adapted to different regions of the world and that can incorporate other, improved models in the future. In our initial model, we bring together food production, food trade, population, GDP shock, and conflict.

1.1 Related Work

Classic methods of exploring cascading effects in a system of systems usually involves a group of subject matter experts analyzing individual scenarios and influences between systems to predict isolated outcomes. However, in recent years, groups such as Janetos et al. (2017) lay out a need for improved modeling capabilities that improve dynamic interplay between models and that can model the impact of global events. In some areas, such as the food-energy-water (FEW) nexus, integrated approaches to modeling have been increasing over the past couple of decades. For instance, the University of Maryland and Pacific Northwest National Laboratory (PNNL) have developed the Global Change Assessment Model (GCAM) (Edmonds and Reiley 1985; Edmonds et al. 1997). However, this effort currently does not include much food modeling, nor does it allow models to be swapped out when different ones are preferred. At JHU/APL, we have recently developed a model integration framework, Systems Integration with Multiscale Networks (SIMoN) (Hughes et al. 2020), which allows a researcher to integrate independently designed models that operate at different geographic scales. We describe the specifics of SIMoN in a later section.

There are certainly other models that seek to understand the fragility of our food system. For instance, The Economist publishes a Global Food Security index (The Economist Intelligence Unit 2019) which provides a robust set of indices for 113 countries, evaluating their ability to feed their people based on climate and socio-economic factors. Puma takes a network modeling approach to food trade analysis (Puma et al. 2015) that considers trade, climate, and agricultural factors. However, these and other similar efforts focus only on food and trade, and do not consider the impacts on local or regional conflict. The University of Denver's Pardee Center has a large system of systems International Futures model (Pardee Center Denver University 2019) that considers both food and conflict. However, they do not connect food security or socio-economic factors more generally to their conflict model. The SEAMLESS model (Van Ittersum 2008) is a rich integrated assessment model for agricultural systems, focused on relationships between agricultural, economic, social, and environmental factors within the European Union (EU), at both the micro and macro levels. SEAMLESS does not link these factors to conflict. The International Food Policy Research Institute (IFPRI) developed the International Model for Policy Analysis of Agricultural Commodities and Trade (IMPACT), which is a multi-market economic model linking economics, water, and crop models (Rosegrant 2008). IMPACT includes food production, consumption, environmental factors, and more with food security in mind. However, it does not currently look at the link to conflict.

2 METHODS

2.1 Data

For this research effort, we chose to focus our analysis on the East African country of Uganda. The food consumption and trade data for Uganda was collected from publicly available databases published by the Food and Agriculture Organization of the United Nations. Food supply (in both kilograms and calories) is derived from Food and Agriculture Organization of the United Nations Food Balance (2019), while import and export quantities, as well as prices, are provided from Food and Agriculture Organization of the United Nations Trade (2019). Historic population data for Uganda is collected and reported by the United Nations (United Nations Population Division 2018), and food consumption data is available through the World Bank Consumption Database (World Bank Global Consumption 2019). Initial GDP per capita data were also obtained from the World Bank (World Bank GDP 2019). Daily weather data for Uganda is available from the Climate Forecast System Reanalysis research, conducted by the National Centers for Environmental Prediction (National Centers for Environmental Prediction 2019).

We model our country of analysis after Uganda, as the conflict model outlined in this paper holds for sub-Saharan African countries. Thus, any historical data, such as those listed above, are Ugandan data. It should be noted that in its current form, the fidelity of our system of systems model is not high enough to aid decision makers. Rather, it serves as a prototype model and a tool to start to understand the relationships between food-related domains, the economy, and conflict.

2.2 System Model

Our system of systems model brings together models and datasets/data sources for food production, food trade, and population change, in order to understand the impact of shocks in the food system on civil conflict within a single country. Furthermore, because of certain model assumptions, we consider a sub-Saharan African country, where agriculture is a significant portion of the economy. More specifically, we consider shocks to GDP, which we then tie to changes in civil conflict. As civil conflict can have many causes – for instance, the feedback loop where conflict begets more conflict – we address civil conflict caused by GDP shocks. Specifically, we focus on shocks in the absence of other changes in the environment, recognizing that this is one of many potential sources of pressure within a country.

