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Shocks, seasonality, and disaggregation: Modelling food security through the integration of agricultural, transportation, and economic systems

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ABSTRACT

Food insecurity is a complex phenomenon with biophysical, climatic, economic, and infrastructure facets. Despite this understanding, there are few stakeholder-based modelling tools that can capture these dynamics and thereby evaluate the direct and indirect impacts that climatic change, economic change, and policy interventions can have on food security. To address this need, we have developed the Food Distributed Extendable COmplementarity (Food-DECO) model. The Food-DECO model represents individual aggregated stakeholders as decision-makers within the agricultural, transportation, and economic systems. In this paper, we demonstrate the model's capabilities by applying it to a food system based on characteristics of Ethiopia, a frequently food-insecure country. Food-DECO produces results that show the effects of seasonality and regional distribution networks on human nutrition while disaggregating those effects by age, gender, and per capita income. We explore the impacts of a regional crop failure and evaluate the possible effectiveness of several commonly proposed food security interventions. The economic integration of agriculture and transportation in Food-DECO enables us to see, counterintuitively, that improving the capacity of the existing food distribution network between regions can negatively impact the nutritional outcomes in the region experiencing crop failure; the increased ability to meet high demand elsewhere leads to an increase in regional exports – even during a food shortage.

1. Introduction

Food security is a global concern, and one way to understand this phenomenon better is through the use of mathematical modelling tools. We begin our paper with some background on food security, an overview of some past modelling work related to food security, and a description of our own approach and contribution.

1.1. Food security

More than one-quarter of the world's population has an insecure food supply, and those populations are also in parts of the world expected to be strongly affected by climate change (Wheeler and von Braun, 2013), which will further impact their food security. Food production has been the most prominent aspect of food security under consideration, but food security is about more than just food production, and food policy needs to reflect this.

The Food and Agricultural Organization of the United Nations (FAO) defines food security as consisting of the availability, access, utilization, and stability of food (FAO, 1996). Availability concerns the ability to *produce* sufficient amounts of food (or to import it from other areas that are able to produce it). Food access is the ability of households to purchase or otherwise obtain sufficient food. Utilization concerns absorbing and using the nutrition in consumed food; the biggest

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issues here pertain to disease and sanitation. Finally, stability deals with the degree of change, over time, in food systems. For further discussion of food security metrics, see Jones et al. (2013).

The effects of food security drivers such as climate change on food distribution, access and stability have been investigated far less than the impacts on production (Wheeler and von Braun, 2013). Studies that have combined trade models with crop production models have provided *producer* prices (von Lampe et al., 2014), but *consumer* prices, which are a key indicator of food access, also depend on other factors such as transportation infrastructure. Furthermore, cereal crops are important (and widely studied), but livestock, fisheries, and other crops also need to be considered in measuring food security.

Livestock are particularly relevant because of the interconnections between livestock, crops, and subsistence income in developing countries (Cameroni and Fort, 2017; Thornton et al., 2009) as well as livestock contributions to greenhouse gas emissions (Gerber et al., 2013). Moreover, as developing countries continue to improve per capita incomes and increase overall consumption, the proportion of animal source foods in their diet is expected to increase (Nardone et al., 2010). That, combined with increases in population, will drive demand for even greater numbers of livestock.

Finally, global food losses are significant, but their causes and magnitudes vary both along the supply chain and with geography (FAO, 2011). The developed world throws away large amounts of otherwise edible food while developing nations suffer from large amounts of spoilage. All in all, food loss can total up to about a third of total production (Searchinger et al., 2014). It is not clear how food systems and food security would change if losses were reduced, though, so developing new models is important to answer such questions.

Food security modelling is interdisciplinary because of the diverse climatic, economic, and societal factors that impact food security. Precipitation and temperature are prominent variables when it comes to food production, but there are also other non-food systems such as energy, soil, and transportation infrastructure that also play important, albeit indirect, roles. Without capturing these linkages, modelling efforts are likely to mischaracterize the effects of food security drivers like climate change and misinform policy makers about the extent and character of associated risks.

Most modelling efforts focus on likely scenarios, which is valuable, but there is a need to investigate plausible if less likely 'catastrophic outcomes' (Pindyck, 2013). Finally, feedbacks and thresholds present within and connected to food systems may magnify or dampen the effects of shocks in nonlinear ways. Thus it is important to capture not only the initial impacts of system shocks but also how those shocks propagate within the system over time. Policy responses to shocks that do not take those shocks' dynamics into account may be ineffective or even counterproductive.

1.2. Current modelling approaches

Farm-level models are useful for investigating the behaviour of individual farms and small farmers – particularly when it comes to adaptation and decision-making processes (Robert et al., 2016b). Janssen and van Ittersum (2007) provide a review of such models with a discussion of model capabilities and characteristics. The scope of farm models is limited, however. For example, the farm models reviewed by Robertson et al. (2012) either did not account for price variations or had prices specified exogenously. This can simply be a result of the boundaries of farm models – food prices are a function of more than just farm activities. Given the strong relationship between food security and food prices, perhaps it is not surprising that farm models do not typically consider the access and stability aspects of food security (van Wijk et al., 2014).

Agricultural systems models are designed to have a broader scope (and possibly less granularity) than farm enterprise models. Modelling of agricultural systems has traditionally advanced as a response to societal concerns, as well as whenever technological advancements have pushed the system in a new direction (Jones et al., 2016a). Data limitations and restrictive modelling capabilities have resulted in few systems models that can be used to inform policy (Jones et al., 2016b), however; advances in integrated modelling efforts that can incorporate individual needs are key for making food-related policy decisions (Antle et al., 2016a). These and other ideas have been laid out comprehensively in a special issue of *Agricultural Systems* (Antle et al., 2016b).

There do currently exist models that are built on the interconnection of different systems and aggregate available data resources. Such food systems models include climatological, biological, and economic submodules, each of which can be formulated and implemented in multiple ways. One significant modelling choice has to do with crop modelling: some food models use biophysical process-based models to estimate crop yield based on climate inputs, while others use statistical methods based on historical yields or simulation (McCown et al., 1996). Another significant aspect of model structure has to do with the economic scope of the model. Models that only consider the microeconomic factors of an economy are known as Partial Equilibrium (PE) models, whereas models that try to capture broader macroeconomic indicators are known as Computable General Equilibrium (CGE) models. For a more detailed description of the differences between PE and CGE models, see Robinson et al. (2014).

The Agricultural Model Intercomparison and Improvement Project (AgMIP) has brought different food systems models together to compare them with respect to their food security predictions (Rosenzweig et al., 2013). Even with the same climatological inputs, however, different models produce different results (von Lampe et al., 2014; Nelson et al., 2014). Part of the AgMIP project has involved explaining some of those disagreements in terms of variations in model structure (Robinson et al., 2014).

GCAM, IMPACT, and GLOBIOM are three examples of large-scale models that have been used for investigating food security. GCAM is an integrated assessment model with a significant agriculture component, and it operates on a 5-year time step for producing long-term predictions (Calvin et al., 2013). The main GCAM model is a global model, but GCAM researchers have also developed country-level versions, such as GCAM-USA (Kraucunas et al., 2015). IMPACT is another global food systems model (Rosegrant and Team, 2012). Like GCAM, it has price equilibria and trade but does not model food system stakeholder decisions or transportation infrastructure (used for trade) explicitly. Its focus is on the production aspect of food security, but it has been used for producing nutrition estimates (Springmann et al., 2016). These national-level nutrition estimates for the year 2050 considered food waste in moving from production estimates to nutrition intake.

GLOBIOM could be considered a land use model: in addition to its agricultural modelling, it also has a significant emphasis on biofuels and forestry (Havlik et al., 2011). Unlike GCAM or IMPACT, GLOBIOM results are produced by maximizing social welfare, but GLOBIOM operates on a comparable time scale. A stochastic version of the original deterministic model has been developed as well (Ermolieva et al., 2015). GLOBIOM is a global model, but there are regional versions of it (e.g., for Brazil Buurman et al., 2015). This regional model accounts for spatial variation due to transportation costs in producing its price equilibrium, but it does not explicitly consider transportation infrastructure.

There have also been a number of modelling efforts looking at regional food security. The paper by Rutten et al. (2014) uses another large-scale model, MAGNET, to solve for global conditions, and those global results are then fed into a local land use model for Vietnam. As a CGE model, MAGNET models international trade (Woltjer et al., 2014), but the regional model does not account for trade within the country. The results are also presented in terms of yearly averages. Butt et al. (2005) look at regional food security in Mali without using a large-scale model like MAGNET. The focus in that paper is strongly on food production with some economic modelling, but the model uses yearly time resolution and fixed trade prices. Moore et al. (2012) perform a similar food security analysis in East Africa: the focus there is on land use and crop production, not trade, seasonal variations in food security, or food access. Finally, Shortridge et al. (2015) use a very different approach than the previously mentioned papers to look at food security. Instead of relying on biophysical crop models and tracking land use changes, they construct a series of regression models to predict food security metrics based on climatic and economic variables. The resulting model is capable of producing accurate results, but those results are still yearly averages of point estimates.

Generally speaking, large-scale food security modelling focuses on food production, and the metrics used for food security are yearly averages of point estimates (over an entire population). Transportation infrastructure, as it affects food trade, is not modelled in any detail. The available models are not typically set up to capture seasonal variations in food security, and without these variations, food storage considerations also do not come into play. As in Springmann et al. (2016), it is possible to consider food waste in a post-processing step, but this does not integrate food waste into the model itself. Food security estimates also tend to take averages over populations rather than accounting for the potentially wide variations in food security between different socio-economic groups within a given region.

1.3. Motivation for modelling approach

To investigate food security shocks, we sought a bottom-up modelling approach that would account for the decisions of stakeholders and the characteristics of particular infrastructures while integrating agricultural, economic, and transport systems explicitly; this would thereby enable us to study a wide variety of interventions. The systems models described in the previous section offer good examples of top-down analyses: they connect the broader trends in individual systems to outcomes for populations. Our goal was to complement this work by focusing on decisions that stakeholders might take when faced with food insecurity and how that would percolate upwards into aggregate trends. To inform interventions that could be taken at the micro level, it was critical to understand how stakeholders would react to these interventions rather than predict what would happen on a larger, macro level. The advantage of this approach is that it can be informed by, and integrated with, existing modelling frameworks that offer the relevant top-down perspective.

At the base of our framework sits a detailed biophysical, process-based model that combines temperature and precipitation data with soil and plant-specific properties to yield rates and harvest times. The scope of this work, however, was intended to be broader than farm enterprise modelling: we intended to model agriculture at a larger scale than the individual farm. To investigate the behaviour of the food system as a whole, we needed to consider other potential stakeholders in the food system as well as relevant non-farm infrastructure. We need to include include these other factors precisely because food security depends on more than just food production. Food prices are a key consideration here. Endogenous model prices make it possible to capture the interactions between stakeholders' decisions and the overall effect of those decisions on food security more effectively.

With this in mind, we developed the Food Distributed Extendable COmplementarity (Food-DECO) model as a PE food systems model. The ‘Food-’ prefix indicates the sectoral scope of the model. Currently, the model only considers food, but we have deliberately set up the DECO framework so that we can consider other sectors with analogous models. The model combines representations of the agricultural, economic, and transport systems associated with food into a unified whole. We explicitly model both stakeholder decisions and infrastructure, thereby enabling a nuanced analysis of policy.

The Food-DECO model builds upon and advances the state-of-the-art in several ways. Firstly, our model captures important food supply chain components: along with the biophysical properties of crop production, we explicitly model trade and food distribution in a way that accounts for infrastructure and geography. Capturing bilateral trade and food distribution enables us to consider transportation costs and regional price variations.

Secondly, our model considers food access. Part of this consideration consists of food loss modelling, and another part of it includes disaggregating consumption by per capita income, age, and gender. This allows us to provide information regarding nutrition (and public health in general) that is more detailed and more accurate. Thirdly, the model is set up to evaluate the effects of seasonality and system shocks. Using a monthly time-step and explicitly modelling storage capacity allows us to consider how food access varies throughout the year as well as across years, and the potential buffering effects of storage and food aid promote a realistic model response to shocks like crop failure.

All of this matters because food security varies with geography and over time, as do relevant food loss considerations. Food waste also means that not all of the nutrition in the food produced actually gets used. Finally, consumption point estimates are insufficient to measure food security – disaggregation by age, gender, and income is necessary to capture human nutrition appropriately. These considerations are highly relevant for any policy measures seeking to address food security.

2. The DECO model and case study

We now briefly describe our model and the scenarios with which we demonstrate its use.

2.1. Model overview

The DECO model is formulated as an economic PE problem and solved as a Mixed Complementarity Problem (MCP). This is a common approach in energy market models (Gabriel et al., 2012) and has occasionally been used for food systems (Kolstad and Burris, 1986). The design of the DECO model is similar to and inspired by the energy model of Huppmann and Egging (2014).

The model divides up the area of interest into separate regions. Within each region, there are representative agents – ‘players' – that act as an aggregation of the decision-makers in that region. Currently in our model, each region has an agent for crop production, livestock management, storage, and consumption; there also exist distribution players between each pair of regions. Each player makes decisions so as to optimize their utility function, and the solution to all of these simultaneous optimizations is an equilibrium. We then solve the MCP that defines the equilibrium using the PATH solver (Munson and Ferris, 2000). The equilibrium solution produces both quantities (e.g., of food transported between regions) and prices (e.g., of purchased food), and the model currently provides these results at a monthly resolution.

Prices are a key part of the model, and among them are shadow prices. Shadow prices represent the value or cost of constraints, and they are naturally produced by our MCP approach. For example, a constraint on maximum available cropping land would have a shadow price associated with it, and that price would indicate the added value given by increasing the amount of available land (or the cost of decreasing the amount of available land). Prices in general, and shadow prices in particular, are useful for dealing with decision overlap.

By decision overlap, we mean the fact that the producer, storage operator, and consumer whom we are trying to model may not be distinct – especially in a subsistence farming context. The prices generated in the model measure the value of commodities at each step of the supply chain. From this perspective, when a producer retains a food commodity and stores it himself, he is effectively selling to himself and paying himself for the food. No money changes hands, but the price of the commodity at that point is still important because it represents what the producer could get by selling that commodity and using the money to do other things; that is, it represents an opportunity cost.

