



# Food security outcomes in agricultural systems models: Case examples and priority information needs

Charles F. Nicholson<sup>a,h,\*</sup>, Emma C. Stephens<sup>b</sup>, Birgit Kopainsky<sup>c</sup>, Philip K. Thornton<sup>d</sup>, Andrew D. Jones<sup>e</sup>, David Parsons<sup>f</sup>, James Garrett<sup>g</sup>

<sup>a</sup> Nijmegen School of Management, Radboud University, Netherlands

<sup>b</sup> Lethbridge Research and Development Centre, Agriculture and Agrifood Canada, Canada

<sup>c</sup> University of Bergen, Norway

<sup>d</sup> CGIAR Research Program on Climate Change, Agriculture and Food Security, International Livestock Research Institute (ILRI), Nairobi, Kenya

<sup>e</sup> University of Michigan, USA

<sup>f</sup> Swedish University of Agricultural Sciences, Sweden and Tasmanian Institute of Agriculture, Australia

<sup>g</sup> Alliance of Bioversity and CIAT, Italy

<sup>h</sup> School of Integrative Plant Science, Cornell University, USA

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## ABSTRACT

Analyses of food security with agricultural systems models often focus on indicators of food availability, with limited treatment of the other three dimensions: food access, stability and utilization. We illustrate how three indicators of access (food consumption expenditures, a food insecurity scale and dietary diversity) and their stability can be incorporated into a dynamic household-level model of a maize-based production system in the Kenya highlands and a dynamic regional model of sheep production and marketing in Mexico. Although stylized due to limits on empirical evidence, the analyses suggest that inclusion of multiple access indicators can provide insights because the indicators respond differently to production shocks, demand growth and programs providing production subsidies. We also illustrate how to examine stability of food security outcomes in response to shocks using metrics of hardness (ability to withstand shocks) and elasticity (ability to return to previous conditions). The data required for more widespread empirical implementation of these methods include measurement—preferably at frequent intervals over time—of food access indicators, but also their determinants and linkages to outcomes in agricultural systems models. Analyses of food access and stability will be most valuable for assessments of food security impacts of climate change, when food systems are undergoing transformative change and to identify priority interventions and target audiences.

## 1. Introduction

Food security is increasingly invoked as a critical motivational factor in agricultural systems research, as a trend within a broader movement towards nutrition-sensitive agriculture (FAO, 2013). Stephens et al. (2018) documented significant gaps in the literature spanning the agricultural systems and food security research communities, with limited exploration of the multiple intersections and interfaces between agricultural system components and food security determinants and outcomes. In a companion paper (Nicholson et al., 2021), we described common indicators of four dimensions of food security (availability, access, utilization and stability), documented their use in agricultural

systems models analyzing food security, and recommended actions to improve the representation of food security in agricultural systems models. The main objectives of this manuscript are to 1) complement the discussion in the companion paper through case examples of how to implement the four recommendations, and to illustrate the potential benefits of doing so, and 2) identify the priority information needs and approaches to allow for practical implementation of these recommendations in a larger number of agricultural systems models.

Our linked paper made four recommendations about how to improve the representation of food security in agricultural systems models, as follows:

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\* Corresponding author at: Nijmegen School of Management, Radboud University, Netherlands.

E-mail address: [cfn1@cornell.edu](mailto:cfn1@cornell.edu) (C.F. Nicholson).

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- 1) Avoid equating “food availability” with “food security”;
- 2) Incorporate food access indicators;
- 3) Assess stability outcomes for food security indicators;
- 4) Develop empirical evidence linking outcomes in agricultural systems models to food access outcomes.

The first of these recommendations concerns primarily the language used to describe research results, so will not be further discussed here. The last of the recommendations is discussed in the previous manuscript and in greater detail below. Our focus here is on the process and challenges of implementing recommendations 2) and 3). We modified two existing dynamic simulation models to serve as case examples. For consistency with our assessment of the literature in the companion paper, one of the models is of a household and the other is a regional model. For each model, we illustrate the process required to adapt the model structure, data inputs and outputs to accomplish the recommendations related to food access and stability. Our focus is on the general lessons that can be learned from this process that may facilitate the achievement of these objectives in other model analyses, and less on the detailed results of model simulations themselves. Thus, the purpose is to provide a template for integration of relevant food security indicators in agricultural systems models and demonstrate the usefulness of this integration.

## 2. Case examples for integration of food security indicators into agricultural systems models

### 2.1. Including food security indicators in CLASSES

#### 2.1.1. Introduction to CLASSES

CLASSES is a bio-economic system dynamics model of a small mixed enterprise farming system, calibrated with survey data on smallholder producers managing a portfolio of maize, livestock, Napier grass and tea in Kenya (Stephens et al., 2012). Several key agricultural and economic systems are represented, including tracking dynamic behavior of key soil nutrients and organic matter stocks. Activities include crop production for representative food, forage and cash crops, livestock investment and management for dairy production. A decision-making structure allows for the household to continually adjust land and labor resources towards their highest returns on the farm. Because CLASSES was designed to evaluate longer-term poverty-trap dynamics, the model uses quarterly time units.

#### 2.1.2. Data and assumptions to include food security indicators in CLASSES

We noted in the companion manuscript that appropriate model structure and data availability are two key challenges for including food access indicators in agricultural systems models. In particular, we noted the desirability of determining food consumption decisions within the model structure using economic logic. To include food consumption expenditures in CLASSES, the model structure needed to be modified to provide linkages between factors such as income (and savings) and food consumption expenditures that had not been previously included. We modified CLASSES using one approach in the existing literature (e.g., Wossen et al., 2018), adding consumption functions for five food item categories (cereals, animal source foods, oils, fruits and vegetables and other). The use of information from Wossen et al. highlights the need for a better empirical evidence base in this setting. The consumption functions are based on the net income to the household relative to the total expenditure required for the household to consume the minimum recommended quantities of each of the five food items and make adjustments to consumption choices when there are cash constraints. (See Appendix 1 for additional detail.)