Our system has two high-level metrics. The first, aimed at measuring food security, is the average number of available calories consumed, per day and per capita. (The desired amount is roughly 2000 calories per day, per capita.) Note that this metric does not capture whether people can afford to buy an adequate amount of food or whether food is distributed to the entire population. Nor does it address economic inequalities within a country and how this may result in additional uprisings or other conflict (this would be a separate source of conflict to be modeled separately as mentioned in the previous paragraph). Rather, it addresses whether the country has enough food physically available for distribution. One might argue that this metric does not adequately address food security since Sen's seminal work (Sen 1981) on famines indicates that famines are note due to lack of food, but rather to the inability of a nation to adequately distribute food to its people. However, for the purposes of this model and analysis, food production/availability is tightly coupled with GDP, which is our current avenue for examining change in civil conflict. The second metric is the expected change in the number of civil conflict related deaths, which is calculated based on the severity of the GDP shock.

The models have several dependencies. For instance, the trade model outputs the amount of each food source/type consumed by the country, which is ultimately used to calculate the GDP shock and the number of calories available per capita. Figure 1 is a simplified system diagram demonstrating the relationships between models.

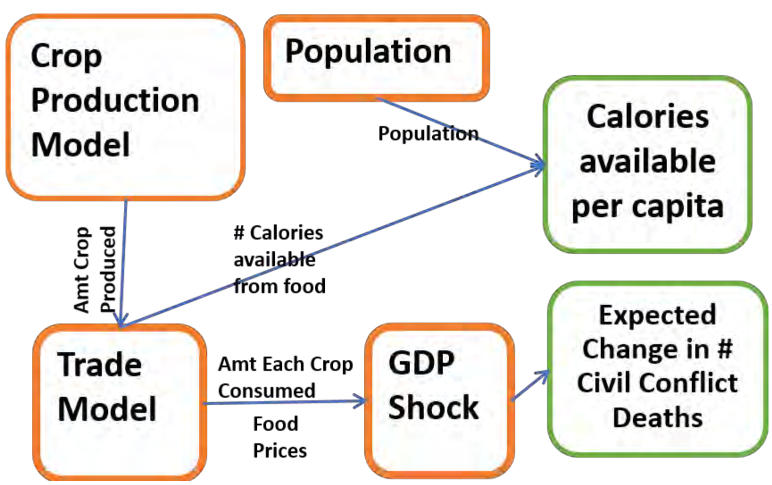

Figure 1: Simplified system diagram.

These models, although logically related, are implemented in different programming languages and provide different interfaces to the user. In order to practically integrate them into a unified system of systems, we use the SIMoN framework, a software application developed at JHU/APL that can run independently-designed computer models synchronously, manage their interdependencies at different granularities of time and geography, and share each model's data outputs with the other models. SIMoN provides the infrastructure necessary to package these disparate models into a single cohesive system. By using SIMoN, one can easily implement the same diagram shown in Figure 1, but insert their preferred models of each piece of the system, thereby obtaining a system of systems model that more accurately allows them to address their simulation question. Open source code for the SIMoN framework is available at https://github.com/JHUAPL/SIMoN.

2.3 Trade Model

The Armington trade model (Armington 1969) is a standard economic model, used to understand international trade under the assumption that consumers maximize utility functions according to a budget. The utility function is given as a function of preferences for each good, as well as an elasticity of substitution, which governs the consumer's willingness to substitute one good for another as relative prices change.

There are several factors that the Armington model does not take into account. For instance, unlike the Ricardian model (Feenstra 2003), there is no concept of comparative advantage present. Furthermore, prices are exogenously determined. There is no supply and demand model embedded into Armington. That is, while Armington allows one to represent the supply of a particular good produced by a country, this number, as well as the prices of the good, is exogenous to the model. Rather than go into a detailed description of the Armington model here, we refer the reader to standard references (Feenstra 2003; Armington 1969).