The model's agents represent different decision-making stages, (shadow) prices capture commodity value at each stage, and the linkage of prices in the model ensures consistency between and within stages. For example, storage costs may be borne by subsistence farmers, consumers, or third parties, but regardless, those costs increase the value (or price) of food over time. The model is agnostic regarding who is doing the storing.

A detailed description of the model is provided in Appendix A.

2.2. Representative Ethiopian case study

To produce a proof-of-concept for the Food-DECO model, we developed a simplified representation of Ethiopia; this model used representative crops and representative geographical regions (i.e., several different regions that would represent different political and agro-ecological zones present in Ethiopia). We then ran the model on a baseline case and tested several intervention strategies against a regional crop failure.

2.2.1. Region and crop choice

We considered four representative crops (cereals, tubers, other vegetables, and pulses) and two animal products (meat and milk) modelled over five regions (based on Addis Ababa, Amhara, East Oromia, Somali, and SNNPR). For our case study, we focused on Ethiopia because of its current food insecurity, expected population growth, and multi-cropping behaviour; Ethiopia has two major cropping seasons: the belg (planted in boreal spring) and kremt (planted in boreal summer). One of the key uses for this model is to test and analyze potential food-related policies, and Ethiopia is a prime target for such efforts. Climate change is expected to exacerbate present Ethiopian food insecurity, but the Ethiopian food system has the potential for significant improvement through improved transportation networks, increased fertilizer and irrigation use, and new crop varieties.

The top-down nature of Ethiopian agricultural planning also increases the relevance of this kind of modelling from a policy perspective. For example, Ethiopia has policies dictating what crops will be grown on irrigated lands (mostly favouring sugarcane as a cash crop). These kinds of policies could be revisited in the context of our food systems model.

2.2.2. Baseline case, crop failure, and interventions

This paper initially presents baseline results from a 6-year period of normal model behaviour. After that baseline case, we ran a scenario over the same 6 years but with a 25% crop failure (all crops, both cropping seasons) in East Oromia in the third year. Losses of this magnitude are large but not unrealistic in relatively dry parts of Ethiopia, such as East Oromia; 25% loss is comparable with losses seen during the El Nino drought of 2015 (CSA, 2015/2016). This kind of failure could result from events such as civil unrest or pestilence (which could reduce the ability to harvest crops in the field); climate-related factors such as drought or flooding (which would reduce the quantities available for harvest); or various combinations of these.

Following that, we tested several interventions having similar costs against this 25% failure case to investigate their relative benefits. We considered direct food aid, direct cash aid, consumer subsidies, producer subsidies, and transportation expansions. Specific details for each intervention are given in Section 3.3, and additional information regarding how the interventions were modelled is presented in Appendix A. The first four interventions have costs associated with them that are directly calculated in post-processing for cost-benefit analysis; costs for the last scenario can be calculated with location- and situation-dependent infrastructure development scenarios.

3. Model projections and observations

The following results are projections of a numerical model that has not been validated; for a simplified model such as this, it would be difficult to do model validation in the traditional sense. As such, these results should not be viewed as ‘predictions'. However, we believe that the food system behaviour captured by the model provides useful qualitative information (regarding food security responses to policy interventions) that can direct future research and provide insights to policy makers on possible policy effects.

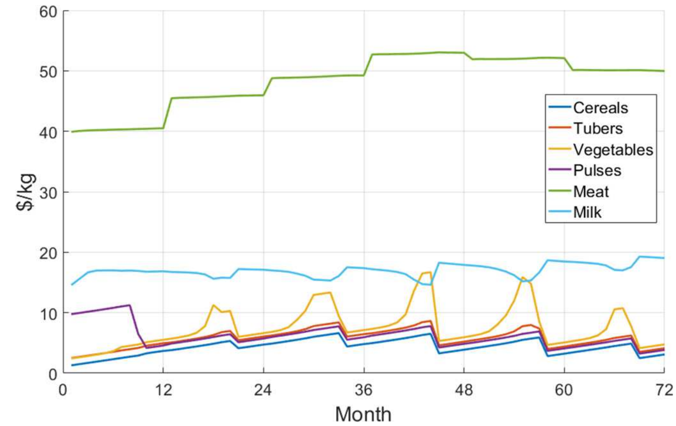

Fig. 1. Food prices, E Oromia (Baseline case).

3.1. Baseline case

The model showed three primary types of food security variation: seasonal, socio-economic, and geographic. We begin with seasonal variation. The plot in Fig. 1 shows prices for harvested foods dropping immediately after harvest (approximately three-quarters of the way through each year) and then climbing until the next harvest; note that in this discussion we ignore the first year of model results, as this year is used to get the model to an equilibrium, so we end up with 5 years of usable results.

Nutrition improves right after the harvest and then drops until the ‘hungry season’ just before the next harvest, as Fig. 2 shows. The quantities of food in storage also clearly show the yearly harvest cycle, with post-harvest peaks followed by steady consumption, as in Fig. 3. Note that the decrease in stored food is not entirely linear. Food imports and exports notwithstanding, that decrease occur at an increasing rate because of food storage losses.

Fig. 2 shows clear differences in caloric intake between income levels and gender groups: individuals in higher income brackets consume significantly more than those in lower income brackets, and men consume more than women. The latter is primarily due to the different

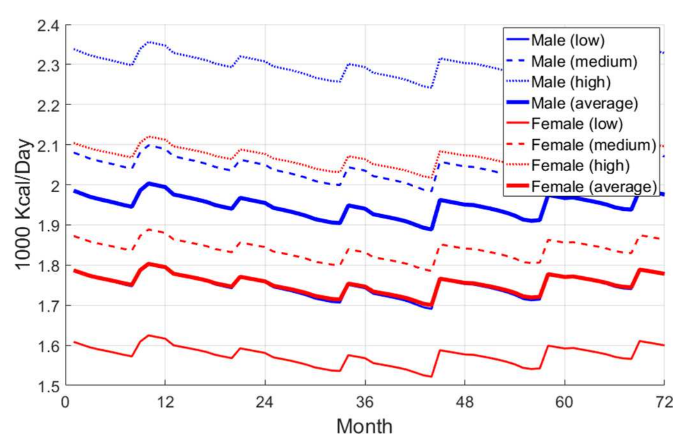

Fig. 2. Adult caloric intake disaggregated by gender and income, E Oromia (Baseline case).

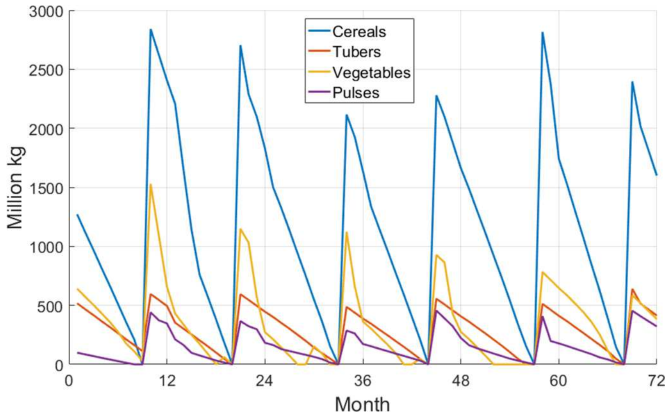

Fig. 3. Food in storage, E Oromia (Baseline case).

caloric needs of men and women and to intra-household food allocation practices. However, the changes in consumption with income reflect how per capita income changes *demand* (irrespective of gender). Figs. 1–3 also show variations in storage levels, caloric intake, and food prices from year to year. These are mainly due to differences in crop yield each year.

Finally, Addis Ababa acts as an internal trade hub. Fig. 4 shows the sum total of all food trade in the second year of the model. For ease of presentation, the figure separates trade with the capital from trade that does not pass through the capital. The model's transportation capacities between pairwise regions were calibrated so that the flow of commodities between a given region and Addis Ababa would be much higher than between that region and the other regions in the model, which reflects reality. There is some direct trade between regions, but more typically, a region sends its goods to Addis Ababa, and those goods are then sent out from there or consumed in Addis Ababa.

With respect to transportation costs and food losses, this is less efficient than direct bilateral trade, but that is how Ethiopia operates. We also see that there are definite producer and consumer regions: for example, E Oromia exports a lot of food to other regions (especially Addis Ababa), while Somali imports a lot of food without exporting any. This reflects, at least qualitatively, the real-world behaviour of those regions.

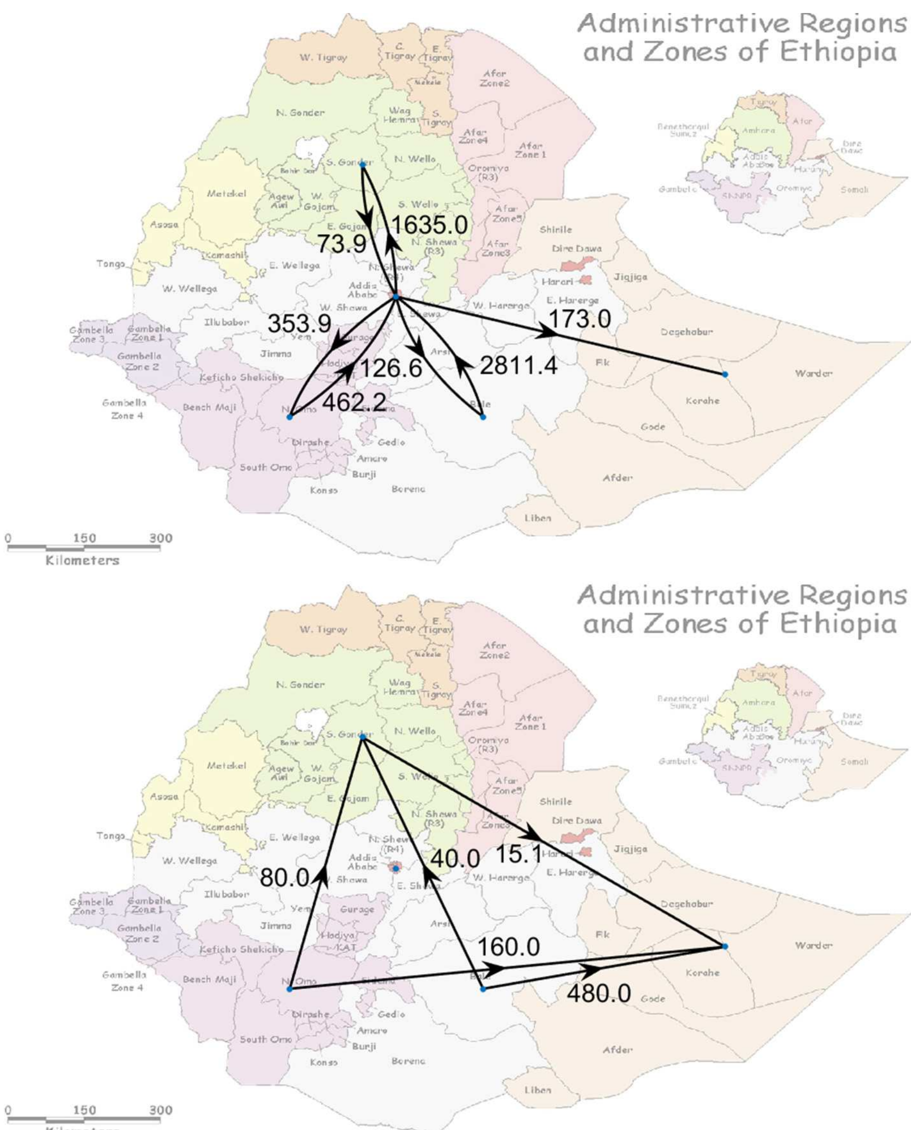

Fig. 4. All food trade with Addis Ababa (Top) and excluding Addis Ababa (Bottom) in year 2 (millions of kg), Baseline case; map background from USAID (2000).

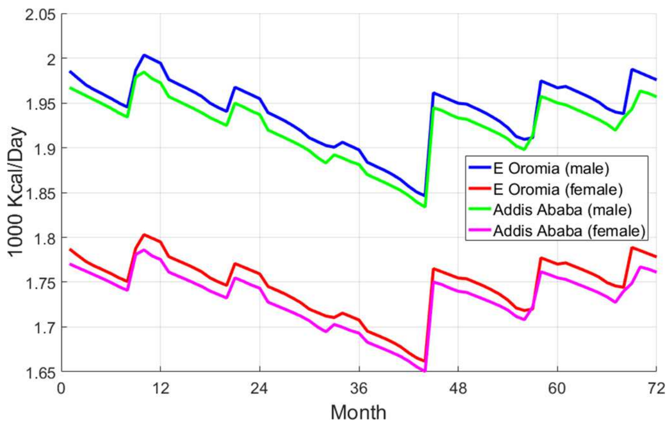

Fig. 5. Adult caloric intake disaggregated by gender (25% Crop failure).

3.2. Crop failure

When we have a crop failure (in this case, in E Oromia in the third year), the nutrition levels do not rebound at harvest time and continue to decline; food prices, similarly, continue to increase rather than dropping. Trade between regions plays a role in this. In a region with a roughly neutral balance of trade, like SNNPR, a poor harvest would result in an increase in imports. In E Oromia, though, we see a decrease in exports. As a result, the nutrition in other parts of the country suffers, as seen in Fig. 5: Addis Ababa experiences the same continuing drop in caloric intake at the end of the third year that E Oromia does. Furthermore, the seasonal nutrition patterns in Addis Ababa closely match those of E Orormia because E Oromia provides Addis Ababa with most of its food.

Fig. 6 shows the results of the 25% crop failure on food prices; compare this with the baseline case in Fig. 1. Normally, food prices would drop and caloric intake would jump at the end of year 3 (corresponding to the kremt harvest). Instead, with the 25% crop failure, food prices continue to climb, and consumption levels continue to drop as a result. Prices reset to more normal values, however, after the successful harvest in year 4.

Having a crop failure also increases vegetable multicropping in the year after the crop failure; there is more area devoted to vegetables in the belg harvest of the following year than there otherwise would be. This regularly happens for vegetables because of their short shelf life – even if the belg harvest has a low yield, it is still profitable to have vegetables harvested from the belg season because the previous year's kremt vegetables are almost all gone. The effect of a crop failure is somewhat similar: having food sooner but less efficiently is more valuable than having it later but more efficiently. We note, however, that the model does not currently include trade with external entities (or endogenously determined food aid) as a mechanism to compensate for deficits in food production.