We also modified the model structure to include the other two indicators of food access recommended in the companion paper, the Food Insecurity Experience Scale (FIES) and the Household Dietary Diversity

Score (HDDS). FIES and a similar construct the Household Food Insecurity Access Scale (HFIAS) both use a series of yes/no questions to assess the food security experience of an individual or household. The Household Dietary Diversity Scale (HDDS) measures the quantity and quality of food access at the household level by measuring consumption of 12 food groups by any household member in the previous 24 h. Based on the literature of the empirical determinants of FIES and HDDS (summarized in Table 3 of the companion paper), we linked these two indicators of food access to both model inputs (household size, number of dependent children and education of household head) and model outputs (wealth, net income, and off-farm income). In practice, FIES and HDDS are the summed responses to a series of yes/no questions, resulting in integer-value scores. For FIES, a higher score implies a higher degree of food insecurity (lower food security). A higher score of HDDS implies greater dietary diversity and thus lower food insecurity (higher food security). We used thresholds for linking variables in CLASSES to the FIES and HDDS food security indicators, starting with assumed base values, to which integer additions or subtractions from the base value were made when values from CLASSES reached the thresholds.

Specification of the structure of the linkages in CLASSES was reasonably straightforward, although we acknowledge that other agricultural systems models have adopted more sophisticated demand relationships based on utility maximization (e.g., Bakker et al., 2018). Developing the empirical evidence to implement these relationships in a quantitative model was more challenging. CLASSES was developed using information from a series of studies conducted beginning in the late 1990s, including information on the socio-economic status of household (Brown et al., 2006). Thus, some of the needed information about household characteristics was available, but not initial savings, FIES or HDDS scores (Table 1). For HDDS, we used a value within the reported range for lower-income households in Western Kenya (Waswa et al., 2014). We could not find published estimates of FIES scores for Kenya, so we assumed a value that is within the usual definition of food secure (FIES from 0 to 4) based on Wambogo et al. (2018), which included analysis of data from Kenya. We assumed that initial cash holdings of the household equaled the value of one quarter’s minimum consumption, and the impact of this assumed value could be assessed with sensitivity analysis but is not undertaken here. Recommended quantities of consumption per quarter for the household were stylized estimates based on Ministry of Health (2017).

Because new product categories and consumption functions were added to CLASSES, we needed to parametrize the consumption functions with information on prices and the response of household food demand to net income (Table 1). Information on prices for the five food categories are stylized estimates based on the original socio-economic data from household used for the development of CLASSES (Brown et al., 2006) and Chemonics (2013). The responsiveness of household consumption to income was represented with income elasticities of demand modified from Wossen et al. (2018).

Many of the data inputs to describe food consumption expenditures can be collected by household surveys and initial values of FIES and HDDS by inclusion of the questions for these indicators in a household survey (as in Hammond et al., 2018). In contrast, data and analyses to describe the determinants of FIES and HDDS and their linkages to other model variables are very limited. Thus, we used the available evidence summarized in Table 3 of the companion manuscript in a stylized manner to represent the linkages between model-simulated outcomes and determinants (Table 2). We distinguish between endogenous determinants that modify FIES and HDDS values based on simulated model outcomes, and exogenous determinants based on initial household characteristics.

#### 2.1.3. Analysis of food access impacts with modified CLASSES

In this case example, we examined the impact of a negative maize yield shock, with households experiencing two consecutive maize crop

**Table 1**

Key data needs and source for analyses of food access with the CLASSES model.

Model Variables and Dimensions	Household Value	Source <sup>a</sup>
<i>Household Characteristics</i>		
Land area, ha <sup>b</sup>	0.5	Household survey
Adult laborers, persons	2	Household survey
Children, persons	4	Household survey
Total household size, persons	6	Household survey
Initial education level, years	4	Household survey
Initial savings <sup>c</sup> , KSh	6960	Household survey
Initial FIES Score <sup>d</sup>	4	Household survey
Initial HDDS Score <sup>d</sup>	3	Household survey
<i>Recommended minimum food consumption</i>		
Cereals, kg/quarter	360	MOH-Kenya <sup>e</sup>
Animal Source, kg/quarter	72	MOH-Kenya <sup>e</sup>
Oils, kg/quarter	72	MOH-Kenya <sup>e</sup>
Fruits & Vegetables, kg/quarter	54	MOH-Kenya <sup>e</sup>
Other, kg/quarter	36	MOH-Kenya <sup>e</sup>
<i>Market Characteristics</i>		
Price of food, KSh/kg		
Cereals	8.33	Household/market survey
Animal Source	25	Household/market survey
Oils	10	Household/market survey
Fruits & Vegetables	25	Household/market survey
Other	10	Household/market survey
<i>Income Elasticity of per-capita consumption<sup>f</sup></i>		
Cereals	0.2	Wossen et al. (2018)
Animal Source	0.8	Wossen et al. (2018)
Oils	0.3	Wossen et al. (2018)
Fruits & Vegetables	0.5	Wossen et al. (2018)
Other	0.5	Wossen et al. (2018)

<sup>a</sup> Includes both actual and potential sources for the required information.

<sup>b</sup> All land is assumed to be planted to maize (no tea or Napier) and there are no livestock for the entire simulation period of 28 quarters. Note that livestock could be purchased but sufficient cash is not accumulated to do so. We further assume no use of inorganic fertilizer for both households.

<sup>c</sup> Set equal to the minimum food consumption expenditures per quarter.

<sup>d</sup> Household surveys (e.g., RHOMIS, Hammond et al., 2018) can be used to collect this information.

<sup>e</sup> MOH Kenya is National Guidelines for Healthy Diets. Kenya Ministry of Health, 2017.

<sup>f</sup> Income elasticity values are adapted in a stylized manner from Wossen et al. (2018).

failures during both the short and long rains. For this analysis, CLASSES is simulated for a time horizon of seven years, long enough to examine initial behavioral patterns before the yield shock and the adjustment process afterwards. A production shock directly affects food availability, which is the main focus of much of the literature on agriculture and food security. Although the results are stylized due to the limited information linking food access indicators to other model outcomes, the modifications to CLASSES illustrate how this shock affects indicators of both food availability and access indicators.

The impact of the maize yield shock on yields (food availability) begins at quarter 9 and lasts 4 quarters (Fig. 1). Maize yields and food access indicators are shown as relative to their values prior to the shock to facilitate comparisons across indicators. The analysis illustrates a number of key points. First, availability and access indicators are correlated but differ in degree and timing. Maize production falls to essentially zero, but food consumption expenditures do not because they are buffered by cash held by the household. The FIES and HDDS indicators are immediately affected by the production shock because they depend in part on income, which is affected by having less production to

**Table 2**

Representation of assumed determinants of food access indicators in CLASSES.