In this paper, we are not interested in using the Armington model to simultaneously maximize the utilities of several countries trading with each other. Rather, we seek a trade model that describes consumption behavior of a single country in the face of shifting food prices. The Armington trade model allows one to calculate how the average member's consumption basket changes along with prices. In particular, the utility function for the average consumer is given by

$$U = \left(\sum_{i=1}^{n} (\gamma_i x_i)^{(s-1)/s} \right)^{\frac{s}{s-1}}. \tag{1}$$

Here, n is the number of goods in the system, γ_i is the preference for good *i* while x_i is the quantity of said good consumed. The elasticity of substitution is given by *s*. This utility function is maximized according to a budget constraint

$$B = \sum_{i=1}^{n} p_i x_i$$

where *B* is the amount of money the country spends on goods in the model.

In this paper, our country of interest is Uganda, where we consider a suite of seven goods: beans, cassava, maize, millet, plantain, sweet potato, and all other foods. The first six are selected because they have historically been the top six calorie sources for Uganda from 1980 to 2013. The consumed quantities for all other food is calculated from the World Bank's Global Consumption Database (World Bank Global Consumption 2019). Similarly, the food budget *B* is derived from this source.

The initial quantities for this model are computed for 2010, which is the year where (World Bank Global Consumption 2019) provides consumption data. That is, preferences and food budget are computed as based on available price and consumption data. At this point, *B*, the food budget is approximately a third of Uganda's GDP. Note that we do not use the country's total GDP, nor do we model everything consumed by Uganda, only comestibles. Therefore, as shocks to GDP are introduced, we manipulate the percentage of GDP spent on food in order to understand the effects of substitution on food security.

Table **1** shows the values we use for the average price of each good and the relative preferences among the goods. The preferences, derived from real price and consumption data, reflect the average utility that Ugandans gain by consuming a particular food, and how Ugandans favor one food over another. Note that maize is the most preferred crop. However, maize's high price restricts Uganda's consumption of it. In contrast, because cassava and plantains are very inexpensive, they would dominate Uganda's food consumption if all foods were equally preferred. However, because their preference is very low, in aggregate, Ugandans choose to consume relatively small quantities of these goods, despite their low prices.

Table 1: Average food price per metric ton in 2010 (Food and Agriculture Organization of the United Nations Trade 2019) and relative preferences.

Food	**Average Price**	**Preference**
Beans	\$0.44	0.15
Cassava	\$0.04	0.01
Maize	\$0.81	0.33
Millet	\$0.21	0.05
Plantains	\$0.07	0.02
Sweet potatoes	\$0.50	0.20
All other foods	\$0.46	0.24

2.4 Civil Conflict Model

The Civil Conflict model we use is this paper comes from (Miguel et al. 2004), where the authors show a strong causal relationship between GDP shock and civil violence: *a negative 5% GDP shock increases the likelihood of violence incidence the following year by 50%.*

A **GDP shock** is a change in GDP that is *caused* by an unexpected event. In the context of this and the above paper (Miguel et al. 2004), this event is the difference in rainfall from the expected level. Note that a GDP shock is not the same as a change in GDP from one year to the next. Note that the change in GDP from one year to the next is observable. How much of this change is due to the unexpected event in question is not directly observable. For instance, it is easily observable that a country's GDP increased by 2% in a given year. However, it is much harder to attribute numbers to various events that may have occurred during that year: how much growth was caused by the lifting of trade sanctions, how much was due to the drought experienced, how much of this was the expected year on year increase caused by technological advancement and neighbors getting wealthier? Part of the innovation in (Miguel et al. 2004) is to estimate the amount of GDP shock that can be attributed to a standard deviation change in rainfall.

In this paper, we use the result (Miguel et al. 2004) as given, and do not attempt to validate it with further data. Instead, the approach taken in this document is to calculate the effect on violence caused by sudden changes in agricultural production via the pathway of GDP shock.