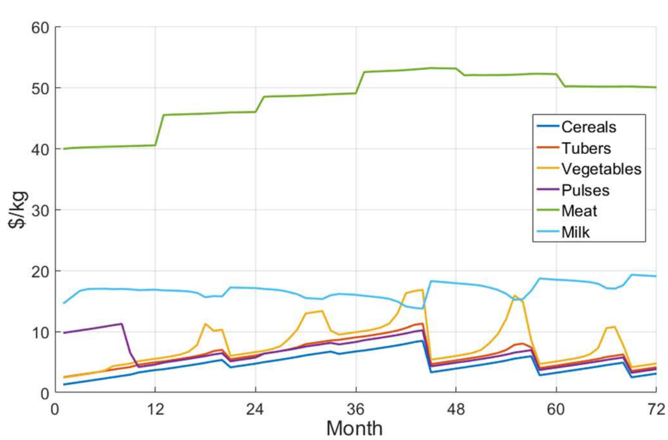

Fig. 6. Food prices, E Oromia (25% Crop failure).

3.3. Interventions

We tested the following interventions in the 25% crop failure scenario:

1. Direct Food Aid: 30 million kg of cereals per month delivered to storage in E Oromia during the fourth year (i.e., the year that would have been fed by the harvest in year 3). The estimated cost of this intervention was $2.0 billion. This cost estimate was determined by assuming that the cereal provided cost approximately the average cereal price in Addis Ababa over the last 5 years of the baseline scenario's results. The actual cost of this intervention will depend strongly on the source of the cereals, but this average price provides a reasonable baseline.
2. Direct Cash Aid: $7 per person per month to the poorest 50% of the population (the model's 'low' income bracket) over the whole country in year 4. Based on the population levels used in the model, this had an estimated cost of $2.2 billion. The intent of this intervention is to enhance consumer buying power, which may in turn incentivize greater production.
3. Consumer Subsidy: a 20% subsidy of consumer purchases of cereals in E Oromia in year 4. This had an estimated cost of $2.1 billion, and that cost estimate was calculated using the price and consumption data produced by the model in that year. A consumer subsidy policy has both an income effect (like cash aid) and a price effect (which encourages more consumption in that area because net prices are lowered).
4. Producer Subsidy: a 10% subsidy to producers for cereals grown in E Oromia in year 3. This had an estimated cost of $2.0 billion, and that cost estimate was calculated from the harvest yield and the price paid to farmers by storage during that harvest month. The intent of this policy is to encourage greater production by making that production more profitable.
5. Transportation Expansion: the maximum bilateral transportation capacity was doubled everywhere for the whole duration of the model; we are most interested in the results during years 3 and 4, but this approach seems more realistic than suddenly doubling transportation infrastructure in response to a crop failure. The model itself does not directly provide the information needed to calculate the cost of this intervention, but such calculations could easily be incorporated if pertinent data were available. This policy makes it easier for surplus production from other regions to reach consumers everywhere (including the region experiencing crop failure).

The quantities used in each intervention were chosen so that, excepting the transportation expansion, they would have similar costs. Note also that the first four interventions happen during years appropriate to the type of intervention: direct food aid, direct cash aid, and consumer subsidies are applied to the year after the crop failure (i.e., the year that would have relied on the food from the failed harvest), and the producer subsidies are applied during the year of the crop failure. The transportation intervention covers the years of interest, which is sufficient for our current purposes.

Fig. 7 shows the effects of the different interventions (or no intervention – just the crop failure), relative to the baseline case, on average adult female caloric intake; the trends were similar for average adult male caloric intake. The effects of the interventions on cereal prices (Fig. 8) and pulse prices (Fig. 9) are also shown relative to the crop failure without intervention. Note that the transportation intervention has slight differences with the other cases outside of years 3 and 4

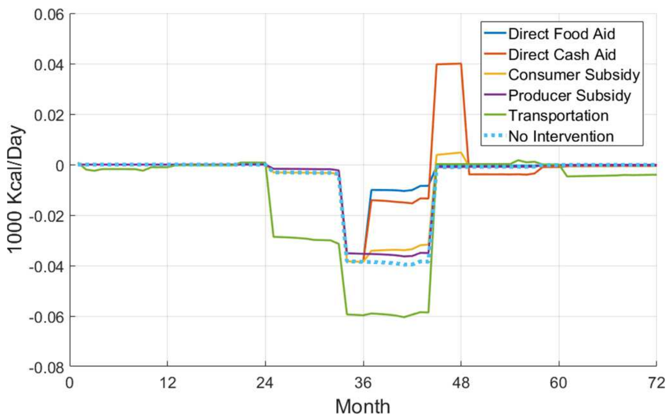

Fig. 7. Average adult female caloric intake relative to baseline, E Oromia.

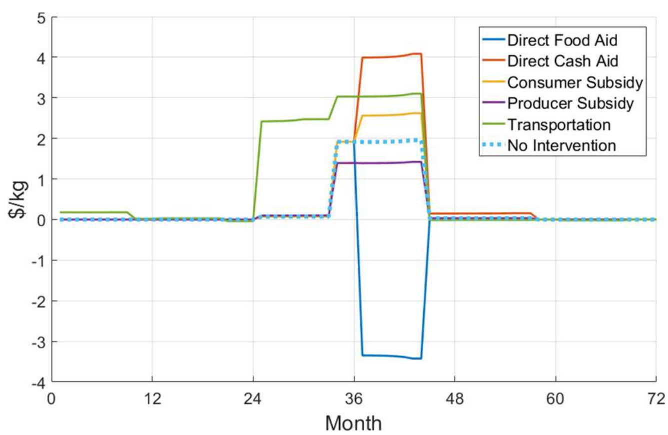

Fig. 8. Cereal prices relative to baseline, E Oromia.

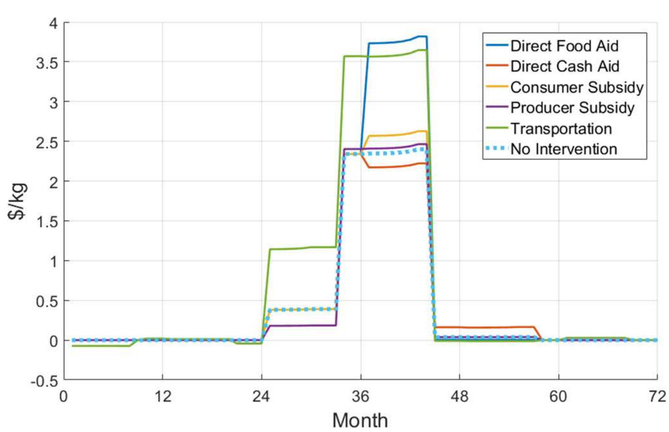

Fig. 9. Pulse prices relative to baseline, E Oromia.

because it extends for the full duration of the model. We are primarily interested in the results from years 3 and 4, though.

Direct food aid had a strong positive impact on caloric intake by significantly blunting the edge of the hungry season. Direct cash aid had a comparably beneficial effect, but the mechanism was different. There was a significant improvement in average caloric intake relative to the failure without intervention, but that improvement came entirely from the poorest income group. This aid actually reduced medium and high income groups' consumption slightly as compared to the crop failure with no intervention (see Fig. 10), but with the increase in low-income nutrition, average nutrition improved. This is a key example of why it is important to disaggregate consumption with respect to income when it comes to evaluating food policies.

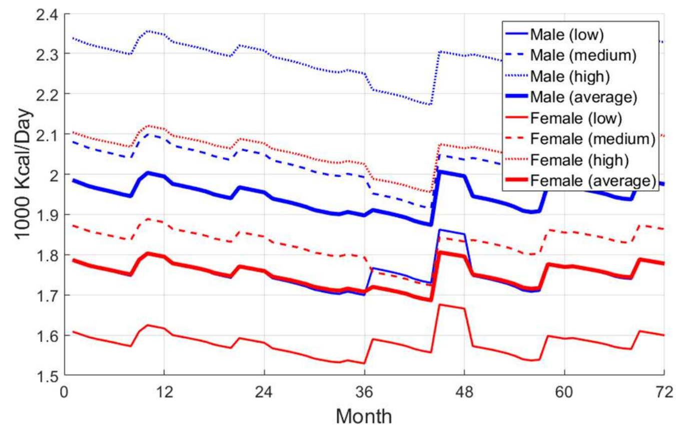

Fig. 10. Adult caloric intake disaggregated by gender and income, E Oromia (25% Crop failure, Direct Cash Aid).

Unlike direct food aid, direct cash aid *increased* food prices on average relative to the crop failure without intervention (pulses saw a slight decrease, but all other crops significantly increased in price). That is why the groups that did not receive additional cash had reduced nutritional outcomes – for the low-income group, the increase in buying power outweighed and actually caused that increase in prices. Normally, this kind of increase in prices would spur an increase in production, but limits on available cropland prevented this from happening. Subsidies to both consumers and producers ran into the same issue. Direct cash aid also had longer term effects. The extra buying power in year 4 led to more consumption through the entire year, and this meant that by the end of year 4, there was less food set aside to last until the harvest in year 5; the magnitude of this effect was relatively small, however.

Producer and consumer subsidies both had small effects. Even in Addis Ababa (not shown), the nutrition outcomes were very similar, but the two subsidies had different effects on food prices. This is not entirely unexpected. Producer subsidies effectively reduce production costs, while consumer subsidies increase consumption. Both are meant to encourage greater production, albeit by different mechanisms. The restriction on available land frustrates that intention, however, and thus food prices change without significantly impacting nutritional outcomes. Note that in this case, differences in both production and demand, combined with applying subsidies only to cereal crops, cause pulse prices to respond differently than cereal prices.

Had there been more land available into which to expand, we might have seen a greater difference in outcomes between the two interventions. However, the inability to increase cropping area reflects actual conditions in Ethiopia, so effectively using producer subsidies in Ethiopia would likely require some intervention to increase available cropland as well. Increased demand (due to increased effective purchasing power) with correspondingly higher prices would also provide an impetus to increase crop area. As a result, despite their different mechanisms, either subsidy would likely promote the same kind of response.

Finally, increasing transportation capacity increased food prices and decreased consumption slightly in E Oromia. This reduction may seem counterintuitive, but it is the result of increasing the capacity on a distribution system that is saturated (at least along certain routes – see Section 4.2 for more details on saturated routes). As a producer region in the baseline case, E Oromia was not able to ship enough food to importing regions because of limited transportation capacity, so it had a relative surplus of food (which meant lower food prices and better nutrition). Increasing distribution capacity equalized conditions across regions and E Oromia was worse off; importing regions, like Somali, benefitted. The effect here was small because the potential for distribution was not much higher than the distribution capacity. Had the

Table 1
Percentage changes in caloric intake extremes relative to Baseline case in years 3 and 4, E Oromia.

Case	Adult male	Adult female
No Intervention	−2.3	−2.3
Food Aid	−0.5	−0.5
Cash Aid	−0.8	−0.8
Consumer Subsidy	−1.9	−1.9
Producer Subsidy	−2.1	−2.1
Transportation Expansion	−3.4	−3.4

Table 2
Percentage changes in food price extremes relative to Baseline case in years 3 and 4, E Oromia.

Case	Cereals	Tubers	Vegetables	Pulses
No Intervention	27.8	30.7	0.8	30.8
Food Aid	1.5	12.5	0.1	49.0
Cash Aid	59.9	59.0	9.1	28.5
Consumer Subsidy	37.8	29.7	0.8	33.7
Producer Subsidy	19.7	30.9	0.8	31.6
Transportation Expansion	45.0	46.7	−1.0	46.8

Table 3
Percentage changes in average caloric intake relative to baseline case in years 3 and 4, E Oromia.

Case	Adult male	Adult female
No Intervention	−1.1	−1.1
Food Aid	−0.5	−0.5
Cash Aid	−0.2	−0.2
Consumer Subsidy	−0.9	−0.9
Producer Subsidy	−1.0	−1.0
Transportation Expansion	−2.2	−2.2

Table 4
Percentage changes in average food prices relative to Baseline case in years 3 and 4, E Oromia.

Case	Cereals	Tubers	Vegetables	Pulses
No Intervention	17.4	18.2	12.0	19.3
Food Aid	−16.4	10.8	11.5	26.5
Cash Aid	31.1	29.9	17.8	18.7
Consumer Subsidy	21.6	17.8	12.0	20.5
Producer Subsidy	13.0	18.6	12.3	18.6
Transportation Expansion	44.1	38.3	17.0	32.5

potential been greater or the capacity been smaller, the effect of doubling transportation capacity would have been even greater.

Tables 1–4 provide a summary of our results. For all tables, we focus on years 3 and 4 in E Oromia and consider how the crop failure (with and without interventions) affected food security measures within that period; years 3 and 4 are, respectively, the years of and following the crop failure. Tables 1 and 2 consider the extremes (minimum caloric intake and maximum food prices), while Tables 3 and 4 consider the averages.

We have shown both extreme and average behaviours here because they are sometimes different from each other. Peak vegetable prices, for example, were almost unchanged by the crop failure while average vegetable price increased significantly. This is primarily due to the short shelf life of vegetables: the peak prices hit when the local supply starts to run out and produce is imported from other regions, at which point it tends to stabilize around that peak until the next local harvest. This is why increased transportation capacity actually reduced peak vegetable prices slightly while still allowing an increase in the average. Direct cash aid also performed slightly better, relative to direct food aid, at improving average caloric intake than it did at improving minimum caloric intake.

As we saw in earlier figures, direct food aid (in the form of cereals) significantly reduced cereal prices in the process of improving consumption, but it also increased the prices of other food commodities. Both producer and consumer subsidies did little (e.g., the reduction in caloric intake was almost the same for both subsidies as it was without any interventions), and improved transportation increased prices while decreasing caloric intake.

Although direct food aid was effective in meeting immediate nutrition needs, this kind of intervention might also have negative side-effects. As shown above, direct food aid significantly reduced cereal prices. In reality, this could be a problem for cereal producers because it means that their revenue drops while the costs of production either remain constant or increase (due to lower yields). This could put local producers out of business and thereby negatively impact future production. Conversely, because cash aid increased prices, that intervention could have a positive long-term impact on local production. In reality, effective income is tied to food prices because so much of the Ethiopian population is involved in agriculture. The model does not explicitly close this feedback loop, and it could be a difficult feedback loop to model, but the price information contained in the model results help us to consider these kinds of indirect effects.

