Food Security (2022) 14:1553–1568
https://doi.org/10.1007/s12571-022-01302-y

ORIGINAL PAPER

Inter-district food flows in Malawi

Maxwell Mkondiwa[1,2] · Jeffrey Apland[3]

Received: 4 October 2021 / Accepted: 3 June 2022 / Published online: 2 August 2022

Abstract

Data on inter-district food flows are typically not collected and are thus unavailable for most sub-Saharan African (SSA) countries and for many parts of world. Given the volatile and frequent regionally specific deficits in food production in Malawi, evidence on food flows under different scenarios is needed for food policy decisions. This paper develops a spatially explicit mathematical programming model for the Malawian food sector to calibrate inter-district food flows and to assess how transport cost variations affect these flows. The food sector modeling approach we develop and implement allows for a natural estimation of inter-district trade flows in data sparse environments. In addition, we restrict crop mixes to those within the range of observed historical crop land use unlike modeling approaches that are prone to overspecialization. The calibration results for our baseline model indicate that about 7% of Malawian maize production flows between districts as compared to 66% for rice, 74% for beans, and 46% for groundnuts. A simulation experiment of varying unit transport costs shows that reductions in per unit transport costs increase the share of production that is traded inter-regionally, although the traded shares vary among the crops included in our model. The effectiveness of spatially targeted food production and marketing policies in Malawi therefore depends on these baseline food flows and the associated inter-district trade costs. Future research agenda on generating agricultural statistics in Malawi should focus on introducing intra-national commodity flow surveys.

Keywords Mathematical programming · Inter-regional food flows · Malawi

1 Introduction

The quest for smart and well targeted agricultural development policies in sub-Saharan Africa has never been more important than now due to ever increasing financial demands on government budgets. In this quest, the effect that policies have on the flow of agricultural produce between districts within a country is usually neglected or poorly understood, with much of the emphasis placed on the international trade implications of such policies. Understanding how food moves within a country is an important food policy issue, not least because of the likely spill-ins and spill-outs of policy impacts across regions/districts within a country as agricultural interventions are brought to scale. Absent effective spatial trade and price transmission information, substantial regional deficits or surpluses may emerge, even when nationally produced (or accessible) supplies can ostensibly meet the needs of all the households within a country at prevailing average prices. Therefore, inter-district trade is an important part of an effective food security strategy, especially considering that most sub-Saharan African countries still protect their food sectors especially during deficit years (Myers, 2013). Inter-district commodity trade data are, however, not collected on a systematic basis and thus unavailable in most sub-Saharan African (SSA) countries and many parts of the world.

In this paper, we develop a mathematical programming, agricultural sector model to calibrate food flows between districts in Malawi. Spatial mathematical programming models rely on spatially specific production and consumption data to

✉ Maxwell Mkondiwa
mkond001@umn.edu

Jeffrey Apland
japland@umn.edu

[1] International Maize and Wheat Improvement Center (CIMMYT), National Agricultural Science Centre (NASC) Complex, DPS Marg, G-2, B-Block, 110012, New Delhi, Delhi, India

[2] Center for Agricultural Research and Development, Lilongwe University of Agriculture and Natural Resources, Bunda Campus, P.O. Box 219, Lilongwe, Malawi

[3] Department of Applied Economics, University of Minnesota-Twin Cities, Minneapolis, MN 1994 Buford Avenue, St. Paul55108, USA

calibrate flows which if validated can be used in making policy decisions, e.g., fuel subsidies to reduce transport costs. Specifically, we use a price endogenous, nonlinear mathematical programming model (following Chen & Onal, 2012) as a general modelling framework. The advantage of this model is that the optimal solution includes calibrated volumes of produce traded. We implement the spatially specific mathematical programming model for six major food crops (maize, rice, cassava, potatoes (both sweet potatoes and Irish potatoes), beans and groundnuts) in Malawi— a largely rural agricultural country with high domestic transport costs. Based on an approach first proposed by McCarl (1982) and further developed by Chen and Onal (2012), equilibrium crop mixes for each of the 27 districts[1] are constrained to convex combinations of ten years of observed crop mixes. The approach produces more realistic supply responses by using crop mixes that reflect important product-product relationships involving rotation effects and efficient use of fixed resources. Input supply and product demand schedules are calibrated to 2009/10 agricultural season levels. We implemented the model using the commercial version of GAMS – the General Algebraic Modelling System (https://www.gams.com/).

The equilibrium results for the base year show that 7% of produced quantities of maize flow across districts as compared with 66% for rice, 74% for beans, 46% for groundnuts, and zero for cassava and potatoes. The results of the paper show that instead of concentric rings, there exists "arrows" of product flows across the different separated but not isolated districts that reflect the spatial shadow price differences in relation to transport costs. To show how this model can be applied to inform policy decisions and public investments, we conduct simulations of changes in transport costs—a major component of marketing costs in Malawi. A transport cost simulation experiment shows that a reduction in the per unit cost of transport nonlinearly increases by a small margin, the share of production traded. Given the importance of trade flows in making credible food policy decisions, it is important that statistical agencies in SSA introduce commodity flow surveys within countries. These can be implemented together with well-established agricultural surveys like the Living Standards Measurement Surveys (LSMS). The contribution of this paper is in calibrating trade flows of food crops within Malawi and thus provides a benchmark for future agricultural policy making in Malawi.

The rest of the paper is organized as follows. The policy context motivating the modelling approach is discussed next. The model and a description of the data and agricultural statistics used in the calibration is presented in Sect. 3. The baseline results and discussion of the calibration are presented in Sect. 4. We finally conclude in Sect. 5.

2 Malawi's food policy context

The pursuit of food self-sufficiency is evident in Malawi's historical and current food policies. The key priority of Malawi's post-independence era agricultural policy has been to attain food self-sufficiency through domestic production of staple foods. On the production side, Malawi has been implementing a farm input subsidy program for staple food production since 2005/06. On the trade side, Malawi occasionally invokes import and export bans when the country experiences crop production surplus and deficits, respectively. In addition, the government annually recommends minimum farmgate prices, and supports a grain marketing board and food reserve agency (Pauw & Edelman, 2015). While many economists advocate for principles of free trade and its benefits, these principles are often not heeded by governments and policy makers for both political and practical economic reasons. Malawi's policy makers are suspicious of free international trade as a food policy solution. However, fostering increased domestic food trade is likely to be embraced among policy makers. This position is unlikely to change in the foreseeable future. In this paper, we take a neglected "intra-country, inter-district" view of the Malawi economy. We rely on the fact that heterogeneity within a country can generate free-trade-like benefits across the different districts or regions of the country that would result in a second-best food policy under self-sufficiency. Benson et al. (2016) similarly argues that the implication of farming diversity in Malawi is that the comparative advantage of different areas of the country for production of different crops, livestock and other agricultural products differs significantly from place to place. The focus of the paper is on domestic trade, not regional and international trade as most of the literature.