There are many reasons why observable GDP levels and violence levels change. This paper is not making claims about whether upward pressures on GDP or violence dominate over downward pressures in any particular case. Rather, we are interested in quantifying (both the direction and a point estimate of the magnitude) the pressure on GDP due to agricultural price shocks; then, given this number, we use the results of (Miguel et al. 2004) to calculate a pressure on violence. We explicitly ignore any other factors that may influence a country's GDP or the levels of violence it experiences.

2.5 GDP Shock Model

The shocks of interest in this paper are some of those that may lead to food insecurity, specifically occurring in food trade, food production, and population. However, to connect to violence, they must be converted to GDP shocks. We do this by measuring the inflationary effects of food shocks.

We write the pre-shock, or initial, price vector for the seven goods of interest as:

$$\vec{p}^0 = (p_b, p_c, p_{ma}, p_{mi}, p_p, p_s, p_o).$$

We represent a food shock by a change in the prices of certain comestibles. That is, we define a new price vector $\vec{p}^t = (p_b^t, p_c^t, p_{ma}^t, p_{mi}^t, p_p^t, p_s^t, p_o^t)$, where p_*^t is the new price (or price at time *t*) of the good indicated in the subscript. Note that this allows for both crop failures, i.e., food shortages resulting in price increases, and increases in production, modeled by decreases in prices of certain comestibles.

We call the initial GDP, for comparison purposes $GDP^0 = \vec{p}^0 \cdot \vec{x}^0$. We call this our reference GDP. At the time of the food shock, we label the new GDP as GDP^t. We default to setting $\mathrm{GDP}^\mathrm{t} = \mathrm{GDP}^0$ unless there is specific reason to believe otherwise. For instance, if a good produced by Uganda is affected by the food shock in question, then GDP^t will be different from GDP^0 (either greater or smaller, depending on the type of shock).

Given this new GDP number, and the new prices, we maximize the utility function given in equation . #(1) with respect to the new budgetary constraint (B^t now calculated as a percentage of GDP^t):

$$B^t = \sum_{i=1}^{n} p_i^t \, x_i^t$$

where the $\vec{\mathrm{x}}_\mathrm{i}^\mathrm{t}$ is the new consumption levels after the food shock.

We then compare the cost of the new basket of goods $\vec{\mathrm{x}}^t$ under two price vectors, $\vec{p}^t$and $\vec{p}^0$. We call the cost of the new basket of goods under the old price vector $RGDP^0$, where the R implies that this is a “real GDP” calculation: $RGDP^t = \vec{p}^0 \cdot \vec{x}^t$.

Then we can calculate the percent inflation caused by the price shock as

$$\Delta\, GDP = \frac{(RGDP^t - GDP^0)}{GDP^0} \quad . \tag{2}$$

We use the quantity defined in equation (2) as the GDP shock for calculations involving the results of (Miguel et al. 2004) to calculate increases in violent events. Throughout this paper, we assume a modest 2% annual growth in the overall economy, ceteris paribus. That is, apart from any other GDP shocks that may occur, overall GDP is assumed to increase at a rate of 2% per year. This small rate of growth will keep pace with a growing national population, rendering GDP per capita steady across time, but also exposed to the effects of an unexpected shock. A less stagnant economy (e.g., one with a 4 or 5% growth rate) will be more robust against shocks.

Note that although this is an attempt to look at inflation, it is not the same as other measures of inflation, such as Consumer Price Index (CPI) (U.S. Bureau of Labor Statistics 2019). In particular, CPI is measured via detailed household level surveys of actual consumption and local prices. The work here is a country-level prediction of aggregate consumption, given a set of aggregate prices.

2.6 Crop Yield Model

In order to model cassava production, we rely on AquaCrop, a preeminent crop growth model developed by the Food and Agriculture Organization of the United Nations (Raes et al. 2009). In particular, we use AquaCropOS, a free and open source implementation of the crop model (Foster et al. 2017), which can be more easily integrated into the SIMoN framework.