Finally, we have not yet discussed dietary diversity, but it is clear from the price data above that different interventions affect dietary diversity differently. In the most extreme case, we see that direct food aid decreases cereal prices while other crop prices increase. When we consider the average diet composition of the low income bracket in year 4 (Fig. 11), we see that direct food aid, in this case, actually decreases dietary diversity slightly by lowering the consumption of vegetables, pulses, and tubers relative to cereals. Direct cash aid, by contrast, improves dietary diversity by increasing the relative consumption of meat. It is easy to overlook dietary diversity and focus simply on caloric intake, but diet composition is a food security concern – it is an aspect of food access. As such, dietary diversity is also a consideration for food security policies.

4. Discussion

Having looked at price, nutrition, and diet composition data, we now want to step back and consider food security variation in the model and the information provided by shadow prices. We follow that with some brief comments on the interaction between transportation and food security; given the prominence of transportation in the Food-DECO model formulation and results, we think it appropriate to discuss that interaction outside the context of our model and thereby provide some perspective on our results. Finally, we conclude this section with an overview of key avenues for further model development.

4.1. Food security variability

Food-DECO currently captures food security variation, at least qualitatively, with respect to seasonality, geographic distribution, and per capita income. It also shows how those variations can be affected by policy measures. The geographic nutrition disparities displayed by the model correspond to real-world spatial variations. Nutrition in places like Somali, which import most of their food, depends strongly on the capacity and efficiency of the distribution network. All regions, whether importer or exporter, showed a strong degree of seasonal variation in consumption levels and food prices, however.

Disaggregation by age, gender, and income produced clear nutritional differences between the different categories. The differences in consumption by age and gender are an approximation to actual intra-household food distribution. Food allocation within households can play a significant role in determining food security – particularly for women and children in patriarchal societies. The model is still

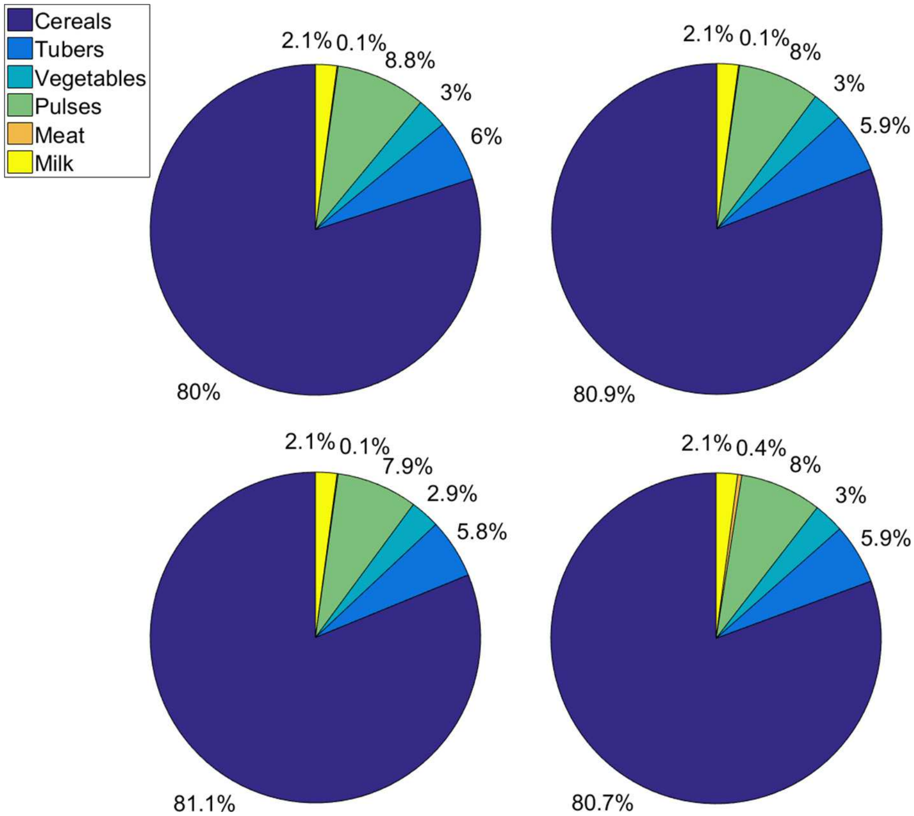

Fig. 11. Low income diet composition by calories in year 4: Baseline case (Top left), 25% Crop failure with No Intervention (Top right), 25% Crop failure with Direct Food Aid (Bottom left), 25% Crop failure with Direct Cash Aid (Bottom right).

providing a reasonable approximation at a population level, though, and that could be further improved by using a finer resolution for age and income brackets.

The model also showed the effects of food losses. Vegetables had the highest storage losses. The overall amount of vegetables stored was also smaller than that of cereals or pulses, so the relative losses were even more disparate. One future use of the model could be to explore how improvements in food storage efficiency could potentially improve food security throughout the country.

4.2. Constraints and shadow prices

We can look at the significance of a constraint by considering the shadow price associated with that constraint. If the constraint is not binding, then the shadow price is zero. If the constraint is binding, then the shadow price gives the value of relaxing that constraint or the cost of tightening it further. Here we consider two key constraints: total land area available for crops and transportation capacity. We will refer to the former constraint's shadow price as the shadow price of land (units of $/m^2) and the latter's shadow price as the shadow price of transportation (units of $/kg).

4.2.1. Available cropland

The hard cap on land availability for crops was a significant limitation on model regions' ability to react to crop failures or, in general, to improve nutritional intake. Normally, producers would respond to increased prices by increasing production, but the limits on available land kept them from doing so significantly; consumers, then, reduced their consumption in response to higher prices. Such limited availability of crop land corresponds to the present reality in Ethiopia.

In the baseline case, the price of that constraint was relatively high in Addis Ababa (generally 0.5–1.0), as might be expected from the large population and small amount of available land. As a city, though, it would not have much room to expand crop production, so we will not focus on its results. Amhara and Somali did not use their maximum cropping areas, and SNNPR only hit its upper bound in years 2 and 3 with relatively small shadow prices (< 0.1). E Oromia fully exploited its area in all years except the last one, and its shadow prices in years 3 and 4 were 0.34 and 0.08, respectively; we will focus on the results from years 3 and 4 in considering the effects of the crop failure and interventions.

The crop failure significantly increased the shadow price of land in E Oromia, SNNPR, and Amhara in year 3 (to 0.43, 0.48, and 0.29, respectively) but not year 4. Increasing transportation capacity served to increase the shadow price of land further in all three areas in year 3, to 0.66, 0.75, and 0.53, respectively. Of the other four interventions, the only one that produced a significant change in the shadow price of land was direct cash aid, which increased the shadow price of land in E Oromia in year 4 to 0.12. E Oromia's shadow price of land dropped below that of SNNPR in year 3 because of E Oromia's drop in yield that year.

These prices are directly tied to the price of food in the model regions. The subsidies had small impacts on food prices, so it is not entirely surprising to see that they had minimal effect on the shadow price of land. Conversely, increasing transportation capacity increased overall food prices more than any other intervention, and thus that intervention had the strongest effect on the shadow price of land. Food prices (and thus the shadow price of land) are not directly tied to nutritional outcomes, but the connection between transportation capacity and the shadow price of land suggests that increasing transportation capacity will be most effective if it is also accompanied by an increase in available cropland; direct cash aid has a similar but weaker relationship.

Note also how the effects of a regional crop failure propagated through the transportation network to affect other areas – areas that may not necessarily even trade with each other directly. In our model,

Table 5
Average shadow price of transportation over years 3 and 4.

Origin\destination	Addis Ababa	Amhara	E Oromia	Somali	SNNPR
Addis Ababa	0	0.05	0.08	0.55	0.13
Amhara	0.06	0	0	1.00	0.10
E Oromia	0.23	0.09	0	1.57	0.15
Somali	0	0	0	0	0
SNNPR	0.14	0.29	0.28	0.88	0

there is little to no trade between E Oromia and SNNPR or Amhara (see Fig. 4). However, our results suggest that increasing available cropland in both of those regions could help reduce the impacts of crop failure in E Oromia.

4.2.2. Transportation capacity

As mentioned in Section 3.1, we set up the distribution network in our model as a hub-and-spoke design: there is relatively high capacity to and from Addis Ababa and low capacity otherwise. When we looked at the trade flows produced by the model, we found that the route from E Oromia to Somali was almost always at full capacity, while the routes from Amhara and SNNPR to Somali and the routes from E Oromia, Amhara, and SNNPR to Addis Ababa were sometimes at full capacity; the other routes were seldom or never at capacity.

To represent the value of increasing capacity on these routes, we took an average of the shadow prices for each route over years 3 and 4 (in the baseline case); note that the shadow price of transportation varies from month to month. These values are presented in Table 5. The shadow price of transportation is a measure of the value of increasing capacity, not a measure of how often a route is at capacity (though the two will be related). This value, furthermore, depends on the difference in prices between two regions. A positive shadow value indicates a higher price of food at the destination than at the source as well as a binding capacity constraint, and the magnitude of the shadow price of transportation reflects the magnitude of the price difference between those regions minus the out-of-pocket costs of transport.

The crop failure in year 3 reduced most of these values (especially SNNPR to E Oromia and Addis Ababa to Somali) and increased the shadow price of transportation from Addis Ababa to E Oromia; Amhara and E Oromia to Somali were unchanged. Essentially, this is the result of E Oromia being an exporting region: the food prices in E Oromia increase, there is less food to send to other regions, and there is greater need to import food.

Of all the interventions, increasing transportation capacity produced the greatest changes in the shadow price of transportation. There were small decreases across the board except for all routes with Somali as a destination (the shadow price of transportation reduced by roughly 30%) and except for all routes from E Oromia (which saw a small increase). Somali was by far the greatest beneficiary of this intervention, and the changes in the shadow price of transportation reflect this.

Direct food aid increased the shadow price of transportation from E Oromia to Addis Ababa and Somali. The drop in cereal prices in E Oromia, as noted above, would create a greater price differential between E Oromia and the two regions to which E Oromia sends most of its exports, and this leads to the observed change. Direct cash aid produced some small changes, but none of these were on routes connected with E Oromia. Producer subsidies increased the shadow price of transportation from Addis Ababa and E Oromia to Somali while slightly decreasing the price from SNNPR to Somali. Consumer subsidies produced a slight reduction in the shadow price of transportation from E Oromia to Addis Ababa.

Overall, we observed that Somali was perhaps the region mostly strongly affected by crop failure and interventions in E Oromia – and not always through direct exports from E Oromia to Somali. The high shadow prices of transportation from any other region to Somali would have suggested this even prior to simulating the interventions. That price reflects differences between regions; *ceteris paribus*, the greater the price, the greater the disparity. Increasing transportation capacity helped to reduce the price differences between regions, while direct food aid actually made some of those differences worse.

4.3. Food security and transportation

Transportation infrastructure had a strong effect on our model outcomes. We do not want to overstate the significance of the results. It is the directions and relative magnitudes of trends that provide the insights we seek, not the exact numbers; this kind of model is not meant to provide high levels of precision. There is evidence that improved transportation infrastructure correlates with improved food security over the long run (Harding and Wantchekon, 2012), in large part because consumers benefit from more integrated markets. However, transportation infrastructure takes many years to build.

In contrast to policies like export controls, improving transportation infrastructure is not a policy option for addressing acute food shortage events (Ivanic et al., 2012), nor is it necessarily pursued with the problem of acute food shortages in mind. In fact, integration to urban and international markets can have uneven impacts on food prices in rural areas in Africa. In West Africa, for example, relatively isolated rural areas have asymmetric exposure to external prices: their remoteness insulates them from external price volatility under normal conditions, but it makes them sensitive to external price shocks in times of food shortage, when more food needs to be obtained from outside the local region (Brown et al., 2009).

This general phenomenon has been studied in Ethiopia at the national scale. For example, Ethiopia is relatively isolated from global grain markets, because most grain produced in Ethiopia is consumed locally and vice versa. This, combined with government policies to restrict exports and imports, meant that the 2008 global food price crisis had very little impact on Ethiopia – producers could not rush to profit by exporting products because the channels to do so were limited, and consumers did not depend on imported products to meet their needs (Admassie, 2013).

Transportation does, of course, provide important benefits for responding to crop failure when appropriate policies or interventions are considered. It is critical for the distribution of food aid (Pirie, 1993), for example, and can facilitate food imports through market mechanisms when there is sufficient relative purchasing power in the affected region. In the particular scenario studied here, transportation capacity is increased with no other economic or demographic change; the region experiencing crop failure typically exports food; there is greater purchasing power in other regions; and there is no other food or cash aid. Given those conditions, it is not a surprise that increased transportation capacity would be used for export, further exacerbating the rise in local prices. It is not uncommon for food insecure countries to limit food exports. They do this because they know that demand drives food trade, which could threaten local food security in poor places. A policy of easing export restrictions is, on a different scale, analogous to a policy of increasing transportation capacity in a model driven by economic principles.

4.4. Further model developments

We have identified three main areas of further development for the DECO model. The first relates to model foresight. Model players currently operate with perfect foresight on a rolling time horizon, and the model includes constraints that limit their ability to utilize this foreknowledge; for more on this, see Sections A.1 and A.2. With the constraints that we have imposed to restrict players' ability to act on their foreknowledge, the model can handle relatively small deviations from normal behaviour. However, to see the effects of major shocks more accurately, we need to change the model so that the players operate based on their *beliefs*, not knowledge, about the future. Doing this properly may require moving from a strict optimization-based approach to a rule-based approach for some players or turning the model into a stochastic MCP (Shanbhag et al., 2011). This can be done within the current MCP framework.

Secondly, the model is currently using a combination of approximate calibrations with readily available data. This is sufficient for a proof-of-concept, to display the qualitative behaviours we have highlighted, but we will want more detailed, accurate results when applying the model to inform food policy. Doing this will require a substantial data discovery and, potentially, data collection effort involving broad interdisciplinary collaboration.