Food Access Indicator, Determinants	Model Representation
<i>FIES</i>	
Endogenous effects	
Effect of income	Step function linked to integer impact
Effect of wealth	Step function linked to integer impact
Effect of off-farm employment	> 2500 KSh/quarter = -1
Exogenous effects	
Effect of education	> 10 years = -1
Effect of household size	> 4 = +1
Effect of number of children	> 2 = +1
<i>HDDS</i>	
Endogenous effects	
Effect of food consumption expenditures	< 0.8 of minimum recommended consumption for -1 and > 1.5 of minimum recommended consumption = +1
Exogenous effects	
Effect of off-farm employment	> 5000 KSh/quarter = +1
Exogenous effects	
Effect of land area	> 1 ha = +1
Effect of education	> 10 years = +1

Note: Endogenous effects are determined by other variables in the model simulations. Exogenous effects depend on initial assumptions about household characteristics and are not affected by other variables in the model simulations.

sell. The recovery of these access indicators does not occur immediately when the maize yield shock ends, because they also depend on wealth, which requires time to rebuild. This supports the desirability of a focus on access and not just availability. Second, the access indicators illustrate different dimensions and degrees about severity of the impacts. Food consumption expenditures drop to about 20% of baseline consumption, but the HDDS score only falls to about 80% of the pre-shock level. The FIES indicator increases (a higher FIES value means more food insecurity) by 60%. Moreover, the timing of impacts differs for the different indicators. Information about how different indicators are affected differently at different points in time may be useful for the development of more effective responses to short-term food availability shocks. Third, the indicators suggest different dynamic behavior patterns for yields and food access after the shock. Maize yields are higher post-shock because of soil nutrient dynamics (fewer nutrients were extracted by maize during the year of the shock). This supports higher levels of food consumption expenditures, improved HDDS (albeit temporarily) and an improvement in FIES for 10 quarters. Ultimately, depletion of soil nutrients results in lower maize yields that suggest future decreases on food availability, food consumption expenditures and FIES.

#### 2.1.4. Assessment of stability metrics with CLASSES

We can also assess the “stability” of food security indicators based on the information above. We noted in the companion paper that one approach to assessment of stability is to assess the extent and duration of departures of food security indicators from reference or threshold levels. The analysis above suggests that there are substantive departures from reference values for each of the indicators and the duration of that departure varies by indicator (Fig. 1). However, we also argued in the companion paper in favor of stability analyses with a focus on *hardness* and *elasticity* (Herrera, 2017) derived from resilience concepts. The *hardness* metric denotes the maximum disturbance that the indicator can tolerate before its behavior changes significantly (within a 5% confidence bound) with respect to its behavior in the absence of a disturbance. It can be thought of as the maximum disturbance before the system “bends”. The larger the hardness value, the larger the disturbance needed to produce a change in behavior of the two indicators. The *elasticity* metric describes the maximum disturbance the indicators can tolerate before they never recover to their reference behavior (within a

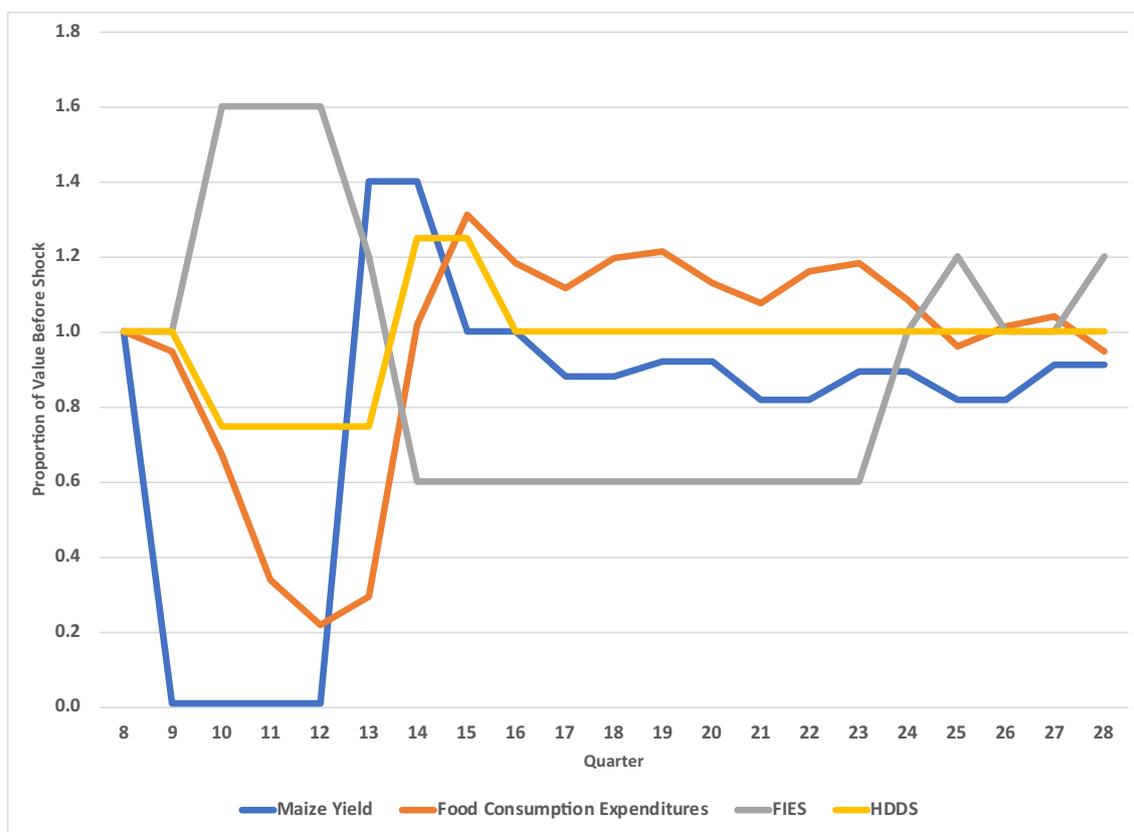


Fig. 1. Simulated Impacts of a Maize Yield Shock on Three Food Access Indicators in the CLASSES Model. Note: A higher FIES score implies decreased food security.

5% confidence bound). It can be thought of as the maximum disturbance before the system “breaks”. The more elastic the system, the larger the disturbance it can absorb without shifting into an alternate regime. Application of this stability analysis requires specification of which indicators will be assessed and the range in the magnitude and duration of shocks that will be evaluated. A set of stochastic simulations with different values for shock magnitude and the duration is assessed to determine hardness and elasticity metrics.