AquaCrop was developed to simulate yields of major crops based on available water sources, whether rainfall or irrigation. Other inputs include soil characteristics, as well as daily weather data such as temperature and precipitation, allowing a great deal of customization of the model to different regions. We specifically consider cassava yield, which is considered the food security crop of Africa due to its tolerance to drought. We use "sandy clay" as our soil type, which is similar to soil found in Uganda (European Soil Data Centre, 2019). AquaCrop estimates the cassava yield per hectare, which is then scaled to the entire country based on estimates of the amount of farmland used for cassava growth. This estimate is based on the average area of farmland used for cassava production in Uganda from 2000 to 2009 (Food and Agriculture Organization of the United Nations Crops 2019). This production quantity is scaled downward in order to account for food waste and other inefficiencies, which are estimated to take up 19.5% of gross production (Epstein 2019; Breto 2012). Similarly, we use AquaCrop to estimate Uganda's national production of cotton, a key non-food crop that contributes to the country's economy.

A key input to the AquaCrop model is the crop profile, which provides a detailed description of the crop and the biological properties that relate to its farming, such as its planting density, harvest index, and canopy cover. Although AquaCrop provides verified profiles for several staple crops, including cotton, cassava is not among the crops that have been calibrated for the model. Thus, we take the same approach as a related research project (Hunink et al. 2014) and use the AquaCrop maize profile, with several key modifications, as our cassava profile. The predicted cassava yield from the AquaCrop model averages roughly 10 metric tons per hectare farmed, and the predicted national output averages roughly 3 million metric tons. Both of these figures are in agreement with historic cassava production (Food and Agriculture Organization of the United Nations Crops 2019).

2.7 Population Model

To predict population growth based on previous years' population data (Food and Agriculture Organization of the United Nations Population 2019), we use the Holt's linear trend method, which is an extension of simple exponential smoothing that incorporates a trend equation (Holt 2004). Although this is not a model specific to population prediction, the data indicate a trend which can be modeled well in the short-term using Holt's method. If longer-term outlooks are desired, it is simple enough to incorporate an alternative population model into the SIMoN framework.

Once population is projected forward and the trade model determines consumption values, we perform a straightforward calculation for the percentage of people potentially fed based on food availability. The FAO provides food supply data, both in terms of kilograms per capita and calories per capita (Food and Agriculture Organization of the United Nations Food Balance 2019). We use this to calculate the total number of calories from each of the staples we track directly, as well as the aggregate caloric contribution of the remaining available food. Note that this is only food supply, not food consumption. Thus, it is a measure of calories available to a population, not what they actually consume.

3 RESULTS AND DISCUSSION

Our model allows for shocks to occur in three different areas. We artificially insert these shocks into a future timeline, beginning in the year 2020, layering them to demonstrate the potential impact of multiple shocks over time. Here we describe one scenario occurring in Uganda from 2020 to 2039 with the first shock in 2027 and continuing through 2039, the second shock in 2031 and continuing through 2039, and the third from 2035 to 2039. First, we consider a shock in other parts of the world, impacting food production and thus food prices. For instance, severe weather events may cause a multiple breadbasket failure in multiple major grain-producing nations (Janetos et al. 2017). We assume this initial shock occurs in 2027. All food, except homegrown cassava, doubles in price. The second shock we consider is cassava also doubling in price. This might happen, for example, because of a cassava blight or other regional catastrophe. With this shock to cassava, all food goods are now double their original prices. Third, we consider conflict in an unstable neighboring country, such as South Sudan, resulting in an immigration surge in 2035 and lower per-capita GDP. Throughout this scenario, we assume a modest 2% annual growth in the overall economy.

Figure 2 shows how consumption levels of each good change over time. These numbers are calculated from the Armington trade model, with the objective of maximizing utility. Note that in 2027, the consumption of many goods decreases greatly due to increased food prices. Consumption of some goods rebounds a bit, as Uganda responds to the price shock by allocating a greater share of its total budget toward food. Maize consumption in particular increases, due to Uganda's strong preference for this food. Cassava remains inexpensive and can theoretically provide extra calories to the population. However, presumably all neighboring countries are also struggling with similar food price shocks. Therefore, we assume that Uganda is unable to import and consume much more than what it produces, creating a cap on the amount of cassava available.