Thirdly, the monthly time resolution, regionalization, and demographic disaggregation are all important for evaluating system shock and food policy impacts, but they also increase the model's computational cost. The model used for this paper had approximately 60,000 variables and the same number of constraints (being a square system) for each year of results produced. Six years of results therefore required sequentially solving six of these 60,000-variable systems; running the model for those 6 years took about a day to complete on a computing cluster. The computational cost for solving an MCP increases super-linearly with the number of variables, so simply solving larger and larger systems will eventually become impracticable. We will need to decompose the model computationally if we are to increase its size significantly.

5. Conclusions

Using a representative system based on Ethiopia, Food-DECO produced results that showed the effects of seasonality and regional distribution networks on human caloric intake while disaggregating those effects by age, gender, and per capita income. We then investigated the effects of a regional crop failure and evaluated the effectiveness of similarly-priced interventions. In our experiments, direct food aid and direct cash aid were the most effective policy measures at increasing overall caloric intake, though we recognize that these approaches can have numerous secondary effects that are not currently considered in our model. Improving the capacity of the existing food distribution network between regions in our model actually ended up reducing the nutritional outcomes for the population experiencing the crop failure: food was instead sent in larger quantities to regions that had a high demand for imports. We were able to see this unexpected behaviour because we integrated agriculture and transportation modelling in an economically consistent way.

Despite the limitations of this case study, the application presented here demonstrates the use of models like Food-DECO for the formulation of informed food policy. When formulating short-term disaster preparedness or long-term development plans that involve or affect regional food security, it is valuable to be able to evaluate demographically-specific food security outcomes, consider the potentially counter-intuitive impacts of trade during a food shock, and evaluate a range of intervention policies in a socio-economic context. Further development of Food-DECO and models like it can transform our current production-focused lens on climate-resilient development to a more complete, and ultimately more effective, approach to managing evolving food systems.

Appendix A. Model description

Here, we provide a description of the Food-DECO model. In doing so, we briefly describe the temporal aspects of the model (the rolling time horizon and model foresight), the optimizations constructed for each of the different players, the analysis modules, the intervention components, and model calibration. Note that these are details about how the model is formulated, not how the model is implemented. A detailed description of the MCP implementation of the model (e.g., assembling all of the optimality conditions) would be long, technical, and unnecessary for the purpose of explaining the model's structure.

A.1. Model foresight and the rolling time horizon

The optimization in the model operates on a 3-year rolling time horizon. For each year i, the model solves years i, $i + 1$, and $i + 2$ (using monthly time steps) but only keeps the results from year i; the results for year $i + 1$ are obtained by solving years $i + 1$, $i + 2$, and $i + 3$ while only keeping year $i + 1$, and so on until the model has kept results from all of the years of interest. We use a rolling time horizon to mitigate finite horizon effects – model artefacts that can appear at the end of the optimization window. On the one hand, a 1-year horizon would fail to capture how one year's decisions affect the food system in the next, but an excessively long horizon would be computationally expensive and disregard the shorter time horizons that participants (especially less wealthy participants) in food markets have.

Assuming that all of the entities represented by the model are thinking 3 years in advance is not the point of this approach. In fact, the structure of the current optimization problem formulations for crop producers, distribution operators, and consumers makes each year's decisions independent of the previous year's for those players, and even storage operators' decisions only depend on results approximately a year in advance (essentially the timing and yield of the next harvest). Livestock managers are the only players for whom long-term consequences affect present decisions, and the strength of that effect is relatively weak. The point of keeping only the first year's results is to mitigate the effects of finite horizon artefacts on the model's outputs, which are greater for years closer to the end of the horizon. We will discuss this issue more in the player descriptions as it becomes relevant.

Closely related to the rolling time horizon is the issue of model foresight. Right now, the players have perfect foresight up to the rolling horizon time period, which can produce optimistic results based on their decisions – particularly when dealing with crop failures or other shocks. However, removing the assumption of foresight would require us to model decisions with some description of uncertainty (a stochastic or possibly Bayesian optimization approach). This would entail further research into the application and computational development of these approaches. The first steps of this would require us to describe possible scenarios, and their associated probability distributions. Secondly, the model would need to be set up to solve under these different scenarios, exponentially increasing computational effort. Our intention is for this paper's model to form a stepping stone to this future extension.

To address the issue of foresight in our current work, we have taken steps to limit the impact from foresight along the rolling horizon. Firstly, we have limited the length of the rolling horizon to 3 years, so foresight is not available for the entire time horizon. Secondly, we have added constraints (where appropriate) to prevent players from taking advantage of this foreknowledge. For example, farmers do not have the ability to increase crop area drastically based on future projections, though they can change the way that land is used. One can think of this as a tractable approximation to imperfect foreknowledge with greater planning flexibility; being unable to use foreknowledge has a similar impact to not having perfect foresight for that action. Finally, we calibrate our baseline so that foresight does not produce unreasonable outcomes. Our results nevertheless have to be viewed in this context, which can be thought of as looking at ‘what-if’ scenarios in the context of shocks but with limited ability to act on perfect foresight.

As with the rolling time horizon, we will address foresight, as it pertains to specific players, in the player descriptions.

A.2. Model players

Before introducing each of the model players, we begin by noting some key concepts. Simply listing all of the relevant variables and parameters would be more rigorous but less helpful than explaining how the nomenclature generally works. The first important concept to mention is decision variables. Decision variables are quantities that players directly control and thus can manipulate in order to increase their utility (usually profit). For example, crop producers can vary the area devoted to each crop in a given cropping season ($A_{crop,season}$); that crop area is a design variable.

Secondly, we denote commodity quantities with q. Subscript text provides more information about what kind of commodity is being represented. The amount of beef sold to storage in region i would be $q^{L}_{beef,store,i}$, for instance. Superscript text indicates which player controls that variable: $q^{L}_{beef,store,i}$ is controlled by the livestock producer, and $q^{S}_{beef,store,i}$ is controlled by the storage operator. In order for the mode to be consistent, we require that $q^{L}_{beef,store,i} = q^{S}_{beef,store,i}$. These are known as equilibrium constraints, but we do not generally show them in order to avoid excessive repetition.

Thirdly, we denote prices with p. Again, as with commodity quantities, subscript text provides more information about the price in question. Note, however, that there is no superscript – prices are not directly controlled by any players (they are only obtained in solving the MCP) and are the same for all players, so the superscript is not necessary. Finally, we use $\widetilde{R}$ and $\widehat{R}$ to indicate quantities associated with the advisory years in the rolling time horizon optimization approach, but the formulae for calculating them are the same as for R in the first year. For completeness' sake, we include a discount rate δ for future years, but our results all use a discount rate of $\delta = 1$.

A.2.1. Crop producer

Farmers' decisions involve a number of technical, economic, climate, and land factors that make decisions at the individual level difficult to represent (Robert et al., 2016a); these decisions can be modelled better at the aggregate level as crop producers. In Food-DECO, crop producers manage cropland and sell harvested crops to storage. Subject to a constraint on the maximum total crop area in each region and production costs, they make decisions regarding how much of each crop to plant, and in which multi-cropping season, so as to maximize their profit.

The model assumes perfect foresight (within the 3-year rolling time horizon) regarding quantities such as crop yield. For crop producers, this effectively means knowing yearly crop yields prior to planting. To reduce the impact of this assumption on model results, we implemented a constraint on our producers: the total crop area available is set such that an average year uses almost all of the available cropland. That way, there is no room to increase crop area significantly (though the relative areas of different crops may change). The crop producers still 'know' what will happen, but this limitation restricts their ability to act on that knowledge. Without this limitation, they would simply increase crop areas to meet demand. Prices would still rise, because the lower yields effectively mean a larger price of production, but the shortages would be less severe.

For crop producers, this approximation to imperfect foreknowledge breaks down when a given year's deviation from the norm becomes too large. The total crop area is fixed, but as yields drop, the crop area composition shifts to producing more cereals (relatively speaking) at the expense of other crops. This behaviour is driven by factors such as greater demand and lower production prices (relative to energy content) for cereals compared with other kinds of crops.

The optimization problem for each region is

$$\max U = \sum_{t=1}^{12} R(t) - C + \delta\left[\sum_{t=12}^{24} \widetilde{R}(t) - \widetilde{C}\right] + \delta^2\left[\sum_{t=25}^{36} \widehat{R}(t) - \widehat{C}\right] \tag{1}$$

$$g_1 = q^{C}_{crop,store,i} - \sum_{season} m_{crop,season} A_{crop,season} r_{sq} r_{sf} \leq 0 \tag{2}$$

$$g_2 = \sum_{crop,season} A_{crop,season} - A_{tot} \leq 0 \tag{3}$$

with decision variables

$$A_{crop,season},\ q^{C}_{crop,store,i} \tag{4}$$

where

$$R(t) = \sum_{crop} p_{crop,store,i}\, q^{C}_{crop,store,i} \tag{5}$$

$$C = r_{labour,ave} p_{labour} \sum_{crop,season} A_{crop,season} t_{crop} + p_{fuel} \sum_{crop,season} A_{crop,season} q_{fuel,crop} \tag{6}$$

Crop producers cultivate land and sell harvested crops to storage; they maximize profit with discounted futures by controlling crop area, $A_{crop,season}$, and the amount of crops sold to storage, $q^{C}_{crop,store,i}$. In doing so, they cannot sell more produce than they harvest (g_1) or cultivate more land than they have available to them (g_2). Their revenue is the product of the price at which they can sell produce to storage, $p_{crop,store,i}$, and the quantity of sold produce summed over all crops, while they have costs associated with labour and fuel, which are respectively

$$r_{labour,ave} p_{labour} \sum_{crop,season} A_{crop,season} t_{crop} \tag{7}$$

$$p_{fuel} \sum_{crop,season} A_{crop,season} q_{fuel,crop} \tag{8}$$

Note that labour costs depend on worker productivity, $r_{labour,ave}$, which is calculated in Section A.3.1.

A.2.2. Livestock producer

Livestock managers control the number of livestock in the model regions. They sell meat and milk to storage, and they sell live animals to distribution as part of live animal trade in the model. Livestock managers make decisions about how many animals to trade or slaughter for meat (and hides), and they seek to maximize their utility subject to milk production and livestock reproduction rates as well as labour and operational costs. Their utility is a combination of profit plus the estimated value of the herd at the end of the 3-year horizon; that estimated value is based on an average animal value over the 3-year period multiplied by the number of animals. This optimization has some risk of finite horizon effects: the livestock producers manage an asset that grows over time, so the rolling time horizon approach is valuable for dealing with this. In our numerical examples, however, model foresight is not a significant issue for this player. The average of future livestock prices is used as a measure of livestock value, but this average tends to be relatively stable over time, so the effect is minimal.

The optimization for each region each month is

$$\max U = \sum_{t=1}^{12} (R - C) + \sum_{t=13}^{24} (\widetilde{R} - \widetilde{C}) + \sum_{t=25}^{36} \delta^2(\widehat{R} - \widehat{C}) + p_{cattle,ave}N_{cattle,i,final} \tag{9}$$

$$g_1 = q^L_{milk,store,i} - \eta_{production}r_{dairy}N_{cattle,i}\mu_{production}r_{month} \le 0 \tag{10}$$

$$g_2 = -N_{cattle,i} \le 0 \tag{11}$$

$$\begin{aligned} h_{1,n} \;=\; & N_{cattle,i,n} - (1 + k - \kappa)N_{cattle,i,n-1} + \frac{q^L_{beef,store,i,n}}{r_{meat}m_{cow}} \\ & + \sum_j (q^L_{cattle,transp,i\to j,buy,n} - q^L_{cattle,transp,j\to i,sell,n}) = 0 \end{aligned} \tag{12}$$

with decision variables

$$q^L_{milk,store,i},\ q^L_{beef,store,i},\ q^L_{cattle,transp,i\to j,buy},\ q^L_{cattle,transp,j\to i,sell} \tag{13}$$

where

$$\begin{aligned} R \;=\; & p_{milk,store,i}q^L_{milk,store,i} + p_{beef,store,i}q^L_{beef,store,i} \\ & + \sum_j p_{cattle,transp,i\to j,buy}q^L_{cattle,transp,i\to j,buy} + q^L_{beef,store,i}\frac{p_{hide}}{m_{cow}r_{meat}} \end{aligned} \tag{14}$$

$$\begin{aligned} C \;=\; & \sum_j p_{cattle,transp,j\to i,sell}q^L_{cattle,transp,j\to i,sell} \\ & + (r_{feed}\mu_{feed}p_{feed} + r_{labour}p_{labour}t_{cattle})N_{cattle,i} \end{aligned} \tag{15}$$

$$\eta_{production} = 1 - \alpha_{dairy}\sum_t \tau_t \tag{16}$$

$$\tau_t = \max\{[1.8(0.35T_{db} + 0.65T_{wb}) + 32] - 74,\ 0\} \tag{17}$$

Livestock producers manage cattle populations (total number of cattle $N_{cattle,i}$) to produce milk, $q^L_{milk,store,i}$, and beef, $q^L_{beef,store,i}$, that are sold to storage; in slaughtering cattle for beef, they sell the hides from the dead animals (at price p_{hide}). They can also buy and sell live cattle with other regions via distribution operators. The amount sold to region j via the distribution operator (i.e., the amount that distribution buys from them) is $q^L_{cattle,transp,i\to j,buy}$, and the amount bought from region j (i.e., the amount that distribution sells to them) is $q^L_{cattle,transp,j\to i,sell}$. The cattle population in a given region changes over time with live animal trade and animal slaughter for meat, but it also changes with reproduction and death due to illness (given by constants κ and k, respectively). Milk production depends on production efficiency, $\eta_{production}$, which in turn depends on weather, average production levels $\mu_{production}$, and the total number of dairy cattle $r_{dairy}N_{cattle,i}$.

Livestock producers maximize profit plus an estimate of herd value at the end of the optimization time horizon $p_{cattle,ave}N_{cattle,i,final}$. They obtain profit by selling live cattle, beef, milk, and hides, and they have costs for buying live cattle, buying cattle feed $r_{feed}\mu_{feed}p_{feed}N_{cattle,i}$, and paying for labour $r_{labour}p_{labour}t_{cattle}N_{cattle,i}$.

A.2.3. Distributor

Distribution operators ship food between storage in different regions and ship live animals between livestock managers in different regions. They make decisions about what to ship where so as to maximize their profit subject to limits on the maximum weight they can ship each month. In doing this, they experience some food losses during transportation, and they also have labour and fuel costs. Model foresight and finite time horizon effects are not problems for this player because decisions are effectively made 1 month at a time, and each month's decision is unconnected to behaviour in previous months.