Assuming a closed staple food sector economy in the case of Malawi is plausible because although Malawi is an occasional importer and exporter of maize (the main staple food), the internationally traded volumes are typically less than 5% of production (Benson, 2021). There is virtually no recorded trade in the other key staples like cassava and sweet potatoes because of low value-bulk ratio (Minot, 2010). A much lower percentage (2%) for traded maize is reported by Adam et al. (2018) for Tanzania to justify the use of a closed economy model.

Maize is the most important food crop in the country (both by area, production volume, production value and consumption), followed by cassava, potatoes (sweet potatoes and Irish potatoes) and Sorghum (Minot, 2010). Precisely, Minot (2010) estimates that per capita

[1] Likoma district, made up of small islands in Lake Malawi is excluded from the model due to lack of data.

Table 1 Food consumption (kg/person/year) in urban and rural areas

Food Crop	**Verduzco-Gallo et al. (2014)**				Minot (2010) **based of FAO 2009 Food balance sheet**	
	Urban		Rural		National	Share of caloric intake (%)
	2004/05	2010/11	2004/05	2010/11	2009	
Maize	144	159	154	177	133	54
Rice	13	16	4	5		
Cassava	15	9	20	15	89	7
Potato	22	39	16	19	88	8
Beans	10	10	9	7		
Groundnuts	4	6	10	6		

Table 2 Spatial flows and market analysis studies in Malawi

Study	Period studied	Data and Methods	Crops and total volumes	Share of traded produce (national)
Panel a: Spatial flows studies				
Gabre-madhin et al. (2001)	2001	Trader survey	Maize, rice, beans and pulses, soybeans	Not given
FEWSNET (2014)	2009	Expert opinion	Maize	Not given
FEWSNET (2018)	2018	Expert opinion	Maize, pulses in southern region	
Jayne et al. (2010)	2009	Trader survey	Maize	12.9%
Haggblade et al. (2009)	2009	Mapping of administrative and survey data	Food staples (Maize, Cassava)	12.2%
Myers (2013)	2001–2008	Spatial cointegration models	Maize	Not given
Panel b: Market analysis studies				
Mapila et al. (2013)	2010	Agricultural Statistics and linear programming	Maize	Not given
Kachulu (2018)	2010	Malawi Agricultural Sector Model	Cassava, Cotton, Groundnuts, Maize, Paprika, Rice, Sorghum, Soybean, Sugarcane, Tobacco	Not given

consumption of maize is 133 kg, accounting for about 54% of caloric intake of households in Malawi (Table 1). Using nationally representative survey data for 2005/06, Ecker and Qaim (2011) report that on average, more than 60% of the total food quantity consists of staple foods, primarily maize. Maize accounts for 46% of total food quantities, more than 60% of energy, and almost half of protein consumption. It is also the source for 67% of total iron, 65% of total zinc, and almost 70% of total riboflavin consumed (Ecker & Qaim, 2011). In selecting the food crops to include in the model, we were guided by the long-term importance of the food crop to the Malawian population. Therefore, the major food crops—Maize, rice, cassava, and potatoes were chosen. We however included two other food crops that offer other major nutrients apart from calories available through the staple food crops. Two pulses (i.e., Beans and groundnuts) were thus also included in the model.

There is a dearth of articles that attempted to estimate spatial maize flows in Malawi (see Table 2). This is because of a lack of data and the difficulty in collecting data from traders who for practical and strategic reasons may not be willing to publicly share their volume of operations. Specific efforts that collected spatial flows include Gabre-madhin et al. (2001) and FEWSNET (2014, 2018).[2] These efforts relied on trader surveys and expert opinion interviews to assess the direction of flows and in the case of Gabre-madhin et al. (2001) both the direction and volume of flows (Table 2). The estimates from these studies are not updated and though required are not given attention in the data collection efforts by the government or its development partners. This lack of knowledge affects decision making in that it is difficult to target production and consumption policies to where they would be most effective.

[2] Famine Early Warning Systems Network, an initiative led by the United States Agency for International Development (USAID).

3 Materials and methods

3.1 Model

3.1.1 Non-linear, multi-district food sector model

This study is based on two chronologically related economic models— the spatial equilibrium models of Samuelson (1952) and Takayama and Judge (1971), and sector programming models as introduced by McCarl (1982). Mathematical programming sector models have been widely used in developed countries to predict the impacts of changes in public policy, technology and infrastructure as well as in the general economic conditions on an agricultural economy and to evaluate alternative policy choices (Apland & Andersson, 1996). Alternative approaches to estimating trade flows usually used in international trade include gravity models (Limao & Venables, 2001), co-integration models (Myers, 2013), input–output regional models (Uribe et al., 1966) and trader surveys. The advantage for using spatial sector programming models is that these models can help generate some nonexistent estimates that can then be used in future for improving the collection of agricultural statistics. This advantage motivates the use of the model since Malawi lacks agricultural statistics on inter-district trade flows of food crops. The major challenge of using these models is that they are data intensive, some of which may not be readily available in a developing country. In this study, we show how compromises can be made to make the model operational for policy making with readily available data.

We assume more than two regions (or districts) trading in more than two homogenous commodities. Each district constitutes a single and distinct market that is separated but not isolated by a transportation cost. In addition, districts within the sector model allow for differences in available technology, resource supplies, and product demands (Apland & Andersson, 1996). The key assumptions for the model include competitive behavior for the participants and districts, and no legal restrictions to limit the actions of arbitragers in each district. These assumptions are plausible for Malawi because as reported by Myers (2013), spatial price transmission and seasonal price patterns in private sector maize markets in Malawi are generally consistent with long-run competitive inter-regional trade.

Using the assumptions stated, we can set up the net benefit function or net quasi-welfare maximization problem for a static, multi-region, multi-crop, non–linear programming model of the food sector in Malawi. The model captures the market equilibrium by maximizing economic surplus subject to market clearing and land allocation constraints. Consider the following nonlinear programming model of a closed food sector with a set of regions, Ω_G; set of multiple products, Ω_Y; set of multiple variable inputs,Ω_{ZV}; and a set of production activities in region g, Ω_{XG}:

$$\begin{aligned} Maximize\ :\ W = & \sum_{g\in\Omega_G}\sum_{i\in\Omega_Y}\left[a_{gi}Y_{gi} + 0.5b_{gi}Y_{gi}^2\right] \\ & - \sum_{g\in\Omega_G}\sum_{k\in\Omega_{ZV}}\left[c_{gk}Z_{gk} + 0.5d_{gk}Z_{gk}^2\right] \\ & - \sum_{g\in\Omega_G}\sum_{h\in\Omega_G,h\neq g}\sum_{i\in\Omega_Y} ty_{ghi}TY_{ghi} \\ & - \sum_{g\in\Omega_G}\sum_{h\in\Omega_G,h\neq g}\sum_{k\in\Omega_{ZV}} tz_{ghk}TZ_{ghk} \end{aligned} \tag{1}$$

Subject to:

Commodity balance

$$\begin{aligned} & Y_{gi} - \sum_{j\in\Omega_{XG}} e_{gij}X_{gj} + \sum_{g\in\Omega_G,h\neq g} TY_{ghi} \\ & \quad - \sum_{g\in\Omega_G,h\neq g} TY_{hgi} \leq 0\forall g \in \Omega_G, i \in \Omega_Y \end{aligned} \tag{2}$$

Input balance

$$\begin{aligned} & \sum_{j\in\Omega_{XG}} v_{gkj}X_{gj} - Z_{gk} + \sum_{g\in\Omega_G,h\neq g} TZ_{ghk} - \\ & \sum_{g\in\Omega_G,h\neq g} TZ_{hgk} \leq 0;\forall g \in \Omega_G, k \in \Omega_{ZV} \end{aligned} \tag{3}$$

Non-negativity constraints

$$\begin{aligned} & Y_{gi}, X_{gj}, Z_{gk}, TY_{ghi}, TY_{ghk} \geq 0;\forall g \in \\ & \Omega_G;i \in \Omega_Y, j \in \Omega_X, k \in \Omega_Z;h \in \Omega_G, h \neq g \end{aligned} \tag{4}$$

Crop mix restrictions

$$X_{gj} \leq \sum_{t=2000}^{2009} \Phi_{gt}X_{gjt} \tag{5}$$

$$\sum_{t=2000}^{2009} \Phi_{gt} \leq 1 \tag{6}$$

where

g is the region/district;
Y_{gi} is the quantity demanded of product i in district g;
Z_{gk} is the quantity supplied of variable input k in district g;
X_{gj} is the level of production activity j (area of land under crop j) in district g;
TY_{ghi} is the quantity of product i shipped from district g to district h;
TZ_{ghk} is the quantity of variable input k shipped from district g to district h;
e_{gij} is the output of product i per unit of production activity j in district g (or yield coefficient);
v_{gkj} is requirement of variable input k per unit of production activity j in district g;
ty_{ghi} is transport cost from district g to district h per unit of product i;

tz_{ghk} is transport cost from district g to district h per unit of variable input k;
Φ_{gt} is the endogenous weight for historical crop mixes.

The market demand function for product i in region g, in quantity dependent form is, $P_{gi} = a_{gi} + b_{gi}Y_{gi}$. The related terms in the objective function, $a_{gi}Y_{gi} + 0.5b_{gi}Y_{gi}^2$, are demand function integrals. The market supply function for variable input k in region g, in quantity dependent form is, $R_{gk} = c_{gk} + d_{gk}Z_{gk}$. The related terms in the objective function, $c_{gk}Z_{gk} + 0.5d_{gk}Z_{gk}^2$, are input supply function integrals. The constraint in Eq. 2 represents the product balance where total use of each product is restricted to its total supply. The constraint in Eq. 3 is the input balance constraint which restricts the use of input k in region i to its availability. The constraint in Eq. 4 is the usual non-negativity requirement constraint for all the endogenous variables. The constraint in Eq. 5 and 6 represent convexity restrictions on historical crop mixes. This is discussed next. A discussion of the complexity of generating analytical results are presented in Mkondiwa (2020).

3.1.2 Crop mix approach

The use of aggregate level supply responses instead of individual supply response functions in the sector model has its caveats. There may be discrepancies for the following reasons: (i) details on production are typically much less in a sector model than in individual farm models, (ii) sector models typically ignore market factors like product differentiation and quality, and (iii) transaction costs are often omitted (Wiborg et al., 2005). In addition to these sources of aggregation bias, extreme specialization in mathematical programming models is also not consistent with observed production patterns. There are three main approaches of dealing with the aggregation bias and extreme specialization: adhoc flexibility constraints, positive mathematical programming (PMP) and crop mix approach (for details, see Merel & Howitt, 2014). Each of these approaches has its limitations.

The adhoc flexibility constraints are the least desirable because they introduce unwarranted subjectivity such that response of the model to policy is determined by percentage bounds set by model builder. For trade flows calibration, the PMP approach requires prior knowledge of crop flows (Paris et al., 2011) which are not available in the case of Malawi and for many countries limiting its purpose for within-country analyses. The limitation of the crop mix approach is that it does not fully replicate input allocation in the reference year. Nonetheless, overspecialization problem is mitigated (Merel & Howitt, 2014). We also mitigate the challenges in replicating input allocation by using the best available crop budgets from the Ministry of Agriculture and Food Security that represent well the production practices of majority of the smallholder farmers as such the input allocation is likely to be reproduced by construct.

In this paper, we use the crop mix approach because it is consistent with the Dantzig-Wolfe Decomposition (Dantzig & Wolfe, 1961) commonly used in transportation economics to approximate trade flows across locations and our goal is to get a general picture of the nature of the flows not necessarily to reproduce trade flows in a particular year. The crop mix approach was introduced by McCarl (1982)[3] to reduce the potential aggregation biases. The crop mix approach captures implicit product-product relationships among crops related to rotation effects and the efficient use of fixed resources and is less prone toward unrealistic crop specialization. This approach restricts the crop mix to the space spanned by a convex combination of historical crop mixes. The main assumption when using this approach is that there is a duality between solving an aggregate model with the full detail of all the farm firm models included on the one hand, and on the other building an aggregate model without the farm firm models which is constrained to the production possibility set spanned by a convex combination of all possible optimal solutions of the farm firm models (Wilborg, et al. 2005; Merel & Howitt, 2014).

There are two important deficiencies when using the historical crop mixes. Firstly, the use of historical crop mixes does not constitute as rich a production possibility set, as one would have the full detail in a model. Historical crop mixes are reflections of producer decisions in the face of prevailing prices.[4] Thus, the crop mixes will not be an accurate representation either if the expected prices confronted by the model are outside the historical range or if the situation to be examined substantially revises the production possibilities. Second, the approach does not take account of changes in production costs, inputs and yields when crop mixes change. Several extensions considering these have been made. These include; supplementing the historical crop mixes with expert information or survey information and in a recent study, Chen and Onal (2012) suggested combining historical crop mixes with synthetic crop mixes that are based on acreage response elasticity. The justification for the modification is that though historical crop mixes may be valid when simulating farmer's planting decisions under normal conditions, they may be too restrictive for future land

[3] Theoretical details linking the crop mix approach to the Dantzig-Wolfe decomposition can be found in McCarl (1982), and Onal and Chen (2021).

[4] Crop mixes are also determined by many ecological, cultural, and behavioral factors that we abstract away from including the need for subsistence consumption, historical experience with the crop, culinary preferences, and religious factors.