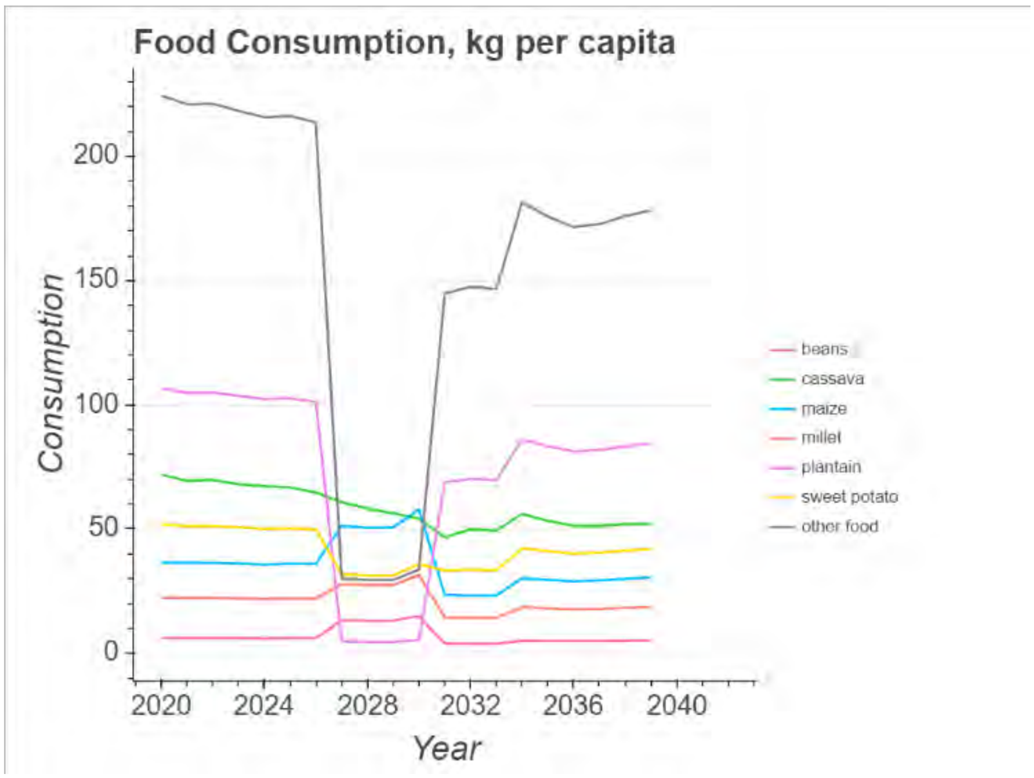

Figure 2: Consumption of food goods 2020-2039, kg per capita.

The result of the 2027 price shocks is a sharp decrease in the total number of calories available per capita per day across all food goods (see the blue curve in Figure 3). The histogram portion of Figure 3 shows the change in the expected number of extra deaths due to civil conflict. Note that the dotted vertical lines in Figure 3 mark the years in which shocks started (2027, 2031, 2035). As expected, in 2027, we see a jump in the expected number of extra deaths (319). While this is a small number compared to the total population, which is projected to be approximately 55 million people in 2027, it makes no claim about the baseline level of violent death in 2027. Further, recall that we are measuring a single pressure on conflict, and considering what happens if only a GDP shock occurs and all other country-specific issues remain the same. Also, for every extra death, there are certainly many more severely impacted by the GDP shock. For instance, this amount of extra conflict would likely lead to additional subsequent conflict or exacerbating events, which is not captured in this model. If the shock occurs in a country where there are multiple economical, geopolitical, or climate-based pressures, then the conflict contributed by food insecurity-related GDP shocks would compound with additional sources likely resulting in an increasingly unstable situation.