The optimization for each distributor is

$$\max U = \sum_{t=1}^{12} (R - C) + \sum_{t=13}^{24} \delta(\widetilde{R} - \widetilde{C}) + \sum_{t=25}^{36} \delta^2(\widehat{R} - \hat{C}) \tag{18}$$

$$g_1 = q^D_{food,transp,i\to j,sell} - (1 - \eta_{loss,food})q^D_{food,transp,i\to j,buy} \le 0 \tag{19}$$

$$g_2 = \sum_{food} q^D_{food,transp,i\to j,buy} + m_{cow}q^D_{cattle,transp,i\to j,buy} - q_{transp,capacity} \le 0 \tag{20}$$

$$g_3 = q^D_{cattle,transp,i\to j,sell} - q^D_{cattle,transp,i\to j,buy} \le 0 \tag{21}$$

with decision variables

$$q^D_{food,transp,i\to j,buy},\ q^D_{cattle,transp,i\to j,buy},\ q^D_{cattle,transp,i\to j,sell},\ q^D_{food,transp,i\to j,sell} \tag{22}$$

where

$$\begin{aligned} R = & \sum_{food} p_{food,transp,i\to j,sell}\, q^D_{food,transp,i\to j,sell} \\ & + p_{cattle,transp,i\to j,sell}\, q^D_{cattle,transp,i\to j,sell} \\ & - \sum_{food} p_{food,transp,i\to j,buy}\, q^D_{food,transp,i\to j,buy} \\ & - p_{cattle,transp,i\to j,buy}\, q^D_{cattle,transp,i\to j,buy} \end{aligned} \tag{23}$$

$$C = (C_{ij,fuel} + C_{ij,labour})(q^D_{food,transp,i\to j,buy} + m_{cow}\, q^D_{cattle,transp,i\to j,buy}) \tag{24}$$

$$C_{ij,fuel} = p_{fuel}\eta_{fuel}\left(\frac{2d_{ij}}{\eta_i + \eta_j} + \frac{\sqrt{A_i}}{\eta_i} + \frac{\sqrt{A_j}}{\eta_j}\right) \tag{25}$$

$$C_{ij,labour} = p_{labour}\mu_{transp}\left(\frac{r_{labour,i} + r_{labour,j}}{2} t_{ij} + r_{labour,i} t_i + r_{labour,j} t_j\right) \tag{26}$$

$$t_{ij} = \frac{2d_{ij}}{v_c(\eta_i + \eta_j)} \tag{27}$$

$$t_i = \frac{\sqrt{A_i}}{v_{c,internal}\eta_i} \tag{28}$$

Distributors have costs associated with purchasing food commodities and live cattle in a particular region, with purchasing fuel ($C_{ij,fuel}$), and with paying for labour ($C_{ij,labour}$), and they obtain revenue by selling those commodities and cattle in another region – at a price that enables them to recover their costs and obtain a profit. Total trade (food commodities and live cattle) from one region to another is limited by a maximum available capacity $q_{transp,capacity}$. The amount that distributors are able to sell is also limited by food loss: we assume that no cattle are lost during transport, but the food available to sell after transport is only a fraction, $(1 - r_{loss,food})$ of what was originally purchased.

To calculate labour costs, fuel costs, and food loss rates, we first measure transportation efficiency between nodes i and j using

$$\eta_{ij} = \frac{d_{ij}}{v_c t_{ij}} \tag{29}$$

where d_{ij} is the distance between the node centres, v_c is a characteristic travel velocity between the two points, and t_{ij} is the time it takes to travel from one node centre to the other; transportation efficiency is implicitly a function of road quality and access. Let us further assume that we can break down η_{ij} into components directly attributable to each node:

$$\eta_{ij} = \frac{\eta_i + \eta_j}{2} \tag{30}$$

Then

$$t_{ij} = \frac{2d_{ij}}{v_c(\eta_i + \eta_j)} \tag{31}$$

There is also a distribution time within each node. Let us assume a similar relationship between efficiency, a characteristic travel speed, and a linear measure of the size of the node. Then

$$t_i = \frac{\sqrt{A_i}}{v_{c,internal}\eta_i} \tag{32}$$

where A_i is the area of node i and $v_{c,internal}$ is the characteristic speed within the node.

Assume that transportation includes collection within a node, transportation to another node, and then distribution within that node. Further assume that fuel efficiency per mass of food transported is constant with respect to the mass transported. Then

$$C_{ij,fuel} = p_{fuel}\eta_{fuel}\left(\frac{d_{ij}}{\eta_{ij}} + \frac{\sqrt{A_i}}{\eta_i} + \frac{\sqrt{A_j}}{\eta_j}\right) \tag{33}$$

where η_{fuel} is the fuel efficiency in volume fuel per distance, per mass of food transported, p_{fuel} is the price of fuel (per unit volume); fuel efficiency could be modified to become a function of mass transported and/or characteristic velocity.

Assume that labour costs are simply a function of time. Then

$$C_{ij,labour} = p_{labour}\left(\frac{r_{labour,i} + r_{labour,j}}{2} t_{ij} + r_{labour,i} t_i + r_{labour,j} t_j\right) \tag{34}$$

where p_{labour} is the employee (hourly) wage.

With these calculated distribution times, we can then calculate food loss using the method described in Section A.3.4

A.2.4. Storage

Storage operators buy food from crop producers, livestock managers, and distributors, and they sell this food to (other) distributors and consumers. They make decisions about how much food to buy and sell each month as they attempt to maximize their profit subject to maximum storage capacity constraints. In addition to storage costs, storage operators can experience significant food losses over time: food spoils at a rate that grows logistically from the time of harvest. Foresight and finite horizon issues are both significant for storage operators.

To address model foresight, we impose a constraint that forces storage to store no more than a small quantity of food right before harvest. This prevents the hoarding of food from previous years in advance of a failed harvest; without this constraint, storage operators would ration food out more slowly and thereby reduce the severity of the food shortage. Like the crop producer, the storage operator knows the future but is constrained so that that knowledge cannot be fully utilized.

In practice, as farmers get closer to harvest time, they will be better able to estimate the crop yield. That information may encourage the population to begin stockpiling food in preparation for a poor harvest. However, food spoilage and immediate nutrition needs will combine with a short horizon of reliable prediction to limit food storage across harvests significantly. As such, as long as the storage constraint is chosen intelligently, this constraint is relatively robust to shocks.

The rolling time horizon is important because storage operators store food across years. This technique enables storage operators to consider, in year 1, the profit they will make in year 2. This gives them the real-world incentive to continue storing food at the end of the first year.

The optimization for each region is

$$\max U = \sum_{t=1}^{12} (R - C) + \sum_{t=13}^{24} \delta(\widetilde{R} - \widetilde{C}) + \sum_{t=25}^{36} \delta^2(\hat{R} - \hat{C}) \tag{35}$$

$$g_1 = Q_{food,i} - Q_{food,i,max} \leq 0 \tag{36}$$

$$g_2 = -Q_{food,i} \leq 0 \tag{37}$$

$$g_3 = \sum_{food} Q_{food} - Q_{food,clear} \leq 0 \tag{38}$$

$$\begin{aligned} h_{1,n} \; = \; & Q_{food,i,n} - (1 - r_{loss,food,storage,n-1})Q_{food,i,n-1} - \sum_j q^S_{food,transp,j\to i,sell,n} \\ & + \sum_j q^S_{food,transp,i\to j,buy,n} - q^S_{food,store,i,n} + q^S_{food,market,i,n} = 0 \end{aligned} \tag{39}$$

with decision variables

$$q^S_{food,market,i},\ q^S_{food,transp,j\to i,sell},\ q^S_{food,transp,i\to j,buy},\ q^S_{food,store,i} \tag{40}$$

where

$$R = \sum_{food} \left(p_{food,market,i}\, q^S_{food,market,i} + \sum_j p_{food,transfer,i\to j,buy}\, q^S_{food,transp,i\to j,buy} \right) \tag{41}$$

$$\begin{aligned} C \; = \; & \sum_{food} \left(p_{food,store,i}\, q^S_{food,store,i} + \sum_j p_{food,transp,j\to i,sell}\, q^S_{food,transp,j\to i,sell} \right) \\ & + \sum_{food} C_{food} Q_{food,i} \end{aligned} \tag{42}$$

Storage operators purchase food from crop and livestock producers ($q^S_{food,store,i}$), sell to consumers ($q^S_{food,market,i}$), and may both buy and sell with distributors ($q_{food,transp}$). In doing this, they manage the total amount of food in storage ($Q_{food,i}$) to maximize their profit over the three-year period of the rolling time horizon; they have costs for purchasing and storing food, while their revenue comes from selling food. Food losses represented by $(1 - r_{loss,food,storage})$ also reduce the amount of food in storage over time (see Section A.3.4 for food loss calculations).

In addition to this, we constrain the amount of food that can be stored from a previous harvest to limit model foresight artefacts: each region can have no more than $Q_{food,clear}$ in storage when the next harvest happens. This helps to prevent the model from hoarding large amounts of food in anticipation of a failed harvest, as discussed above.

A.2.5. Access/consumer

Consumers purchase food from storage and make decisions about the types and quantities of food to consume so as to maximize their utility. This utility is derived from a demand function that incorporates both dietary preferences and price information. The demand function also implicitly accounts for the value of consuming other goods that the consumer could purchase. In our model, food consumption is disaggregated by age, gender, and per capita income level: income affects demand, whereas age and gender affect relative consumption in each income bracket. Model foresight and finite time horizon effects are not significant for these players because each month's decisions are unconnected to other months' decisions.

We specify the (inverse) demand curves for different food commodities as follows:

$$\mathbf{q_{food}} = r_{month}(\mathbf{a}(I) - \mathbf{B}\mathbf{p_{food}}) \tag{43}$$

$$\mathbf{p_{food}} = \mathbf{B}^{-1}\mathbf{a}(I) - \frac{1}{r_{month}}\mathbf{B}^{-1}\mathbf{q_{food}} \tag{44}$$

The demand is normalized to a 30-day month, so r_{month} is used to account for increased/decreased consumption due to increased/decreased month length. We assume that all foods are normal goods $\left(\frac{d\mathbf{a}}{dI} > 0\right)$ and ordinary goods ($B_{jj} > 0 \quad \forall j$); some foods may be complementary to each other. Then, we assume an Engels curve such that demand grows proportionally to the logarithm of income:

$$\mathbf{a} = \tilde{\mathbf{a}} \log I \tag{45}$$

The utility function U is then

$$U = \int_0^{\mathbf{q_{food}}} \left(\mathbf{B}^{-1}\mathbf{a}(I) - \frac{1}{r_{month}}\mathbf{B}^{-1}\mathbf{q}'_{\mathbf{food}}\right) d\mathbf{q}'_{\mathbf{food}} - \mathbf{p}^T_{\mathbf{food}}\mathbf{q_{food}} \tag{46}$$

$$= \mathbf{q}^T_{\mathbf{food}}\mathbf{B}^{-1}\mathbf{a}(I) - \frac{1}{2r_{month}}\mathbf{q}^T_{\mathbf{food}}\mathbf{B}^{-1}\mathbf{q_{food}} - \mathbf{p}^T_{\mathbf{food}}\mathbf{q_{food}} \tag{47}$$

Note that these quantities and utilities are functions of I (but prices are constant across I). To get the total quantities for a particular income group – $I \in [I_1, I_2]$ – integrate over

$$N_{pop} \int_{I_1}^{I_2} \mathbf{q}(I)\rho_I(I)dI \tag{48}$$

Let us further consider consumption broken down by age and gender. Assume that there is a joint population density function of income, I, age a, and gender g: $\rho(I,a,g)$. We also require a function $w(a,g)$ to account for the difference in consumption between different age/gender groups – w is average consumption as a fraction of an average adult baseline (e.g., for a 3-year old male eating 20% as much as an adult male, $w(3,m) = .2$). Note that w is assumed to be independent of income. Then

$$\mu_{w|I} = \int w(a, g)\rho_{a,g}(a, g|I)dadg \tag{49}$$

$$q(I, a, g) = \frac{w(a, g)}{\mu_{w|I}}q(I) \tag{50}$$

The integral in question would in fact end up being a summation over the two different values of g. For this model, we assume that income, age, and gender distributions are all independent of each other: $\rho(I,a,g) = \rho_g(g)\rho_a(a)\rho_I(I)$. Other joint distributions could be used with the above equations, however.

The optimization for consumers is then

$$\max \sum_{t=1}^{12} U(t) + \sum_{t=13}^{24} \delta\tilde{U}(t) + \sum_{t=25}^{36} \delta^2\hat{U}(t) \tag{51}$$

$$U(t) = \mathbf{q}^T_{food,t}\mathbf{B}^{-1}\mathbf{a}(I) - \frac{1}{2r_{month}}\mathbf{q}^T_{food,t}\mathbf{B}^{-1}\mathbf{q}_{food,t} - \mathbf{p}^T_{food,t}\mathbf{q}_{food,t} \tag{52}$$

with $q_{food} = q^A_{food,market,i}$, $p_{food} = p_{food,market,i}$; the notation is simplified for readability. To account for income distributions and population levels, we then end up with

$$q^S_{food,market,i} - \int N_{pop}q^A_{food,market,i}(I)\rho_I(I)dI = 0 \tag{53}$$

This ensures that the total amount of food consumed is the same as the amount purchased from storage.

A.3. Model analyses

Our model also has several components that could be described as non-player technical components – analysis modules that have no optimization or decision-making associated with them. The most significant of these is the crop model, which is based on a simplified crop model created by DSSAT researchers (Porter et al., 1999). This crop model is a biophysical, process-based model that combines temperature and precipitation data with soil and plant-specific properties to yield rates and harvest times. The crop model is driven by downscaled climatological data and soil properties, and we have incorporated harvest losses into the final number produced. We also have components that calculate how temperature and precipitation affect milk production rates. A final component calculates labour productivity as a function of nutrition.

The calculations shown in this section either are not directly associated with a single player or are not solved in the MCP. For example, the utilization calculations are solved in the MCP, but they are not explicitly part of an optimization; the productivity factor calculated there appears in several players' optimizations, but it is not directly controlled by any of them. Conversely, the crop yield parameters are calculated as a preprocessing step and then held constant in the crop producer's optimization (i.e., also not directly controlled).