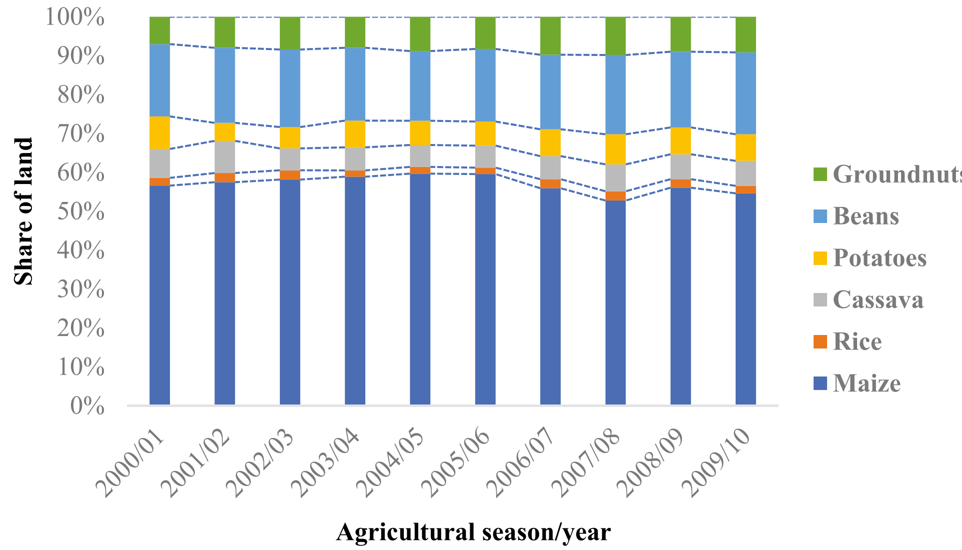


Fig. 1 National crop mix, 2000/01–2009/10

uses. Our application of the crop mixes is however focused on calibrating the current trade flows thus establishing the benchmark for future food policy models. Synthetic crop mixes would be warranted if new production technologies were being considered.

In this paper, we use historical crop mixes[5] because our goal is on calibrating baselines and that during this decade Malawi experienced both worst droughts in 2001/02, 2004/05 and 2007/08 with extreme price spikes, normal, and bumper harvests particularly after the 2005/06 agricultural season, yet the allocation of land to the various food crops has remained stable as can be seen in Fig. 1. For example, due to poor harvest, maize prices rose in 2001/02, 2004/05 and 2007/08 by 354%, 218% and 395% respectively (Ellis & Manda, 2012).

3.1.3 Computation and model chart

The model is calibrated in the commercial version of General Algebraic Modelling System (GAMS) following a structure of Forest and Agricultural Sector Optimization Model for the U.S (Adams et al., 1996) and Minnesota Sector Model documented in Moon et al. (2016). The GAMS code for this study is presented in Mkondiwa (2020). The diagram in Fig. 2 provides a list of the data inputs and outputs of the food sector model.

3.2 Data and model inputs

A mathematical programming sector model is as accurate as the data used for the calibration and careful attention is made to explicitly explain the data assumptions made. The data inputs for the model include the raw food crop prices and quantity demanded, historical crop mixes (hectares under each crop), crop yields, production and marketing costs for each of 27 districts. The model is calibrated and validated using agricultural production estimates by the Ministry of Agriculture and Food Security for the reference year 2009/10. The data are summarized in four broad categories: demand data, production data, transportation data and crop budgets.

3.2.1 Demand

The demand data used in the model included rural and urban own price elasticities for each of the food crops, district level quantities consumed per capita for each of the food crops, district level population and prices of the food crops for 2009/10 agricultural season. The demand functions we use in this study were obtained from a quadratic almost ideal demand system (QUAIDS) elasticities estimated by Ecker and Qaim (2011). Instead of working out the inverse of the Quadratic Almost Ideal System, we use the own price elasticities, price data and quantity consumed in each district to derive the coefficients for the demand system. The slope coefficients for the district demand equations for each food crop are therefore calculated as: $b_{gi} = \frac{\delta_{gi}\overline{Y}_{gi}}{\overline{P}_{gi}}$ where δ_{gi} is the own price elasticity (different for rural and urban districts) and the bars on the variables represent the observed values for prices, P and quantity demanded, Y in each of the districts. The elasticity refers to the percentage change in Y with respect to change in P, but the slope is defined from the inverse demand function, so it is $\Delta P/\Delta Y$ (Hazell & Norton, 1986). The treatment of demand functions in this way implicitly assumes that the demand system in each district

[5] The crop mixes are incorporated in the model using convexity constraint which is part of the input constraints.

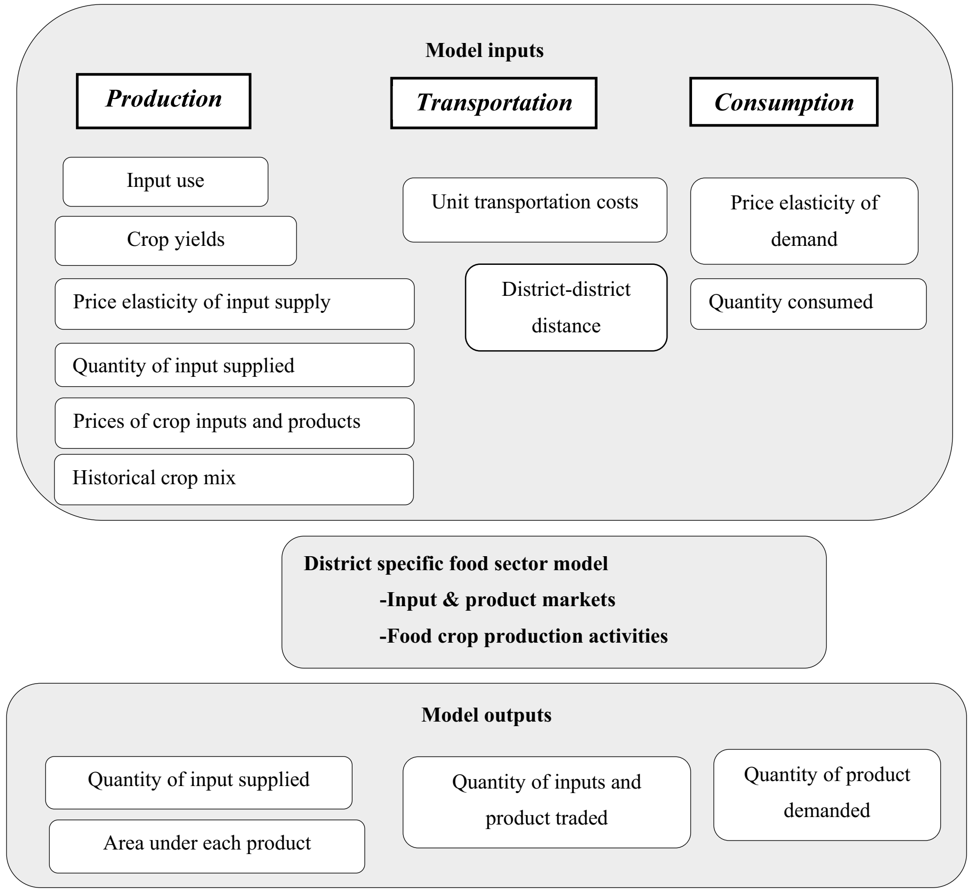


Fig. 2 Model diagram

is proportional to the rural and urban disaggregated demand systems. According to Hall et al. (1975), this does not imply that the quantities demanded in a particular district will be proportional to national quantities; price variations between areas will prevent that. Thus, this treatment ignores intra-rural or intra-urban district differences in preferences. The own price and expenditure elasticities were obtained from a 2009/10 study by Ecker and Qaim (2011). Table 3 summarizes the elasticities used in the study. The urban elasticities were used for the city districts of Lilongwe, Blantyre, Zomba and Mzuzu (in Mzimba District).

