



## Agricultural household effects of fertilizer price changes for smallholder farmers in central Malawi



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### ABSTRACT

This simulation study explored the agricultural household effects of changes in the price of inorganic nitrogen fertilizer for farmers in central Malawi. We selected the Dedza district to conduct this study, which is a district reliant on maize production for household livelihoods. This study used data from a household survey to develop and calibrate an agricultural household model for a representative household. The survey focused on socio-economic and agronomic factors. This included plot-level agronomic details for crop inputs and yields. Using our dynamic model, we found a negative association between fertilizer prices and fertilizer use, maize area, and income. Removing fertilizer prices led to an increased use of nitrogen fertilizer at the household scale from 16.8 kg to 49.6 kg and this helped increase household income by 52%. We calculated an average own-price elasticity of fertilizer demand of  $-0.92$ . Although higher fertilizer prices increased legume acreage, which had potential environmental benefits, household income fell. Our benefit-cost ratio calculations suggest that government actions that deliver changes in fertilizer prices are relatively cost effective. Our study highlights the reliance of households on maize production and consumption for their livelihood, and the effects that changes in fertilizer prices can have upon them.

### 1. Introduction

Governments in Africa south of the Sahara often pursue policies aimed at increasing food security and social welfare. One component of these policies includes subsidizing the purchase of inorganic nitrogen fertilizer. Despite these policy efforts, some countries in Africa south of the Sahara have recently experienced declining productivity of staple crops (Jayne et al., 2006; Tittonnell and Giller, 2013), especially maize (*Zea mays*). Jayne et al. (2006) suggest the low use of external inputs as a contributor to declining productivity in staple crops. Farmers often desire to use more inorganic fertilizers but face cash constraints in purchasing it, as discussed by Duflo et al. (2011) in the example of Kenya. Poor and declining soil fertility presents a constraint to increasing the agricultural productivity of smallholder, maize-based farmers in Africa south of the Sahara (Place et al., 2003; Jayne and Rashid, 2013; Kihara et al., 2016). In this context, the improved management of nitrogen in cropping systems can help address challenges of sustainable food security and depends on both technological

innovation and socio-economic factors (Zhang et al., 2015). Multiple options exist to improve the management of nitrogen in cropping systems including applying inorganic nitrogen fertilizer, growing legumes, applying manure to fields, and retaining crop residues in the field. These options have advantages and constraints, especially the use of fertilizer.

Our study examined the household effects of changes in the fertilizer subsidy component of Malawi's Farm Input Subsidy Program (FISP). The FISP aims to increase maize production, promote household food security, and enhance rural incomes. Beneficiaries of the FISP receive subsidized fertilizer and seed. Lunduka et al. (2013) found that most household-scale studies of the FISP used statistical approaches to show that the FISP generates relatively modest increases in maize production and yields. Earlier studies calculated the benefit-cost ratio (BCR) of fertilizer use. The BCR measures the change in income or value of maize production in relation to the (public) cost of fertilizer use under the subsidy. With the benefit-cost ratio (BCR) ranging from close to zero to over 10, conditional on local context, fertilizer response rates,

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relative prices, and study method (Dorward and Chirwa, 2011; Chirwa and Dorward, 2013; Lunduka et al., 2013; Arndt et al., 2015). Using a computational, economy-wide market model, Arndt et al. (2015) found that fertilizer response rates were the major factor determining the BCR of the FISP, with a BCR of approximately 1 or 1.62, depending on the calculation used. Ricker-Gilbert et al. (2014) showed that higher fertilizer prices reduced fertilizer demand. Holden and Lunduka (2012) showed that a 1% increase in fertilizer prices increased in the probability of manure use by approximately 0.5%. Chibwana et al. (2012) showed a positive association between household participation in the FISP and maize acreage, and that program participation reduced legume acreage. In Ethiopia, Louhichi et al. (2016) used a computational household model to show that changes in simulated fertilizer prices had a limited effect on crop production and household income. Taking into consideration this literature above, this study asked two questions:

- What are the agricultural household effects of changes in the price of inorganic nitrogen fertilizer for smallholder farmers in central Malawi?
- What are the benefit-cost ratios associated with fertilizer price support?