A.3.1. Utilization and health

The analysis equations for utilization and health are as follows:

$$q_{food,a,g,I}(a, g, I) = (1 - r_{loss,food,utilization})\frac{w(a, g)}{\mu_{w|I}}q^A_{food,market,i}(I) \tag{54}$$

$$\mu_{w|I} = \int w(a, g)\rho_{a,g}(a, g|I)dadg \tag{55}$$

$$\nu_{actual} = \gamma_{nutrient}\mathbf{q}_{food,a,g,I} \tag{56}$$

$$\boldsymbol{\nu}_{working} = \int \boldsymbol{\nu}_{actual}(a \geq 16, g = \text{male}, I)\rho_I(I)dI \tag{57}$$

where $\gamma_{nutrient}$ is a matrix of calories, protein, and aggregate micronutrients per unit mass for different food commodities, and $\boldsymbol{\nu}$ is a vector of calories, protein, and micronutrients. To denote labour productivity, we use a function of the form

$$r_{labour} = \exp(-\boldsymbol{\alpha}_{labour}^T \boldsymbol{\nu}_{working}) + 1 \tag{58}$$

where $\boldsymbol{\alpha}_{labour}$ is a vector parameter to be determined empirically, and $\boldsymbol{\nu}_{working}$ is the average nutrient intake for working-age males over all income levels; $r_{labour,ave}$ is the average value of r_{labour} over the course of a given year. Essentially, r_{labour} is an inverse measure of productivity. As nutrition decreases, r_{labour} increases and productivity decreases.

A.3.2. Soil

We divide up soil into 3 classes of soil quality s_q and 3 classes of soil fertility s_f, each with high, medium, and low values (s_q or s_f = 1, 2, or 3, respectively). Soil quality represents characteristics such as soil density, porosity, and structure, and it affects water retention (i.e., how much of the precipitation the soil can hold for the crops) and final yield. Soil fertility represents nutrient availability in the soil, and it affects final yield. For the time being, we consider these to be constant over time.

In calculating final yield, we use

$$r_{sq} = \begin{cases} 1 & s_q = 1 \\ 0.7 & s_q = 2 \\ 0.4 & s_q = 3 \end{cases} \tag{59}$$

$$r_{sf} = \begin{cases} 1 & s_f = 1 \\ 0.7 & s_f = 2 \\ 0.4 & s_f = 3 \end{cases} \tag{60}$$

For water retention, the amount of water available to the plants on a given day, $d_{water,n}$, is

$$d_{water,n} = r_{sq} d_{precip,n} + r_{sq}^{\alpha_{soil}} d_{water,n-1} \tag{61}$$

where $d_{precip,n}$ is the precipitation, in metres, on day n and α_{soil} is a calibrated parameter. This model accounts for the role that soil quality plays in the retention of precipitation and existing water in the ground.

A.3.3. Crop modelling

If planting times d_{plant} are fixed (or calculated from weather data), yields and harvest times can be calculated from weather data. We determine the sowing date by soil moisture content: sowing happens Δd_{early} days before soil moisture reaches $d_{water,threshold}$. Thus

$$d_{plant} = d_{thresh} - \Delta d_{early} \tag{62}$$

$$d_{water}(t = d_{thresh} - 1) < d_{water,thresh} \leq d_{water}(t = d_{thresh}) \tag{63}$$

Each crop, furthermore, has potential harvests in the belg and kremt seasons, but we assume that land used in the belg season cannot be used in the kremt season, and vice versa. If the potential sowing date lands too late – after the end of the sowing season $d_{season,end}$– there is no crop for that season. Crop growth consists of two parts: vegetative growth and food production/growth. Both proceed on a daily time step. For vegetative growth

$$L_n = L_{n-1} + \Delta L_n \tag{64}$$

$$\Delta L = r_{water} r_{temp} \rho_{plant} \Delta A_{leaf,max} \Delta N \frac{a}{1 + a} \tag{65}$$

$$r_{temp} = 1 - 0.0025(0.25T_{min} + 0.75T_{max} - 26)^2 \tag{66}$$

$$a = e^{2\alpha_1(N-\alpha_2)} \tag{67}$$

$$N_n = N_{n-1} + \Delta N_n \tag{68}$$

$$\Delta N = r_{temp} \Delta N_{max} \tag{69}$$

where L is leaf area index, ρ_{plant} is the plant density, $\Delta A_{leaf,max}$ is the maximum leaf area expansion per leaf, N is the leaf number (a measure of plant maturity), and the α parameters are empirical constants. Once $N \geq N_{mature}$, we enter reproductive growth (i.e., seed/food):

$$m_{h,n} = m_{h,n-1} + \Delta m_{h,n} \tag{70}$$

$$\Delta m_h = 2.1 r_{water} r_{temp} E_{PAR}(1 - e^{-Y_1 L}) \tag{71}$$

$$Y_1 = 1.5 - 0.768[(\delta_{row})^2 \rho_{plant}]^{0.1} \tag{72}$$

$$\Delta L = -\rho_{plant} \Delta I \Delta A_{remove} \rho_{SLA} \tag{73}$$

$$\Delta I = \begin{cases} T_{mean} - T_{base} & \text{if} \quad T_{base} \leq T_{mean} \leq 25 \\ 0 & \text{else} \end{cases} \tag{74}$$

$$I_n = I_{n-1} + \Delta I_n \tag{75}$$

$$L_n = L_{n-1} + \Delta L_n \tag{76}$$

where m_h is the total fruit/seed mass, E_{PAR} is the density of photosynthetically active radiation, δ_{row} is the row spacing, I is the accumulated temperature after the reproductive stages starts, ρ_{SLA} is the specific leaf area, and T_{base} is the base temperature above which reproductive growth occurs. To calculate r_{water}, we use

$$r_{water} = 1 - \exp\left(-\frac{d_{water}\ln 2}{\alpha_{water}\rho_{plant}}\right) \tag{77}$$

where α_{water} is a crop-specific parameter describing the water needs of the plant; high values indicate high water needs and vice versa. The crop is mature once $I \geq I_{tot}$, where I_{tot} is the duration of the reproductive stage in degree days. We can then calculate the crop yield

$$m_{crop} = \begin{cases} m_h & \text{in its harvest month} \\ 0 & \text{else} \end{cases} \tag{78}$$

For now, we assume that no fertilizer is used and that final yield can be reduced based on soil quality and fertility/nutrient availability after the rest of the crop model has been calculated:

$$Y_{crop} = \sum_{season} m_{crop,season}A_{crop,season}r_{sq}r_{sf} \tag{79}$$

This biophysical crop model gives us a bottom-up approach for connecting weather data to yield and harvest dates. For this study, the biophysical model was less important than it otherwise might have been – it would have been more important if we had included inputs like irrigation and fertilizer (which we examined in analyses outside of this paper). Similarly, if we had specified a specific weather shock, rather than just a certain percentage loss, this approach may have been more useful than a statistical or black-box model. Choosing the biophysical model instead of a statistical model was more in the interest of creating a basis for future work, though we deliberately built Food-DECO to be modular with respect to the type of crop model.

A.3.4. Food loss

We use a logistic curve to represent the fraction of food in storage lost each month due to spoilage ($r_{food,loss}$). The argument of the logistic function is the time that has passed since the last harvest in the region, $t_{effective}$, and that time is then scaled by the storage quality available in the region $\alpha_{q,storage}$. To orient this food loss curve, we use a 'half-life' concept – we consider the amount of time it would take for 50% of the food to spoil, τ_{food}. Distribution uses the same approach, but the storage quality is much lower, and the time under consideration is much shorter; the reference harvest used is that of the region exporting the food. In general, then, the food loss fraction is calculated as follows:

$$r_{food,loss} = \frac{1}{1 + \exp\left(-\beta\left(\frac{t_{effective}}{\alpha_{q,storage}\tau_{food}} + 1\right)\right)} \tag{80}$$

where β is a shape parameter used for calibration.

A.4. Crop failure and intervention modelling

To model crop failure, we simply reduced the crop yield in E Oromia for the year in question. We did not change the crop yield in the advisory years from previous time steps, so even with foresight, the model players did not 'see' the failure until the year in which it happens, but they did see it as soon as that year began. Their ability to react to that anticipated failure is limited through constraints that we impose on the model, however; see earlier player descriptions for more detail on those constraints and how they approximate behaviour with limited foresight.

Modelling interventions required modifying the original equations of the model to account for how particular interventions change market conditions. We list the intervention components of the model here.

Direct food aid directly deposits food into storage in a region ($q_{food,aid}$). The changed equation is one of the storage operator's constraints:

$$Q_{food,i,n} - (1 - r_{loss,food,storage,n-1})Q_{food,i,n-1} - \sum_j q^S_{food,transp,j\to i,sell,n} + \sum_j q^S_{food,transfer,i\to j,buy,n} - q^S_{food,store,i,n} + q^S_{food,market,i,n} - q_{food,aid} = 0 \tag{81}$$

There is a possibility that, under certain circumstances, this food aid could overwhelm the ability of a region to store food, but barring truly massive deposits of food, this is unlikely: the magnitude of the food aid will likely be comparable to what was lost from the harvest, so the total amount stored will not change much; there is the ability to export that food to other regions, so any excess food could be disposed of profitably; and with that much food available, prices will drop and consumption will rise to reduce the amount of stored food.

There are also potential questions about the logistics of how food is distributed and who benefits from it. This is somewhat outside the scope of our current model, but it relates to the shadow price discussion at the end of Section 2.1. If the model is agnostic with regards to the identity of the storage operators (including whether or not they are the same individuals producing the food in the first place), then depositing food directly into storage is similarly agnostic with regards to the identity of the food aid recipients. Moreover, the food provided by food aid has value and opportunity costs just like locally harvested food.

Direct cash aid temporarily gives money to people to increase their income ($I_{cash,transfer}$). The demand curve intercept for a given month in which direct cash aid is given is then

$$\mathbf{a} = \log(I + 12I_{cash,transfer})\tilde{\mathbf{a}} \tag{82}$$

where the factor of 12 turns a monthly transfer into an equivalent change in yearly income. Consumer subsidies involve the government paying a percentage of the food price for the consumer ($r_{sub,consumer}$). This changes the apparent price of food for consumers, and thus the utility function for customers becomes

$$U(t) = \mathbf{q}_{food,t}^{T}\mathbf{B}^{-1}\mathbf{a}(I) - \frac{1}{2r_{month}}\mathbf{q}_{food,t}^{T}\mathbf{B}^{-1}\mathbf{q}_{food,t} - (1 - r_{sub,consumer})\mathbf{p}_{food,t}^{T}\mathbf{q}_{food,t} \tag{83}$$

With producer subsidies, the government pays an extra percentage to farmers for food produced ($r_{sub,producer}$). This changes the apparent price that producers get for the food commodities they sell without actually increasing the prices that storage operators pay. Thus for crop producers, revenue is

$$R = \sum_{crop}(1 + r_{sub,producer,crop})p_{crop,store,i}\,q_{crop,store,i}^{C} \tag{84}$$

and for livestock producers, revenue is

$$R = (1 + r_{sub,producer,milk})p_{milk,store,i}\,q_{milk,store,i}^{L} + (1 + r_{sub,producer,beef})p_{beef,store,i}\,q_{beef,store,i}^{L} + \sum_{j} p_{cattle,transp,i\to j,buy}\,q_{cattle,transp,i\to j,buy}^{L} + q_{beef,store,i}^{L}\frac{p_{hide}}{m_{cow}r_{meat}} \tag{85}$$

Increasing transportation capacity does not change any equations. It simply multiplies $q_{transp,capacity}$ for a set time period.

For the studies conducted in this paper, all of the interventions were applied over whole years. With the exception of the transportation expansion (which was applied to the entirety of the model timeframe), the interventions did not show up in advisory years. As with the crop failure, therefore, the players did not know of the interventions until the year in which they occurred. Applying the interventions over whole years in this way helped to simplify some of the player foreknowledge issues regarding the implementation of interventions.

We then chose to apply the interventions during years appropriate to the type of intervention: direct food aid, direct cash aid, and consumer subsidies were applied to the year after the crop failure (i.e., the year that would have relied on the food from the failed harvest), and the producer subsidies were applied during the year of the crop failure (to boost production in anticipation of lower yields). The transportation intervention covers the years of interest, which is sufficient to investigate how that increased capacity would interact with a crop failure. It would be possible to time the interventions more precisely, but given that the main harvest typically happens around the tenth month of the year, using yearly boundaries is sufficient for our present purposes.

A.5. Model calibration

For our representative case study, we performed some moderate calibration work so that we could run the model and obtain qualitative insights. The goal here was to motivate further model development and more detailed calibration work. Some model parameters such as region population and area were directly imported from established data sources such as the Ethiopia Central Statistical Agency (http://www.csa.gov.et/). Such parameters also included the distances between regions, which were measured from maps, and relative consumption by age and gender (Strauss, 1986). Other model parameters had to be calibrated by matching model outputs to existing data as described below.

Crop model calibration used reported crop areas and harvest production from Ethiopian agricultural census data (CSA, 2010/2011), downscaled temperature and precipitation data, and local knowledge about multicropping behaviour to modify crop model parameters so as to produce reasonable yield results. For the simulations presented in this study, daily minimum and maximum air temperature estimates were drawn from version 2 of the NASA Modern-Era Reanalysis for Research and Applications (MERRA2) (Rienecker et al., 2011) topographically downscaled to 0.05 degree resolution, and daily rainfall came from the 0.05° resolution Climate Hazards Group InfraRed Precipitation with Stations version 2 (CHIRPSv2) (Funk et al., 2015) merged satellite and gauge gridded dataset. Gridded meteorological fields were averaged for each DECO region, and the climate data for years 1 to 6 of the model were taken from 2001 to 2006, respectively.

We then considered consumer demand, livestock parameters (population, milk production, and reproductive rates), and transportation capacity. We started with approximate figures regarding livestock population (CSA, 2010/2011), milk production (Bohmanova et al., 2007; Kadzere et al., 2002), and livestock reproduction rates (Bellemare and Barrett, 2006). From those baseline numbers, we used nutrition and diet composition statistics (EPHI, 2013) as calibration targets to match by varying our food demand, livestock, and transportation capacity parameters.