These values were considered acceptable since it is generally known that demand for staple crops is usually inelastic (World Bank, 2008). The positive elasticities for cassava and potatoes are inconsistent with demand theory and therefore have implications on the results for these two crops.[6] The demand quantities were calculated by multiplying the per capita food consumption per year as reported in Verduzco-Gallo et al. (2014) by the population size in each district from the 2008 Malawi Population Census. In the case of cities, the district and city population were summed. The income coefficient was calculated from the income elasticities reported in Table 3, and expenditure per capita calculated by the author from the Integrated Household Survey III data (2010/11).

[6] Note that even if we use plausible values for demand elasticities, the input and output data for cassava and potatoes are of poor quality and there is still no consensus on productivity levels. There are discrepancies among international databases, ministerial data sources, and the national household surveys on the production statistics of roots and tubers (Kilic et al., 2021).

Table 3 Expenditure and Marshallian own-price elasticities of food demand among rural and urban households

	Expenditure elasticities		**Own-price elasticities**	
Crop	Rural	Urban	Rural	Urban
Maize	0.948	0.628	-0.877	-0.722
Rice	0.892	0.904	-0.816	-0.959
Cassava	-0.665	0.076	0.618	-1.152
Potatoes	0.712	1.004	-0.770	-1.248
Beans	1.365	0.197	-0.952	0.415
Groundnuts	0.744	0.413	-0.821	-0.013

Source: Ecker and Qaim (2011)

3.2.2 Production and input supply parameters

The Malawi food sector model has the following inputs: seeds for each crop (i.e., maize, rice, potatoes, cassava, beans, groundnuts), basal fertilizer, top-dressing fertilizer, pesticides, transport, packaging materials, labor and land. These inputs can be divided into three groups of inputs: (i) exogenously priced inputs (e.g., seeds, fertilizer, pesticides, packaging, and transport), (ii) available in fixed supply (e.g., land), and (iii) endogenously determined (e.g., labor). For exogenously priced inputs, a unit cost entry is made directly in the objective function. For such inputs, the implicit supply function is infinitely elastic and the supply function integral is linear (Apland & Andersson, 1996). We thus included prices of the inputs as the intercept and a zero slope in the inverse input supply equation. We obtained the price information from crop budgets provided by the Malawi's Ministry of Agriculture and Food Security.

Labor was assumed to be endogenously priced because labor use in smallholder agriculture in Malawi is largely family labor with under 10% of the total labor use being hired labor (Takane, 2008). Casual labor is also common. The data used on wage rates for labor use, labor requirement and available labor were obtained from Ministry of Agriculture and Food Security Crop Budgets for 2010 and were consistent with survey evidence from Takane (2008). The estimated labor supply elasticity was assumed to be (0.15) using the experimental results reported by Goldberg (2016). The only input available in fixed supply is food crop land. Crop land was therefore mapped to specific districts as land types and restricted using convexity restrictions. The crop production quantities, area cultivated and yields in each of the districts were collected from the Agricultural Statistics Bulletins (2000–2010) compiled by the Malawi Ministry of Agriculture and Food Security.

3.2.3 Transportation

Transportation costs from one district to another were computed from district-district distances and per unit per km transportation costs from the literature. We calculated geodesic distances in kilometres from the centroid of one district to another using geosphere package in R (specifically using the distm function). The use of centroids of the districts to calculate distances follows the common approach in the mathematical agricultural sector programming literature (e.g., Chen & Onal, 2016, Egbendewe-Mondzozo et al. 2015) but it is essentially an approximation. This implies that transport costs take the form of iceberg costs as is standard in trade literature. For domestic routes, Tchale and Keyser (2010) estimate transport cost to be 18.00 Malawi Kwacha (0.12 USD) per ton per km (or equivalently 0.018 Malawi Kwacha per kg per km).[7] Though, a spatial sector programming does not include intra-district transportation cost, we got estimates of transportation cost for each of the crops from the crop budgets which were added to the production costs.

3.2.4 Crop budgets

The crop budgets used in the study are based on the 2010 Ministry of Agriculture and Food Security gross margin analyses. We verify the input requirements by comparing to the official guide to agricultural production (Ministry of Agriculture, 2020). The crop budgets are used to define the input and output coefficients for the model. The crop budgets are at national level, but the crop yields are at district level which allows an approximation of agro-ecological comparative advantage of each district to produce a particular crop. We use a 10-year average (2000–2009) as baseline yields in each district.

4 Results and discussion

4.1 Baseline model validation and results

In the previous section, we presented the model and associated data inputs. We now turn to the calibration results starting with the baseline results then transport cost simulations.

The common approach of validating a sector model is to compare the model results to observed values of interest. We are interested in the share of produce that is across districts. We do not have any data on volumes of inter-district food flows in Malawi, as such the model is validated in two ways, (i) validation by construct (McCarl, 1982), and (ii) validation by results or outcomes (McCarl & Apland, 1986). Validation by construct is done through the use of historical crop mixes which guarantees that calibrated land allocation is within the observed land allocation. Even though we use the crop mix approach, its limitation is that it does not fully replicate input allocation in the reference year. Validation by results is therefore needed. In this paper, validation by results involved comparing the equilibrium land allocation and crop production levels of the food crops against the

[7] This takes a value of 0.0252 USD using the 2016 exchange rate of 1 MWK/0.0014 USD (Guo and Hawkins 2016) and 0.12 USD using 2010 exchange rate of 1 MWK/0.0067 USD. Fafchamps et al. (2005) using a trader survey estimated transport costs within Malawi as \$0.70 per ton per km. Another study by Lall et al. (2009) estimated using a survey of tobacco truckers that the average unit transport price (per ton, per km) is 228.4 Malawi kwacha from rural areas to the country's main cities in comparison to 10 and 12 Malawi kwacha per ton per km on routes linking the country to international markets. In the analysis, we assumed the value by Tchale and Keyser (2010) to be the base transport cost.