In this case, we assessed impacts on the household’s food consumption expenditures in response to two types of disturbances, a yield shock and a price shock. This assessment requires a range of assumed changes in yields and prices, rather than just the magnitude of the yield shock described above. The yield shock was assessed for a range of yields between –25% and –99% and a duration between 2 and 10 quarters. For the price shocks, we varied the magnitude of maize price change from –5% to –50% and the duration of the price change from 2 to 10 quarters. For each of the 200 Monte Carlo runs, we calculated the percentage deviation of food consumption expenditures from their reference value (the value produced by the simulations without shocks). We then ordered the simulation runs by size of disturbance and manually identified the maximum disturbance that the food security indicators could tolerate before significantly (at 5% confidence bound) deviating from the reference behavior in the case of hardness or before never returning to the reference behavior after the disturbance in the case of elasticity. The smoothed total household food consumption expenditures deviated significantly (5% confidence bound) from the reference behavior at very small disturbances (very low values of the hardness metrics, Table 3). A hardness value indicates the threshold value for the combinations of the magnitude of yield shock (a negative value between –0.25 and –0.99) times the length of the shock in quarters (2 to 10) required to result in food consumption expenditures more than 5% less than those without the shock. In this case, a hardness value of –0.59

Table 3

Hardness and Elasticity metrics for food consumption expenditures for maize yield and price shocks analyzed for a lower-resource household with the CLASSES model.

Type of Shock and Food Security-Related Indicator	Hardness <sup>a</sup>	Elasticity <sup>b</sup>
<i>Maize yield shock</i>		
Food Consumption Expenditures	–0.59	–8.94
<i>Maize price shock</i>		
Food Consumption Expenditures	–0.20	–4.77

Note: Values are negative because a larger shock has a larger negative impact on the value of food consumption expenditures. The absolute values for the hardness and the elasticity measures are the result of the multiplication of the extent of the disturbance (either percentage yield decrease or percentage price decrease) and the duration of the disturbance (between 2 and 10 quarters).

<sup>a</sup> The hardness metric denotes the maximum disturbance that the indicator can tolerate before its behavior changes significantly (within a 5% confidence bound) with respect to its behavior in the absence of a disturbance. It can be thought of as the maximum disturbance before the system “bends”. The larger the hardness value, the larger the disturbance needed to produce a change in behavior of the two indicators.

<sup>b</sup> The elasticity metric describes the maximum disturbance the indicators can tolerate before they never recover to their reference behavior (within a 5% confidence bound). It can be thought of as the maximum disturbance before the system “breaks”. The more elastic the system, the larger the disturbance it can absorb without shifting into an alternate regime.

indicates that a yield shock of 25% (–0.25) sustained for just over 2 quarters (2.4 quarters) would be large enough to reduce food consumption expenditures by more than 5% (because –0.25 times 2.4 equals –0.59). A larger hardness value indicates that larger or longer yield shocks would be required to reduce food consumption expenditures by more than 5% from a situation without the shock. An elasticity value indicates the threshold value for combinations of the yield shock

and its duration after which the household can never recover its previous level of food consumption expenditures. The elasticity value of  $-8.94$  indicates that a yield reduction of about 90% ( $-0.894$ ) would need to last 10 consecutive quarters ( $-0.894 \times 10 = -8.94$ ) before the household could not ultimately return to within 5% of its previous food consumption values.

A similar interpretation applies to the analysis of the maize price shock, although values of hardness and elasticity are lower. A negative maize price shock of 20% ( $-0.20$ ) that lasted one quarter would be sufficient to reduce food consumption expenditures by more than 5% compared to a situation with a price shock. A negative maize price shock of 50% ( $-0.50$ ) that lasted just over 9 quarters ( $-0.50 \times 9.54 = -4.77$ ) would cause this household never to again reach within 5% of consumption expenditures observed without the shock. In this case, both indicators are able to recover from very large disturbances, as indicated by values of the elasticity metrics. Given the parameter ranges we used for the Monte Carlo simulations, both parameters were able to recover from the maximum disturbance (99% reduction in yield and 50% reduction in maize price). Therefore, while the system seems to be very susceptible to disturbances, it shows the ability to return to previous levels.

Assessment of a variety of food security indicators with CLASSES highlights different potential impacts of the yield shock than is typically presented in agricultural systems analyses focused on food availability. The experience of food insecurity measured by FIES and HDDS highlights new potential questions about how households manage food security across time. Patterns shown here, when calibrated better with known elasticities and empirical relationships, can fill in gaps from survey data alone, and also prompt new questions about household validation of variable food security experiences, or their ability to plan, foresee them, compensate for them.

## 2.2. Including food access indicators in the Mexico sheep sector model (MSSM)

### 2.2.1. Introduction to the MSSM

The Mexico Sheep Sector Model (MSSM) was originally designed to analyze the dynamic impacts of productivity-enhancing technological change, farm subsidies and growth in sheep meat demand (Parsons and Nicholson, 2017). The model represents sheep animal and sheep meat markets in Mexico, but also includes trade linkages because of the importance of imported sheep meat in Mexican consumption. Production is modeled for two different regions (Yucatán and Other), each with two different types of producers: commercial or *tras patio* (Parsons et al., 2006). *Tras patio* (“backyard”) sheep production is characterized by smaller flock size, limited investment other than animals and ownership by households that rely on agricultural activities for a majority of income. The model represents demand for sheep meat in the same two regions that is influenced by income and prices. Sheep production and sheep meat consumption are linked with structures representing the meat processing and transportation activities and their costs. As in the commodity models developed by Meadows (1970) and Sterman (2000), inventories of sheep meat (processed and frozen) are assumed to influence the price of sheep meat, which in turn influences both sales (quantity demanded) and sheep meat imports. The model simulates a 10-year time horizon beginning in 2007 using a monthly unit of observation.

### 2.2.2. Data and assumptions to include food security indicators in the MSSM

We modified the MSSM to include food consumption expenditures, Household Food Insecurity Access Scale (HFIAS) and HDDS. Like FIES, HFIAS is an experiential indicator of food insecurity, chosen in this case on the basis of available empirical evidence (see Appendix 1 in the companion paper for additional detail on HFIAS). Similar to the process for CLASSES, this required structural modification of the model and

**Table 4**

Key data needs and source for analyses of food access with the MSSM model.