Next, we fit income quintile and mean income data (Index Mundi, 2016; World Bank, 2016) to a log-normal distribution and used that to come up with average income and population proportions for our model's income brackets. We used a logarithmic Engels curve on that average income data to vary demand with income. Finally, we used existing data on nutrition and relative labour productivity (Kraut and E.A., 1946; Viteri and Torún, 1975) to calibrate our nutrition-productivity model component.

References

CSA, 2010/2011. Agricultural sample survey. In: Tech. rep. The Federal Democratic Republic of Ethiopia Central Statistical Agency, Addis Ababa.
CSA, 2010/2011. Report on livestock and livestock characteristics. Tech. rep. The Federal Democratic Republic of Ethiopia Central Statistical Agency, Addis Ababa.
Admassie, A., 2013. The political economy of food price: the case of Ethiopia. In: 2013/001 WIDER Working Paper.
Antle, J.M., Basso, B., Conant, R.T., Godfray, H.C.J., Jones, J.W., Herrero, M., Howitt, R.E., Keating, B.A., Munoz-Carpena, R., Rosenzweig, C., et al., 2016a. Towards a New Generation of Agricultural System Data, Models and Knowledge Products: Design and Improvement. Agricultural Systems.
Antle, J.M., Jones, J.W., Rosenzweig, C.E., 2016b. Next Generation Agricultural System Data, Models and Knowledge Products: Introduction. Agricultural Systems.
Bellemare, M.F., Barrett, C.B., 2006. An ordered tobit model of market participation: evidence from Kenya and Ethiopia. Am. J. Agri. Econ. 88, 324–337.
Bohmanova, J., Misztal, I., Cole, J.B., 2007. Temperature-humidity indices as indicators of milk production losses due to heat stress. J. Dairy Sci. 90, 1947–1956.
Brown, M.E., Hintermann, B., Higgins, N., 2009. Markets, climate change, and food security in West Africa. Environ. Sci. Technol. 43 (21), 8016–8020.
Butt, T.A., McCarl, B.A., Angerer, J., Dyke, P.T., Stuth, J.W., 2005. The economic and food security implications of climate change in mali. Clim. Change 68 (3), 355–378.
Buurman, M., Câmara, G., de Carvalho, A.Y., Jones, J., Cartaxo, R., Mosnier, A., Pirker, J., Andrade, P., Affonso, P., Soterroni, A., et al., 2015. Description of the globiom-brazil database available in the RED-PAC WFS server. In: Tech. rep..
Calvin, K., Wise, M., Clarke, L., Edmonds, J., Kyle, P., Luckow, P., Thomson, A., 2013. Implications of simultaneously mitigating and adapting to climate change:Initial experiments using GCAM. Clim. Change 117, 545–560.
Cameroni, F.D., Fort, H., 2017. Towards scientifically based management of extensive livestock farming in terms of ecological predator-prey modeling. Agric. Syst. 153, 127–137.

CSA, 2015/2016. Report on area and production of major crops. In: Tech. rep. The Federal Democratic Republic of Ethiopia Central Statistical Agency, Addis Ababa.
EPHI, 2013. Ethiopian national food consumption survey. In: Tech. rep. Ethiopian Public Health Institute, Addis Ababa.
Ermolieva, T.Y., Ermoliev, Y.M., Havlik, P., Mosnier, A., Leclere, D., Kraksner, F., Khabarov, N., Obersteiner, M., 2015. Systems analysis of robust strategic decisions to plan secure food, energy, and water provision based on the stochastic globiom model. Cybern. Syst. Anal. 51 (1), 125–133.
FAO, 1996, nov. Rome declaration on world food security and world food summit plan of action. In: Tech. rep. FAO, Rome, Italy.
FAO, 2011. Global food losses and food waste ? Extent, causes and prevention. In: Tech. rep. FAO, Rome, Italy.
Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., Husak, G., Rowland, J., Harrison, L., Hoell, A., et al., 2015. The Climate Hazards Infrared Precipitation with Stations - A New Environmental Record for Monitoring Extremes. Scientific Data. 2 150,066.
Gabriel, S.A., Conejo, A.J., Fuller, J.D., Hobbs, B.F., Ruiz, C., 2012. Complementarity Modeling in Energy Markets. Springer, New York.
Gerber, P., Steinfeld, H., Henderson, B., Mottet, A., Opio, C., Dijkman, J., Falcucci, A., Tempio, G., 2013. Tackling climate change through livestock ? A global assessment of emissions and mitigation opportunities. In: Tech. rep. FAO, Rome, Italy.
Harding, R., Wantchekon, L., 2012. Food security and public investment in rural infrastructure: some political economy considerations. In: UNDP African Human Development Report, pp. 2012–2017.
Havlik, P., Schneider, U.A., Schmid, E., Böttcher, H., Fritz, S., Skalskỳ, R., Aoki, K., De Cara, S., Kindermann, G., Kraxner, F., Leduc, S., McCallum, I., Mosnier, A., Sauer, T., Obersteiner, M., 2011. Global land-use implications of first and second generation biofuel targets. Energy Policy 39, 5690–5702.
Huppmann, D., Egging, R., 2014. Market power, fuel substitution and infrastructure - a large-scale equilibrium model of global energy markets. Energy 75, 483–500.
Mundi, Index, 2016. Ethiopia - income distribution. URL http://www.indexmundi.com/facts/ethiopia/income-_distribution, accessed May 8, 2017.
Ivanic, M., Martin, W., Zaman, H., 2012. Estimating the short-run poverty impacts of the 2010–11 surge in food prices. World Dev. 40 (11), 2302–2317.
Janssen, S., van Ittersum, M.K., 2007. Assessing farm innovations and responses to policies: a review of bio-economic farm models. Agric. Syst. 94, 622–636.
Jones, A.D., Ngure, F.M., Pelto, G., Young, S.L., 2013. What are we assessing when we measure food security? A compendium and review of current metrics. Adv. Nutr. 4, 481–505.
Jones, J.W., Antle, J.M., Basso, B., Boote, K.J., Conant, R.T., Foster, I., Godfray, H.C.J., Herrero, M., Howitt, R.E., Janssen, S., et al., 2016a. Brief history of agricultural systems modeling. Agric. Syst. 155, 240–254.
Jones, J.W., Antle, J.M., Basso, B., Boote, K.J., Conant, R.T., Foster, I., Godfray, H.C.J., Herrero, M., Howitt, R.E., Janssen, S., et al., 2016b. Toward a new generation of agricultural system data, models, and knowledge products: State of agricultural systems science. Agric. Syst. 155, 269–288.
Kadzere, C.T., Murphy, M.R., Silanikove, N., Maltz, E., 2002. Heat stress in lactating dairy cows: A review. Livest. Prod. Sci. 77, 59–91.
Kolstad, C.D., Burris, A.E., 1986. Imperfectly competitive equilibria in international commodity markets. Am. J. Agric. Econ. 68, 27–36.
Kraucunas, I., Clarke, L., Dirks, J., Hathaway, J., Hejazi, M., Hibbard, K., Huang, M., Jin, C., Kintner-Meyer, M., van Dam, K.K., et al., 2015. Investigating the nexus of climate, energy, water, and land at decision-relevant scales: the platform for regional integrated modeling and analysis (prima). Clim. Change 129 (3-4), 573–588.
Kraut, H., Muller, E.A., 1946. Calorie intake and industrial output. Science (Washington). pp. 495–497.
McCown, R., Hammer, G., Hargreaves, J., Holzworth, D., Freebairn, D., 1996. APSIM: a novel software system for model development, model testing and simulation in agricultural systems research. Agric. Syst. 50 (3), 255–271.
Moore, N., Alagarswamy, G., Pijanowski, B., Thornton, P., Lofgren, B., Olson, J., Andresen, J., Yanda, P., Qi, J., 2012. East african food security as influenced by future climate change and land use change at local to regional scales. Clim. Change 110 (3-4), 823–844.
Munson, T.S., Ferris, M.C., 2000. Complementarity problems in GAMS and the PATH solver. J. Econ. Dyn. Control. 24, 165–188.
Nardone, A., Ronchi, B., Lacetera, N., Ranieri, M., Bernabucci, U., 2010. Effects of climate changes on animal production and sustainability of livestock systems. Livest. Sci. 130, 57–69.
Nelson, G.C., van der Mensbrugghe, D., Ahammad, H., Blanc, E., Calvin, K., Hasegawa, T., Havlik, P., Heyhoe, E., Kyle, P., Lotze-Campen, H., von Lampe, M., d'Croz, D.M., van Meijl, H., Müller, C., Reilly, J., Robertson, R., Sands, R.D., Schimtz, C., Tabeau, A., Takahashi, K., Valin, H., Willenbockel, D., 2014. Agriculture and climate change in global scenarios: why don't the models agree. Agric. Econ. 45, 1–17.
Pindyck, R.S., 2013. Climate change policy: what do the models tell us? J. Econ. Lit. 51, 860–872.
Pirie, G.H., 1993. Transport, food insecurity and food aid in sub-Saharan Africa. J. Transp. Geogr. 1 (1), 12–19.
Porter, C., Braga, R., Jones, J., 1999, aug, aug. A modular approach for crop model development. In: Tech. Rep. Agricultural and Biological Engineering Department, University of Florida, Gainsville, Florida.
Rienecker, M., Suarez, M., Gelaro, R., Todling, R., Bacmeister, J., Liu, E., Bosilovich, M., Schubert, S., Takacs, L., Kim, G.-K., et al., 2011. MERRA: NASA's modern-era retrospective analysis for research and application. J. Clim. 24, 3624–3648.
Robert, M., Dury, J., Thomas, A., Therond, O., Sekhar, M., Badiger, S., Ruiz, L., Bergez, J.-E., 2016a. Cmfdm: a methodology to guide the design of a conceptual model of farmers' decision-making processes. Agric. Syst. 148, 86–94.
Robert, M., Thomas, A., Bergez, J.-E., 2016b. Processes of adaptation in farm decision-making models. a review. Agron. Sustain. Dev. 36, 64.
Robertson, M.J., Pannell, D.J., Chalak, M., 2012. Whole-farm models: a review of recent approaches. Aust. Farm Bus. Manag. J. 9, 13–26.
Robinson, S., van Meijl, H., Willenbockel, D., Valin, H., Fujimori, S., Sands, R., Wise, M., Calvin, K., Havlik, P., d'Croz, D.M., Tabeau, A., Kavallari, A., Schmitz, C., Dietrich, J.P., von Lampe, M., 2014. Comparing supply-side specifications in models of global agriculture and the food system. Agric. Econ. 45, 21–35.
Rosegrant, M.W., Team, T.I.D., 2012, jul, jul. International model for policy analysis of agricultural commodities and trade (IMPACT) model description. In: Tech. rep. International Food Policy Research Institute, Washington, D.C..
Rosenzweig, C., Jones, J.W., Hatfield, J.L., Ruane, A.C., Boote, K.J., Thorburn, P., Antle, J.M., Nelson, G.C., Porter, C., Janssen, S., Asseng, S., Basso, B., Ewert, F., Wallach, D., Baigorria, G., Winter, J.M., 2013. The agricultural model intercomparison and improvement project (AgMIP): protocols and pilot studies. Agric. For. Meteorol. 170, 166–182.
Rutten, M., Van Dijk, M., van Rooij, W., Hilderink, H., 2014. Land use dynamics, climate change, and food security in vietnam: a global-to-local modeling approach. World Dev. 59, 29–46.
Searchinger, T., Hanson, C., Ranganathan, J., Lipinski, B., Waite, R., Winterbottom, R., Dinshaw, A., Heimlich, R., 2014. Creating a sustainable food future: interim findings. In: Tech. rep. World Resources Institute, Washington, D.C..
Shanbhag, U., Infanger, G., Glynn, P., 2011. A complementarity framework for forward contracting under uncertainty. Oper. Res. 59, 810–834.
Shortridge, J.E., Falconi, S.M., Zaitchik, B.F., Guikema, S.D., 2015. Climate, agriculture, and hunger: statistical prediction of undernourishment using nonlinear regression and data-mining techniques. J. Appl. Stat. 42, 2367–2390.
Springmann, M., Mason-D'Croz, D., Robinson, S., Garnett, T., Godfray, H.C.J., Gollin, D., Rayner, M., Ballon, P., Scarborough, P., 2016. Global and regional health effects of future food production under climate change: a modelling study. Lancet 387 (10031), 1937–1946.
Strauss, J., 1986. Does better nutrition raise farm productivity? J. Polit. Econ. 94, 297–320.
Thornton, P.K., van de Steeg, J., Notenbaert, A., Herrero, M., 2009. The impacts of climate change on livestock and livestock systems in developing countries: a review of what we know and what we need to know. Agric. Syst. 101, 113–127.
USAID, 2000. Map of regions and zones in Ethiopia as of April 2000. URL https://www.commons.wikimedia.org/wiki/File\%3AEthiopia_zone_region.jpg, accessed May 8, 2017.
van Wijk, M., Rufino, M., Enahoro, D., Parsons, D., Silvestri, S., Valdivia, R., Herrero, M., 2014. Farm household models to analyse food security in a changing climate: a review. Glob. Food Sec. 3, 77–84.
Viteri, F., Torún, B., 1975. Ingestión calórica y trabajo fisico de obreros agrícolas en Guatemala. efecto de la suplementación alimentaria y su lugar en los programas de salud. Bol. Oficina Sanit. Panam. 78, 58–74.
von Lampe, M., Willenbockel, D., Ahammad, H., Blanc, E., Cai, Y., Calvin, K., Fujimori, S., Hasegawa, T., Havlik, P., Heyhoe, E., Kyle, P., Lotze-Campen, H., d'Croz, D.M., Nelson, G.C., Sands, R.D., Schimtz, C., Tabeau, A., Valin, H., van der Mensbrugghe, D., van Meijl, H., 2014. Why do global long-term scenarios for agriculture differ? An overview of the AgMIP global economic model intercomparison. Agric. Econ. 45, 1–18.
Wheeler, T., von Braun, J., 2013. Climate change impacts on global food security. Science 341, 508–513.
Woltjer, G.B., Kuiper, M., Kavallari, A., van Meijl, H., Powell, J., Rutten, M., Shutes, L., Tabeau, A., 2014. The magnet model: Module description. In: Tech. rep. LEI Wageningen UR.
World Bank, 2016. Ethiopia overview. URL http://www.worldbank.org/en/country/ethiopia/overview, accessed May 8, 2017.