Table 4 Calibrated yields, area, production, trade, and consumption in Malawi (Baseline)

Crop	Variable	Units	Model results
Maize	Area	1000' Hectares	1,059.65
	Prod = Demand	Tonnes	1,557,311.93
	Yield	Tonnes/hectare	1.47
	Traded quantity	Tonnes	105,367.46
	Share of production traded	%	6.77
Rice	Area	1000' Hectares	59.60
	Prod = Demand	Tonnes	78,411.95
	Yield	Tonnes/hectare	1.32
	Traded quantity	Tonnes	51,869.16
	Share of production traded	%	66.14
Beans	Area	1000' Hectares	136.63
	Prod = Demand	Tonnes	65,348.01
	Yield	Tonnes/hectare	0.48
	Traded quantity	Tonnes	48,439.70
	Share of production traded	%	74.13
Groundnuts	Area	1000' Hectares	115.12
	Prod = Demand	Tonnes	78,400.48
	Yield	Tonnes/hectare	0.68
	Traded quantity	Tonnes	35,722.48
	Share of production traded	%	45.56

observed levels from the Agricultural Production Estimates by the Ministry of Agriculture and Food Security in the reference year (2009/10) (see figures in appendix B). The model production results matched almost perfectly to the reference year data for maize and rice with some discrepancies for groundnuts and beans.

Table 4 shows the equilibrium land uses, yields, production, and traded volumes in Malawi for the model.

Table 4 further shows the percentage of produced quantities of crops that are traded across districts for each of the transport cost scenarios. For the baseline calibration year (2009/10), 6.77% of maize production is traded. Because rice, groundnuts and beans are demanded more in urban districts, the share of traded volumes is over 40% of production (see Table 5).

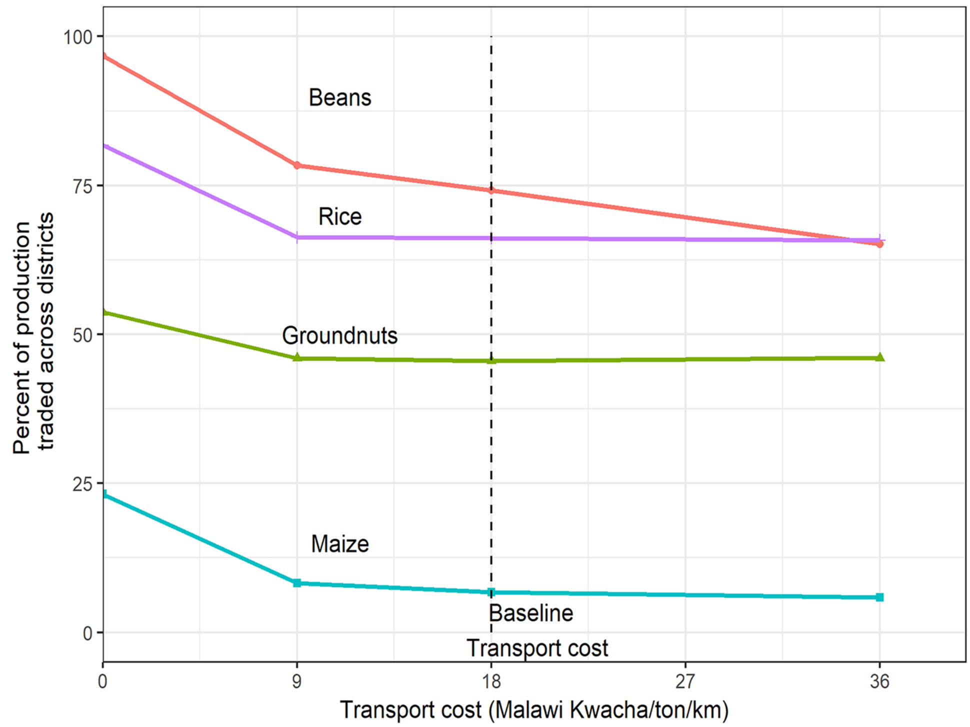
These estimates are consistent with related estimates of proportion of farmers selling their produce reported in other studies. Sibande et al. (2017) estimates the proportion of farmers who sold selected cereals and legumes in nationally representative integrated household surveys (IHS1 and IHS2) and integrated household panel surveys (IHPS 2010 and IHPS 2013) from 1997/98 to 2013. For maize, their estimates range from about 8% to 15% while our baseline model results predicted 6.77%. For rice, their estimates range from 40 to 70% while our baseline model results predicted 66.14%. For common beans, their estimates range from 20 to 50% while our baseline model results predicted 74.13%. Finally, for groundnuts, their estimates range

Table 5 Share of production traded for each of transport cost simulation scenarios

Transport cost (MK per ton per km)	Crop	Percentage of production traded across districts	Percentage change in quasi-welfare (objective function value) from baseline*
0	Maize	23.19	+0.67
	Rice	81.76	
	Beans	96.77	
	Groundnuts	53.71	
9	Maize	8.29	+0.34
	Rice	66.29	
	Beans	78.40	
	Groundnuts	46.01	
18 (Baseline)	Maize	6.77	
	Rice	66.14	
	Beans	74.13	
	Groundnuts	45.56	
36	Maize	5.85	-0.51
	Rice	65.83	
	Beans	65.20	
	Groundnuts	46.05	

*The objective function value is not necessarily a measure of economic surplus thus its absolute has no economic meaning. Its change however a reflection of the change in economic welfare

Fig. 3 Share of production traded across districts under different transport cost scenarios (without cropping restrictions)



from 30 to 40% while our baseline model results predicted 45.56%. Chirwa (2006) as cited in Sibande et al. (2017) also estimated that the proportion of farmers participating in the market as sellers was lower for maize (at 9% in 1997/98) as compared to other crops (at 39% in 1997/98). Benson (2021) using 2016/17 Malawi Integrated Household Survey reports similar trends in percentage of those selling their produce and the proportion of the harvest that is sold.

This implies that the model accurately predicts the market conditions in Malawi. Any deviances may be due to differences in comparison years, definitions of the variables being compared, and data assumptions used for building the model. These include the cost of fertilizer. For instance, while the market cost of fertilizer was about 5500 Malawi Kwacha per 50 kg in 2009/10,[8] during this period a subsidy program (seeds and fertilizer) was provided to about half of the farming population to maize implying the cost of producing maize was much lower due to the subsidy as compared to the market rate. In terms of land allocation, we compared the results from the model to crop suitability maps reported by Benson et al. (2016) and Ministry of Agriculture land area reported for the 2009/10 season. The suitability maps and observed data are consistent with the results of the paper for all the crops in the calibration results (see figures B1 to B5 in the appendix B).

4.2 Transport cost simulations

We consider four transport cost scenarios. These are (i) scenario 1: baseline- current per unit transport cost of 18 Malawi kwacha/MT/Km (0.12 USD), (ii) scenario 2: double transportation costs from 18 to 36 Malawi Kwacha/MT/Km, (iii) scenario 3: half transportation costs from 18 to 9 Malawi Kwacha/MT/Km and (iv) scenario 4: reduce unit transportation costs to zero[9] kwacha per MT per Km. These scenarios capture a range of transport cost changes that may occur under exogenous improvements in infrastructure and changes in fuel costs. Note that for scenario 4, the factor and output price equalization theorem across districts of Samuelson (1952) holds. Figure 3 shows that a reduction in transport costs increases the share of traded volumes for all the crops. The increase in the share is however smaller as compared to the rate of transport cost reduction. For instance, reducing transport costs by half from 18 MK/km/ton to 9 MK/km/ton increases the share of traded volumes of maize from 6.77 to 8.29 percent.