Model Variables and Dimensions	Household Value	Source <sup>a</sup>
Initial <i>Tras Patio</i> Producer income, \$/year	325,400	MSSM calculations
Initial HFIAS Score	5.7	Capron et al. (2018)
Initial HDDS Score <sup>d</sup>	5.0	Capron et al. (2018)
Per capita consumption, kg/year		
Cereals	147.4	Torres (2015) <sup>c</sup>
Meats	36.0	Torres (2015) <sup>c</sup>
Fish	3.0	Torres (2015) <sup>c</sup>
Dairy	78.7	Torres (2015) <sup>c</sup>
Oils	8.0	Torres (2015) <sup>c</sup>
Vegetables	123.7	Torres (2015) <sup>c</sup>
Sugar	10.6	Torres (2015) <sup>c</sup>
Beverages	61.6	Torres (2015) <sup>c</sup>
Income elasticity of per-capita consumption		
Cereals	0.724	Torres (2015) <sup>c</sup>
Meats	1.258	Torres (2015) <sup>c</sup>
Fish	1.664	Torres (2015) <sup>c</sup>
Dairy	0.897	Torres (2015) <sup>c</sup>
Oils	1.019	Torres (2015) <sup>c</sup>
Vegetables	0.914	Torres (2015) <sup>c</sup>
Sugar	1.239	Torres (2015) <sup>c</sup>
Beverages	0.682	Torres (2015) <sup>c</sup>
Income elasticity of food access indicator		
HFIAS	-0.38	Magnaña-Lemus et al. (2013) <sup>a</sup> , Capron et al. (2018) <sup>b</sup>
HDDS	0.12	Capron et al. (2018) <sup>b</sup>

<sup>a</sup> Magnaña-Lemus et al. (2013) found that the probability of being food insecure based on the Mexican Food Security Scale (EMSA) decreased by 9 to 35% as household income increased.

<sup>b</sup> Calculated from HFIAS and HDDS values by income quintiles.

<sup>c</sup> From Torres (2015) for the lowest income decile.

development of empirical evidence. Because this is a regional model, we ignore household-specific characteristics and focus on one group, *tras patio* producers in Yucatán. We do not consider impacts on other groups because commercial producers and sheep meat consumers are higher-income groups for which food security is less likely to be an issue (Parsons et al., 2006). We assumed a given level of aggregate income from sources other than sheep for *tras patio* producers based on Parsons et al. (2006).

Similar to the modification of CLASSES, we needed to add structure to represent food consumption choices and expenditures. We incorporated consumption of eight food groups (Table 4) using the categories from Torres (2015). Consumption expenditures were modeled using:

$$Expenditure_f = Base\ Expenditure_f \cdot (Income/Base\ Income)^\eta$$

Where  $Expenditure_f$  is per capita expenditures on food group  $f$ ,  $Base\ Expenditure_f$  is an initial value of per capita expenditures on food group  $f$ ,  $Income$  indicates total regional income (from sheep production and non-sheep activities) for *tras patio* producers after an intervention,  $Base\ Income$  is an initial value of regional income for *tras patio* producers (also from sheep production and from non-sheep activities) and  $\eta$  is an income-elasticity parameter<sup>1</sup> that relates the average level of food expenditures for Yucatán *tras patio* producers to changes in  $Income$  relative to the  $Base\ Income$ . We also added structure to link food access to regional incomes. Food access indicators HFIAS and HDDS were

<sup>1</sup> This is the common economics definition of an elasticity as the percentage change in an output variable divided by the percentage change in an input variable. Thus, it has a different meaning than the “elasticity” value defined for the stability analyses in the previous section.

modeled with nonlinear (constant-elasticity<sup>2</sup>) response functions, with the formulation:

$$FAI = BaseFAI \cdot (Income / Base\ Income)^\epsilon$$

where *FAI* indicates the food access indicator (HFIAS or HDDS), *BaseFAI* is an initial value of the food access indicator, *Income* and *Base Income* are as defined above and  $\epsilon$  is an elasticity value that relates the average level of FAI for Yucatán *tras patio* producers with respect to income. This formulation is simplistic, but is one approach that minimizes data requirements and facilitates sensitivity analysis with respect to uncertain elasticity parameters. The FAI are means for *tras patio* households and are thus continuous.

Similar to CLASSES, the empirical implementation of food access in the MSSM is challenging due to the lack of data specific to sheep-producing households in the Yucatán. Thus, we developed information on food consumption expenditures and the linkages between income, HFIAS and HDDS using other sources for Mexico (Table 4). Magnaña-Lemus et al. (2013) estimated the linkage between income and food security outcomes measured by experienced-based food insecurity scales for different socio-economic groups in Mexico at the national level. Capron et al. (2018) studied food security outcomes in Mexico City that allowed specification of the elasticity values for HFIAS and HDDS. The negative value of the HFIAS means that the degree of food insecurity would decrease as income increases (which constitutes an improvement), and the positive values for the other elasticities indicate increased dietary diversity or consumption expenditures with higher incomes. Torres (2015) provided information on per capita consumption and expenditure elasticities for a set of eight food categories that can be used to assess changes in food consumption expenditures in response to income changes. Values for expenditure elasticities (Table 4) were selected for the lowest income decile, which have higher numerical values. For the purposes of our analyses, we also need to assume that the values of these relationships apply to the earlier time period covered by our model. Experience-based measures of food insecurity were still under development and less widely implemented in the mid-2000s when work on the MSSM began (Ballard et al., 2013).

### 2.2.3. Analysis of the food access impacts with modified MSSM

We examine the impacts on food security indicators for smallholder (*tras patio*) producers using a scenario that modifies assumptions about demand growth and production costs for commercial producers. The scenario assumes annual sheep meat demand growth of 1.5% per year for three years but constant demand thereafter. Consistent with the policy initiatives undertaken by Mexican state governments in the mid-2000s, this scenario also assumes that commercial producers (but not *tras patio* producers) in both regions are offered a cash payment (subsidy) from the government equal to 40% of their variable costs beginning after the first simulated year. This scenario describes the market context and policy instruments for Mexican sheep markets in the mid-2000s. The scenario is motivated by a concern—frequently expressed at the time—that the subsidies offered to commercial producers would negatively affect the well-being of *tras patio* producers (Parsons et al., 2006). The scenario with changes to demand and commercial producer costs is compared to a dynamic equilibrium scenario that assumes stable demand, production, prices and incomes.