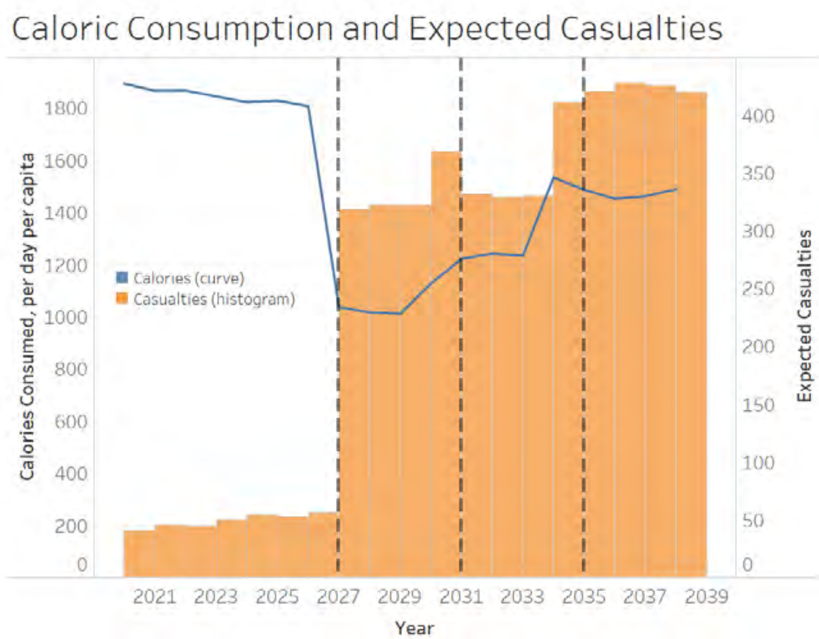

Figure 3: Food consumption 2020-2039, calories per capita per day (blue curve) and expected change in number of casualties per year compared to no GDP growth for Uganda (orange histogram) with shocks occurring in 2027, 2031, and 2035, each lasting through 2039 (dotted vertical lines).

The doubling of the cassava price in 2031 also provides somewhat of a shock. In 2031, when both shocks are occurring, the GDP decreases by 22.41% from baseline, which is only 0.86% more than the GDP shock felt in 2027 (21.55%) when only the first shock occurred. This small difference is likely due to the fact that cassava was inexpensive to begin with. Finally, the immigration surge in 2035 also impacts calories available (~1,480) and the expected number of extra casualties (421, or 89 more extra deaths than the 2031 projected 332 deaths) since the number of calories is calculated per capita and the number of deaths is based on GDP per capita (28.4% decrease from baseline in 2035). Again, the shock is not as extreme as those generated from significant food price increases, but still worth noting.

We also investigate shocks to crop production, not shown in these figures, using historic daily Ugandan weather data from 1989 to 2009. In 2001, Uganda experienced a drought (a decline in rainfall) and unusually high temperatures, which impacted crop yield. We focus on cassava production. However, our model did not exhibit notable impacts of crop production changes on GDP or calories available per capita. There are several possible reasons for this, one being that cassava is an inexpensive good. Therefore, even though Uganda produces a lot of it, it is still only a small portion of its GDP (roughly 1%). To accurately understand how decreased crop production impacts GDP and violence, a more extensive model is required. For instance, it would be beneficial to include all of Uganda's cash crops, such as cotton and coffee, in the GDP numbers, not just cassava production. This could be explored in a subsequent study.

4 CONCLUSION

In this paper, we develop an initial model of the dependencies between food trade, food production, population growth, GDP shocks, and civil conflict deaths, in order to investigate how shocks in various parts of the system impact food security and civil conflict metrics. Extensions of this model would allow decision makers to understand the impact of severe weather events, population migration, and other factors on conflict within a country. Future work would incorporate water and energy models, to move closer to decision-making at the nexus of food, energy, and water (so-called "FEW" systems). It would also be advantageous to understand the relationship between food prices of different goods. In other words, if maize were severely impacted by severe weather, then it is likely that other less robust goods were also impacted, resulting in correlations between food price movement. It would also be possible to consider incorporating additional aspects of civil conflict that have been mentioned in earlier parts of this paper. Ultimately, decision makers and their specific needs should drive which elements of the model are added or improved.

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