The results in the paper are somewhat different from prior studies on effects of transport costs on intra-nationally traded volumes. According to Minten and Kyle (1999), doubling transport costs can reduce trade flows by around 80%. In Uganda, Gollin and Rogerson (2014) find that higher

[8] About 37 USD per 50 kg bag assuming an approximate exchange rate of 150 MK = 1 USD prevailing in 2009/2010.

[9] For technicality issues in GAMS, we set the number to 0.0000000001.

Fig. 4 Map of maize trade flows in a normal year (2009), based on expert opinion. Source: FEWSNET (2014). Note: Production and Market Flow Maps provide a summary of experience-based knowledge of market networks significant to food security. Maps are produced by USGS in collaboration with other FEWS NET staff, local government ministries, market information systems, NGOs, and network and private sector partners

transport costs drive up the size of the agricultural workforce and the fraction in subsistence. Donaldson (2018) for India and Allen and Donaldson (2020) for USA found that the intra-national estimate of the elasticity of trade flows with respect to distance is close to minus one.

Under all transport scenarios, legumes (groundnuts and beans) are traded substantially across districts. This implies that encouraging rural farmers to grow more legumes does not necessary imply that the farmers will consume the legumes which has implications on nutrition since legumes are the cheaper source of protein in these areas. The demand scenarios are such that the grains are traded from surplus to deficit areas.

The results in the paper also provide a caution to researchers who assume large, and uniform effects of transport costs reduction on trade. The Malawi case as presented in this paper shows that the effects are small and vary considerably by crop. In terms of impacts on welfare change, we find small welfare changes with doubling transport costs reducing economic surplus by 0.51%. Halving transport costs from 18 MK/km/ton to 9 MK/km/ton increases welfare by 0.34% while reducing transport costs to almost zero increases welfare by 0.67%.

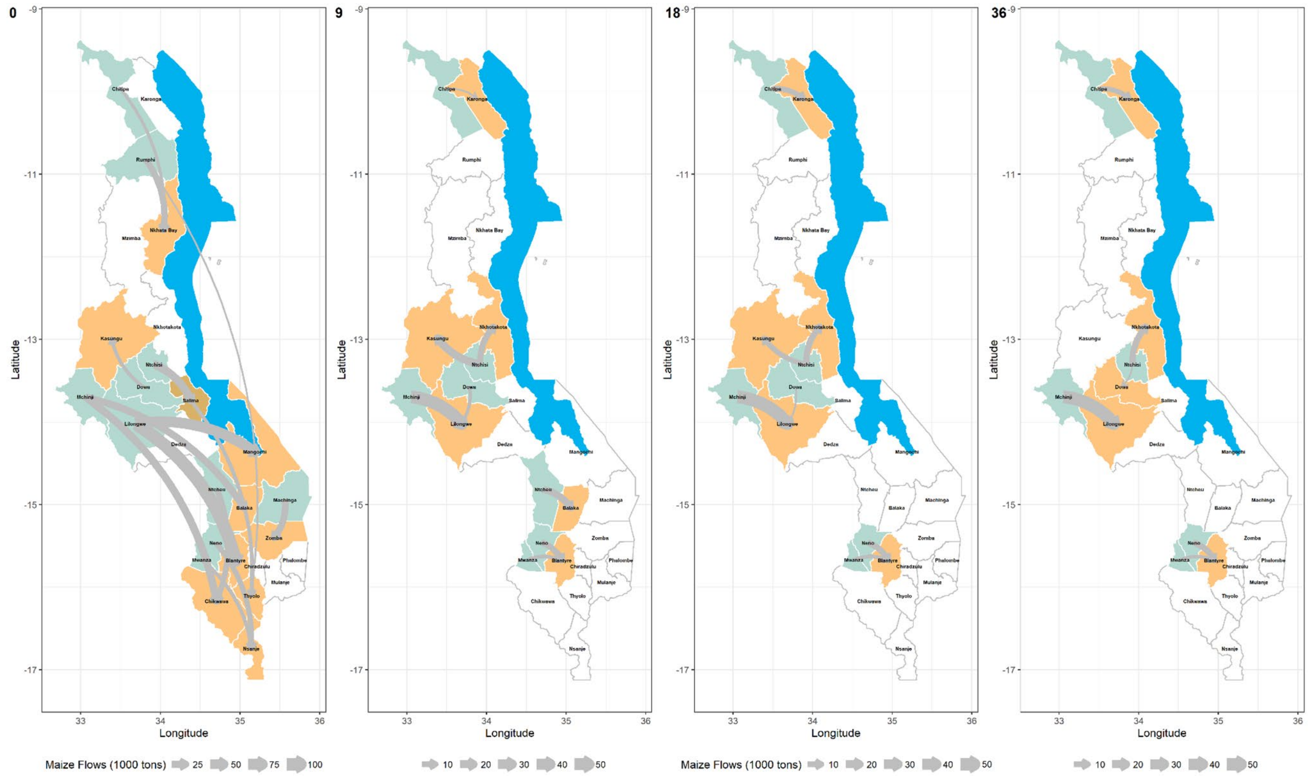


Fig. 5 Calibrated inter-district maize trade in Malawi. Note: The flows are in metric tons. The flows for maize are consistent with expert opinion and literature on marketing of maize (e.g., Benson, 2021, Sibande et al. 2017)

4.3 Spatial food flows within Malawi

The map in Fig. 4 shows the baseline year (2009/10) direction but not the volumes of maize trade flows between the different markets in Malawi reported by the Famine Early Warning Systems Network (FEWSNET, 2014) using expert opinions. Figure 5 shows corresponding flows from the baseline model results. To validate the model, we compare the direction of the flows between Figs. 4 and 5. We then discuss the quantities predicted using the model.

There are several important distinctions between flows in Fig. 4 and what is expected from the model (Fig. 5). First, Fig. 4 shows bi-directional flows which may be due to differences in the timing of the availability of harvests. In the calibrated model, we can only estimate the net inter-district food flows.

It is evident in the Fig. 5 (see the zero-transport cost scenario) that most southern region districts and districts along the Lake Malawi are maize crop deficit districts. To illustrate this, consider districts that are wholly food insecure in the southern part of the country. These include, Balaka, Thyolo, Chikwawa and Nsanje.

The Figs. 4 and 5 also illustrate the intuitive prediction of flows of agricultural outputs into the main cities of Lilongwe and Blantyre. The closer by districts are acting more as service districts providing maize to these urban areas. It is evident from the maps that in each region there are central district markets that import large flows of food crop commodities consistent with an observation by Mapila et al. (2013). In the case of central region, Lilongwe is the main maize market. It is serviced by Mchinji, Kasungu, Dowa and Dedza based on the FEWSNET estimates in Fig. 4 and only Mchinji and Dowa based on our equilibrium results (Fig. 5).