The simulations indicate an initial improvement in all three access indicators in response to demand growth and subsidies and then a deterioration over time leading to worse food security outcomes by month 50 (Fig. 2). The lessons from this assessment overlap to some

extent with those from CLASSES. First, there is a correlation between the availability indicator (production) and food access indicators, but the patterns differ. In fact, the initial improvement in food access indicators is associated with a decrease in overall production, not an increase. This effect occurs because of the supply dynamics for sheep producers in response to increased profitability, which causes a reduction in animals slaughtered to increase the number of breeding animals. This reduction in slaughter (i.e., production) increases prices, which raises *tras patio* producer incomes despite the lower animal slaughter. Higher incomes support increased food expenditures, lower HFIAS (a lower HFIAS value is an improvement in food security given the nature of the scale) and higher HDDS. Second, the magnitude of changes relative to a reference value differs for the three access indicators. For example, the HDDS indicator is less responsive to income changes due to the smaller assumed value for its elasticity with respect to income. Although this is unsurprising given that income is the underlying driver and the values of responsiveness to income differ, this information would still be relevant to inform decisions about how to respond to the different dimensions of the deterioration of food security in later time periods. Similar to the CLASSES analysis, the dynamic patterns of the indicators vary: production, HDDS and HFIAS have long-run values similar to baseline levels, but food consumption expenditures are lower.

### 2.2.4. Assessment of stability metrics with the MSSM

We also assess the stability metrics for MSSM in a manner similar to the analyses with CLASSES. In contrast to the maize yield shock analyzed with CLASSES, the initial effect is a positive one, with demand growth and the initial reduction in sheep marketed by commercial producers (i.e., retained as breeding stock (Parsons and Nicholson, 2017) resulting in higher sheep prices and improved profitability for *tras patio* producers. In this case it would be desirable for the outcomes to indicate both the flexibility to respond (limited hardness) and the ability to sustain the improvements in food access (low elasticity). The shock results in a notable initial increase in food consumption expenditures above baseline levels but this is not sustained after month 50; for the majority of simulated months, food access indicator values are below their baseline values.

We also calculated hardness and elasticity metrics for HFIAS for variation in the size of the variable-cost subsidies to commercial producers from values between 10% and 50% and for annual demand growth of 1.5% lasting from 12 to 60 months. We tested for the sensitivity of HFIAS to variations in these subsidies. As for CLASSES, the hardness and elasticity values represent threshold values based on the combined size and length of the shock.

The proportional change in HFIAS deviates significantly (at the 5% confidence bound) from the reference behavior at very small disturbances (Table 5). The hardness value of 0.98 indicates that a 50% cost subsidy (0.5) for commercial producers would only need to last 2 months to move HFIAS more than 5% from its value in the scenario discussed in detail above (because  $0.5 \times 2 = 1 > 0.98$ ). Thus, a low hardness value implies that when cost subsidies deviate by a small amount from the reference value, they have a substantive effect on HFIAS. The elasticity value of 0.42 indicates that a 40% cost subsidy (0.40) would need to last only about 1 month before the HFIAS value does not return to within 5% of the level in the previous analyses (because  $0.40 \times 1.05 = 0.42$ ). Whereas these high hardness values indicate high susceptibility to the size of the subsidy, HFIAS returns to close to its initial value (low elasticity). Low elasticity in this case suggests the inability to sustain the improvements and thus could be considered a vulnerability for *tras patio* producers.

<sup>2</sup> A constant elasticity response function assumes that the percentage change in the output variable (e.g., FAI) divided by the percentage change in the input variable (e.g., Income) is a constant, regardless of the values of the output or input variables.

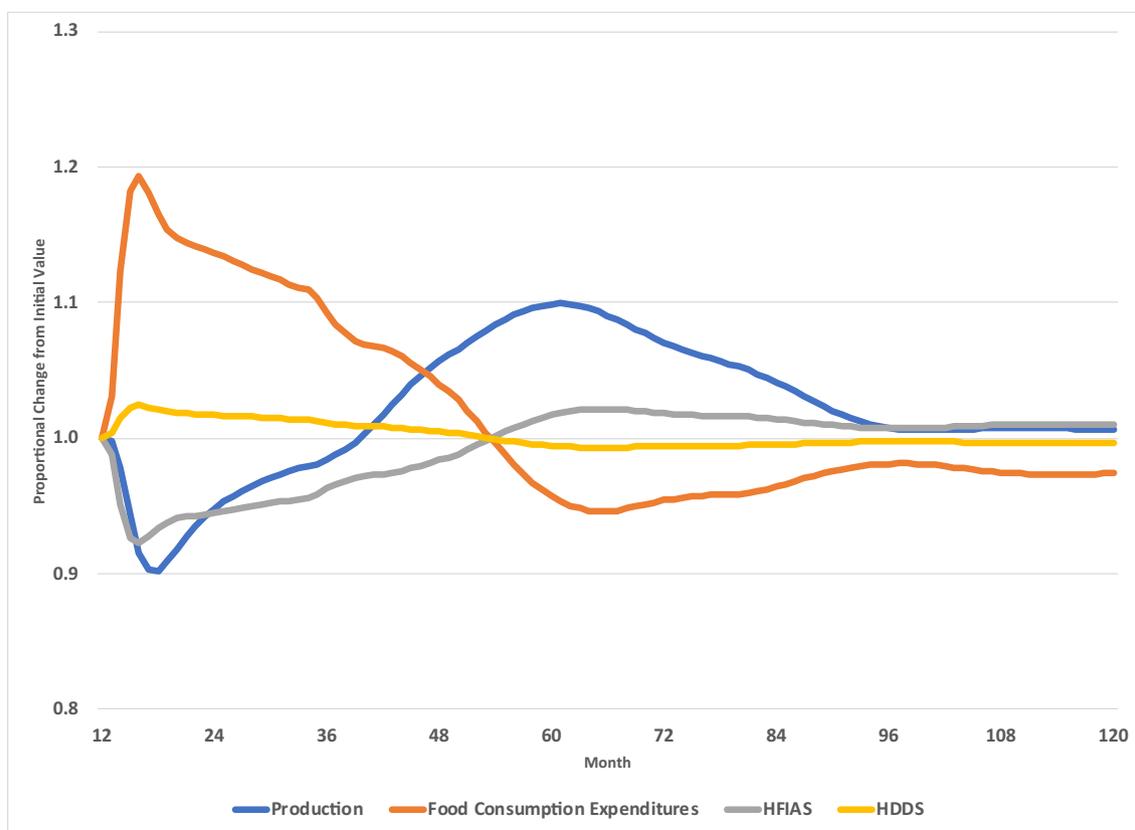


Fig. 2. Simulated impacts of demand growth and commercial producer subsidies on production and three food access indicators in the MSSM model.

**Table 5**  
Hardness and elasticity metrics for HFIAS for *Tras Patio* producers for a commercial producer subsidy analyzed with the MSSM.

Type of Shock and Food Security-Related Indicator	Hardness <sup>a</sup>	Elasticity <sup>b</sup>
<i>Commercial Producer Subsidy</i>		
HFIAS	0.98	0.42

Note: The absolute values for the hardness and the elasticity measures are the result of the multiplication of the extent of the disturbance (relative change in variable-cost subsidies compared to reference value of 40%) and the duration of the disturbance.