In the southern region, Blantyre District is the main market. It is serviced by Phalombe, Mulanje, Thyolo and Mwanza Districts. In terms of inter-regional flows, the results are consistent with the analysis by Myers (2013) who asserted that major inter-regional maize flows are from the centre to the south, with intermittent flows in both directions between the centre and the north, depending on weather patterns and the season. The maps (i.e., Figs. 4 and 5 (baseline)) are generally similar when considered at district level. For instance, Mchinji ships maize to Lilongwe, Ntcheu ships maize to Balaka. It is however difficult to make comparisons in cases where some parts of district are maize insecure while others are not. This is the case because our model is using the available district level data, rather than sub-district level data. Further research should consider disaggregating the agricultural sector programming model to finer spatial units and thus downscaling any policy interventions to such levels. The small disparities between the model results and the FEWSNET map may be due to the assumption of competitive markets and closed economy. Thus, a model that allows for alternative market structures and international trade may be most appropriate to reproduce the observed levels.

The relative values of traded volumes for the food crops including maize (figures in the appendices) are higher than those reported by Gabre-madhin et al. (2001) for 1998–99 season. They concluded that maize was traded in amounts ranging from 400 to 8000 tons. Rice volumes were smaller ranging from 50 to 1000 tons. Beans/pulses trade ranged from 100 to 3000 tons whereas soybeans ranged anywhere from 10 to 5000 tons. This implies that overtime; the amounts of traded volumes have been increasing. Appendix A shows graphical illustrations of inter-district flows for rice, beans, and groundnuts across the transport cost scenarios.

There are three policy implications of the estimated inter-district food flows and transport cost simulations. First, the estimated inter-district flows provide basis for making food marketing and distribution policies especially on which locations to prioritize for consolidating commodities, transport networks improvement, and construction of storage facilities for the various commodities. The understanding of potential welfare improving trade flows and inter-district trade costs can help in unlocking the internal trade frictions. For example, the model provides potential food source districts which would be prioritized to supply food for humanitarian assistance in the case of weather induced (e.g., floods) food shortages in other parts of the country.

Second, the analysis has demonstrated the importance of recognizing the existence of food flows when designing spatially targeted food production policies in Malawi. For example, a rice productivity improvement program in rice growing areas inevitably affects those who consume and those who do not consume rice even in non-rice growing areas. Another example is on the promotion of legume production (e.g., groundnuts and beans) for nutritional purposes in legume producing rural areas. Given that most of these legumes are traded, the program will also positively affect those in other districts. And importantly, this may dampen the purported nutritional outcomes from the intervention in legume growing areas.

Finally, the knowledge on the existence and extent of these flows also provides credence to the need for systematic collection of data on inter-district food flows. Such estimates coupled with the mathematical programming model developed can then guide policies especially those on avoiding distortionary bans of food trade (for example, the bans on trading of maize and soya beans that are instituted frequently). Each agricultural season, there is constant political pressure to implement protectionist policies (both against international and intra-national food trade) on behalf of smallholder farmers without proper evidence. The spatial mathematical programming model we have developed if calibrated and validated with most recent intra-national trade can help in avoiding these internal distortionary policies.

4.4 Limitations

There are at least four areas in which the performance of the model could be improved. First, data on food flows are not collected and thus not available in Malawi— no one knows how much maize, rice, cassava, potatoes, beans, and groundnuts is traded across districts. This paper estimates these flows in food crops under the assumption of perfect competition which may not be the case for some of the crops.

Secondly, the results that even under low transport costs, cassava and potatoes are not traded across districts runs counter to the common sight of trucks carrying these commodities across different parts of the country. This may be largely due to poor quality of production and consumption data for these crops (see Kilic et al., 2021 for a description of the data quality issues for roots and tubers). Benson (2021) also observed that high agricultural production estimates on cassava and potatoes are implausible because though these crops are mainly used as human food in Malawi, the consumption levels are reportedly very low.

Third, for the transport cost data, we assumed a constant per unit cost across crops and used distances based on centroids of districts. Both these assumptions have the potential to be relaxed with possible important empirical implications.

Finally, we have assumed exogenously priced input supply for key inputs (fertilizer, seeds, pesticides) due to lack of data on input supply elasticities for these inputs. This has restricted the model on understanding input trade flows as compared to output responses which have endogenously priced output demands. As also suggested by Komarek et al. (2017, p.174), future research should consider the input trade flow implications of varying unit transportation costs using endogenously priced inputs. In addition, this assumption also affects the effects of increasing transport costs.

5 Conclusion

The paper has demonstrated how a price endogenous mathematical programming model can be used in generating agricultural statistics of commodity flows across districts. As with any other calibration exercise, our results depend on the quality of the underlying data. In this paper, we have been explicit about the nature and sources of the data used, which we made clear so that our results and conclusions are interpreted within the limitations of the data realities we faced including lack of good validation data on inter-district food flows. Despite these limitations, the potential for using spatial programming models in guiding data collection efforts for policy analysis remains huge. This paper has provided a prototype model using readily available subnational data to guide targeted agricultural development planning in Malawi and other data sparse countries in sub-Saharan Africa. In addition, the use of a spatial sector programming model can show the improvements required in the collection of agricultural statistics relevant for policy making. Given the importance of trade flows in making credible food policy decisions, it is important that statistical agencies in SSA introduce commodity flow surveys within countries. These can be implemented together with well-established agricultural surveys like the Living Standards Measurement Surveys (LSMS).

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s12571-022-01302-y.

Acknowledgements This paper was prepared with support from the McKnight Foundation. The authors thank Terry Hurley, Philip Pardey, Jeffrey Coulter, participants at the APEC Food Group Meetings at University of Minnesota led by Metin Cakir and Hikaru Peterson, and Malawi Agroecology Hub Conference participants for comments on earlier versions of the paper. The content of this paper solely reflects the opinions and findings of the authors.

Funding This work was support by McKnight Foundation Grant No. 15–228, Phase II: Appropriately Targeting and Scaling Crop Management Practices for Integrated Maize-Legume Systems in Southern Africa.

Declarations

Conflict of interest The authors declared that they have no conflict of interest.

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Maxwell Mkondiwa is a Spatial Economist at the International Maize and Wheat Improvement Center (CIMMYT) and an Adjunct Research Fellow at Center for Agricultural Research and Development (CARD), Lilongwe University of Agriculture and Natural Resources (LUANAR), Malawi. He has expertise in a wide range of areas including production and marketing economics, spatial bio-economics and GIS, agricultural policy analysis, and mathematical programming.

Jeffrey Apland is a professor emeritus at University of Minnesota, Department of Applied Economics. The general fields in which he conducts research are production economics, managerial economics and economic applications of mathematical programming. Much of the research has emphasized technology choices and risk analysis. Recent projects have focused on energy and environmental dimensions of agricultural production, including those related to biofuel feedstock production and water quality. The application of mathematical programming to economic problems at both the firm and sector levels is featured in some of his research.