<sup>a</sup> The hardness metric denotes the maximum disturbance that the indicator can tolerate before its behavior changes significantly (within a 5% confidence bound) with respect to its behavior in the absence of a disturbance. It can be thought of as the maximum disturbance before the system “bends”. The larger the hardness value, the larger the disturbance needed to produce a change in behavior of the two indicators.

<sup>b</sup> The elasticity metric describes the maximum disturbance the indicators can tolerate before they never recover to their reference behavior (within a 5% confidence bound). It can be thought of as the maximum disturbance before the system “breaks”. The more elastic the system, the larger the disturbance it can absorb without shifting into an alternate regime.

### 3. Assessing food access and stability outcomes in agricultural systems models: Needs and opportunities

#### 3.1. Data issues

Nicholson et al. (2019) indicate that the potential for implementation of food security indicators in agricultural systems models is limited at present. Relatively few of the existing models include appropriate indicators, and for those that do, the most common are consumption indicators such as food amounts, expenditures, or calories. As noted in (Nicholson et al., 2021), almost all model analyses were vague about

defining indicators of stability of food security. This suggests that a low-cost method of improving the treatment of food security in agricultural systems models may be via improvements in their representation of food consumption that take better account of food access and stability. This is not without its challenges, illustrated in the case study examples in section 2 above with respect to the structural changes and additional empirical evidence required. Where empirical data are available, incorporating experience-based food insecurity indicators and household dietary diversity scales can be incorporated into existing dynamic agricultural systems models at relatively low cost.

From the literature reviewed, the most common situation is where additional empirical evidence is needed to integrate food security indicators into systems models. The type of data required will depend on the analyst’s purpose, but might typically include experience-based food insecurity and dietary diversity information, as in the RHoMIS tool (Hammond et al., 2018), for example (and see Table 1). If such data were collected as part of the empirical evidence base underlying model development itself, the additional effort and cost involved would be relatively small.

Multiple rounds of such data collection may be appropriate for dynamic model development, however. The indicator values in the examples above are based on analysis of cross-sectional data rather than the dynamic responses of households or regions. Thus, there is much work to be done to develop analytical methods based on appropriate theoretical foundations and functional forms that can link determinants and indicators, although even relatively simplistic empirical relationships may be useful as this body of work is explored and expanded. As more empirical evidence is generated linking outputs from agricultural systems models to indicators such as FIES, HFIAS and HDDS, it may be possible to use relationships from other, reasonably similar settings in a more stylized manner.

There may also be considerable potential in utilizing recent innovations in data collection, exchange and analysis. The rapid growth of

Information and Communications Technologies (ICTs) globally, and in Africa in particular, is having wide-ranging impacts. Three of many possible examples are: Wefarm ([wefarm.org](http://wefarm.org)), a farmer-to-farmer digital network with more than a million users across Kenya and Uganda, which can be accessed via internet or through text messaging on a mobile phone; in Senegal, weather and seasonal forecasts are being transmitted through 82 rural community radio stations and SMS, potentially reaching 7.4 million rural people (Dinesh et al., 2017); and a public-private partnership in northern Ghana is delivering climate services and agronomic advisories to more than 300,000 smallholder subscribers (Partey et al., 2019). Two of these initiatives involve two- and multi-way information exchange, and suitably anonymized databases with a wide range of information are being rapidly built up. Such methods of data collection have considerable potential for being able to provide near real-time snapshots of the food security of rural populations at frequent intervals and at low cost. Recent increases in the availability of relatively cheap remotely-sensed data across several decades is spurring the development of geospatial impact evaluation (Lech et al., 2018). New methods of data collection and analysis at frequent intervals can be linked with more traditional data collection efforts that use nationally representative sampling frames, such as Demographic and Health Surveys ([dhsprogram.com](http://dhsprogram.com)) and Living Standards Measurement Studies ([microdata.worldbank.org/index.php/catalog/lsms](http://microdata.worldbank.org/index.php/catalog/lsms)).

### 3.2. Opportunities for application

One priority area for assessments of food security with agricultural systems models relates to the impacts of climate change (Thornton et al., 2017). Climate change impacts on food availability have been receiving attention for a long time, but it is only in the last decade that the broader issues of food and nutrition security, such as food access and utilization, have been receiving increased attention (e.g., Tirado et al., 2013; Wheeler and Von Braun, 2013). Several different frameworks have been developed and reviews undertaken (e.g., McKune et al., 2015; Fanzo et al., 2017; Campbell et al., 2018) of the conceptual links between climate change and food security and nutrition outcomes. Robust understanding of the relationships involved is challenging, however, because of the importance of local contexts as modifiers of development outcomes such as poverty and food insecurity. Modification of existing agricultural systems models in response to more and better empirical evidence, as illustrated in our examples above, can help close this gap.

The examples in section 2 are well aligned with common applications of agricultural systems models that have economic content. Many such models allow the assessment of impacts such as yield shocks or yield increases and interventions such as subsidies. Analyses assessing the food access impacts of more transformative changes to food systems will increasingly be needed to inform both intervention and research priorities (Herrero et al., 2020). For example, an analysis of how food access would be affected by large-scale changes in crop and livestock production patterns would be of considerable value in helping to align agricultural value chains more closely with sustainable diets as well as achievement of Nationally Determined Contributions (NDC; adaptation and mitigation targets) under the Paris agreement.

## 4. Conclusions and implications

We have illustrated how food security indicators other than

availability (production) can be incorporated into a household level bio-economic model and a regional-scale agricultural system model. The process provides a template for the changes required to model structure, and the needed empirical evidence. The results provide motivation and justification for future efforts to incorporate food access and stability indicators into agricultural system models. The results of the analyses with both CLASSES and MSSM illustrate the usefulness of a dynamic perspective on multiple food security indicators, but also the challenges to implementation.

Incorporation of selected food security indicators that are more aligned with research concepts in the food and nutrition research community facilitates broader conversations about food security between researchers in food and nutrition security as well as those in agricultural systems concerned and motivated by food security issues. However, the empirical research required is often not available for specification of necessary model structures and parameters. We thus recommend more data collection efforts particularly in agricultural system research projects on multiple measures of food security, such as food access and some of the experiential measures of food security like the FIES and HFIAS used here. In the limited number of cases where detailed data on food security and production is available, as demonstrated by projects like the RHoMIS data collection effort (Hammond et al., 2018), we encourage researchers to identify agricultural system model outputs that can be directly linked to the available food security indicators. These data collection efforts can usefully focus on key opportunities for agricultural systems modeling to facilitate assessments of interventions and targeting, e.g., food and nutrition security impacts and adaptations to climate change and transformative changes to food systems.

In the longer term, more frequent and regular joint modeling efforts of different food security dimensions within agricultural system models can allow for fuller exploration of critical relationships, like better documenting the risks to food security associated with long term agricultural production system changes in different settings, or identification of agricultural system policies that can be prioritized directly for their relative contribution to better food security beyond the availability dimension. This work has demonstrated both the potential scope for this work as well as the existing limitations that need to be addressed to improve and gain from modifying food security modeling practice.

### Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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## Appendix A. Specifics of modifications to CLASSES to incorporate Food Access Indicators

### A.1. Consumption functions

The consumption functions are based on the net income to the household relative to the total expenditure required for the household to consume the minimum recommended quantities of each of the five food items. Net income (NI) is defined as the net inflows per quarter of cash from sales,

wages, off-farm labor earnings, remittances, minus any cash outlays for production (hired in labor, production inputs).

Household consumption of each food item (kg/quarter) is thus calculated for three situations:

- 1) household income is currently adequate to consume at or above the minimum recommended amount of each food item;
- 2) household income is not adequate to consume the minimum recommended amount of each food item, but savings are available to support consumption at the minimum recommended level;
- 3) household income is not adequate to consume the minimum recommended amount of each food item and no savings are available.

The applicable amount of each food item to be consumed is calculated conditional on the situation above, and total food expenditures (in KSh/quarter) are calculated using consumption and prices. The specific consumption functions follow a basic log-linear form, with net income (NI) influencing the household's ability to consume relative to a minimum standard, as shown below:

$$\text{HH Consumption of Food Item } f = (\text{Min. Recommended HH Consumption of Food Item } f) \times \{ \text{NI} + \text{Allowable Savings Draw} / \text{ERC MRA} \}^{\text{Income Elasticity for Food Item } f}$$

where the *Allowable Savings Draw* (ASD) indicates the amount that can be withdrawn from the household's savings and *ERC MRA* is the Expenditure Required for Consumption of the Minimum Recommended Amount of food item *f*. In the first two scenarios described above, the household has sufficient cash resources to afford the minimum required consumption bundle (ERC MRA), either through quarterly net income, or some combination of net income and drawing down savings.

If net income falls below the amount needed to afford the minimum required consumption bundle (the ERC MRA), but the household also does not have savings on hand, existing resources are allocated with priority given first to cereals and oils, and then equally across the remaining three food categories with remaining cash resources. This is reflective of likely prioritization given by severely food insecure households, but relative weights have been chosen arbitrarily, and could be adjusted if there were known rankings and priority weights for a specific set of households.

Amounts of actual consumption by the HH for each of the five food items is also calculated as outlined above. In addition to actual consumption amounts, we calculated the number of food items for which the household consumed more than 25% of the minimum recommended amount, and this was indicated as a proxy for the total number of food groups consumed (and thus, one measure of dietary diversity).

## A.2. FIES and HDDS

The FIES and HDDS include linkages to determinants taken from the literature (like numbers of dependent children per [Table 3](#) in the companion paper). These indicators are the summed responses to a series of yes/no questions, resulting in integer valued scores. (See Appendix Table 1 in the companion paper for additional details.) We thus used discrete thresholds for linking agricultural system model variables to the FIES and HDDS food security indicators, starting with an assumed set of base values, to which discrete additions or subtractions from the Base value are made when agricultural system model values pass the thresholds.

For example, the FIES score is calculated as:

$$\text{FIES Score} = \text{Base FIES Score} + f(\text{Wealth}, \text{NI}, \text{Education}, \text{HH Size}, \text{Children}, \text{Off - farm Income})$$

Where the elements of the  $f()$  are as follows:

$$\text{Wealth Effect} = +2 \text{ if Wealth} < 10,000 \text{ KSh}$$

$$+1 \text{ if } 10,000 \leq \text{Wealth} < 20,000 \text{ KSh}$$

$$0 \text{ if Wealth} \geq 20,000$$

where,

$$\text{Wealth} = \text{Value of Land at } 10000 \text{ KSh/ha} + \text{AccumSurplus} + \text{CashAvailable}$$

$$\text{NI Effect} = +3 \text{ if NI} < 2500 \text{ KSh/quarter}$$

$$+2 \text{ if } 2500 \leq \text{NI} < 5000$$

$$+1 \text{ if } 5000 \leq \text{NI} < 10,000$$

$$0 \text{ if NI} \geq 10,000$$

$$\text{Off - Farm Income Effect} = -1 \text{ if income from off - farm labor earnings} > 2500 \text{ KSh/quarter}, 0 \text{ otherwise}$$

$$\text{Education Effect} = -1 \text{ if Education years of Household Head} > 6, 0 \text{ otherwise}$$

The elements above are determined endogenously by the model simulations. The effects below represent household-specific characteristics that would not be modified during the simulation for a specific household. Rather, they can be changed to examine the impacts for households with different characteristics.

$$\text{HH Size Effect} = +1 \text{ if HH Size} > 4, 0 \text{ otherwise}$$

$$\text{Children Effect} = +1 \text{ if Children} > 2, 0 \text{ otherwise}$$

Note that a higher FIES score implies a higher degree of food insecurity, so positive values in the above indicate a deterioration of food security status and negative values imply and improvement.

The HDDS is calculated as:

$$\text{HDDS} = \text{Base HDDS} + f(\text{Land Area, Education, Food Consumption Expenditures, Off – Farm Employment})$$

Where the elements of the  $f()$  are as follows:

**Off – Farm Income Effect** = +1 if income from off – farm labor earnings > 5000 KSh/quarter, 0 otherwise

**Land Area Effect** = +1 if Land area > 1 ha, 0 otherwise

**Food Consumption Expenditures Effect** = +1 if FCE > 1.5\*ERC/MRA, –1 if FCE > 0.8\*ERC/MRA, and 0 otherwise

**Education Effect** = +1 if Education years > 10, 0 otherwise

In this case, all of the effects are determined by the simulation model given household characteristics.

These are arbitrary both in their formulation and their specific numerical values but illustrate in a stylized manner the information and effects necessary to consider when incorporating food security indicators into agricultural system models. Further consideration of how to collect and analyze data on the determinants of FIES and HDDS will be essential for more appropriate empirical analyses.

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