To answer these questions, we used a mathematical programming model of an agricultural household. The main effects considered were fertilizer use, land use, agricultural productivity, food consumption, and income. Our approach integrated economic and biophysical concepts and data; this included accounting for changes in nitrogen available to crops due to changes in crop management over time and hence any feedback effect this has on household indicators. Our approach complements the statistical and economy-wide studies of Malawi's FISP mentioned above to show BCRs from the alternative perspective of using a farm-household simulation approach. Our approach traces out the linkages between changes in fertilizer prices and its income effects. Our study complements Snapp et al. (2010) and Smith et al. (2016) who analyse partial profitability and grain balances related to the use of fertilizers in Malawi by providing a farm-household perspective on the effects of fertilizer price changes on different indicators of household performance and welfare.

## 2. Methods

### 2.1. Characterization of the case study

We conducted this study in the Dedza district of central Malawi. Households in this district are maize-focused, smallholder farmers. We characterized these households by using data collected as part of a participatory agricultural research for development program called Africa Research In Sustainable Intensification for the Next Generation (Africa RISING). The Malawi Africa RISING Baseline Evaluation Survey provided the household data. The survey design involved a stratified random sample, with stratification based on capturing diversity in agroecological potential and then a random selection of households within the diverse villages (IFPRI, 2015). The survey was conducted in the summer of 2013. The survey interviewed 550 households in the Dedza district. The survey collected baseline household data on, among others, crop management including area cultivated and inputs used, grain yields, livestock numbers, family demographics, off-farm income, human food consumption, and prices and costs of all inputs and outputs in the model. The agricultural production data referred to the cropping season October 2012 to May 2013. We divided the surveyed households into three types using Principal Component Analysis and subsequent Hierarchical Cluster Analysis. Our study followed the approach suggested by Norman et al. (1995) and used by Chenoune et al. (2016) for developing household types. This included considering three groups of factors: household resource endowments, production goals, and pro-

**Table 1**  
Characteristics of the representative household simulated in this study.

Characteristics	Units	Mean	Coefficient of variation
Arable land	ha	0.6	0.03
Land planted to legumes	% of arable total	42	0.26
Maize grain yield	t ha <sup>-1</sup>	1.8	0.65
Fertilizer applied to maize	kg [N] ha <sup>-1</sup>	51	0.9
Household size	total number people	4.8	0.77
Off-farm income	US \$ year <sup>-1</sup>	155	1.35

Notes: Coefficient of variation is the standard deviation divided by mean, based on spatial variation among surveyed households. At the time of study, 1 US \$ = 364 Malawian Kwacha (MWK). [N] represents nitrogen.

duction intensification. We selected 10 variables related to the three groups of factors that capture household livelihoods and expected ability to respond to changes in fertilizer prices, for example, off-farm income, fertilizer use, and farm size. We retained four principal components that had an eigenvalue greater than one. These components explained 68% of total variability in the original data. We used these principal components in a Hierarchical Cluster Analysis that resulted in us identifying three types of households. We examined the household type that covered 72% of the surveyed households, 395 households from the 550 households. We used data on the mean survey characteristics for this type of household to calibrate our model. We call this household a “representative household”.

Table 1 shows the arable land, the percent of land planted to legumes, maize grain yield, inorganic nitrogen fertilizer (hereafter referred to as fertilizer) quantities applied to maize, household size, and off-farm income for the household during the summer of 2012 to 2013. Our data appear broadly representative of farming systems in Malawi. Household maize yields averaged 1.8 t ha<sup>-1</sup> and were generally below the average yield for Malawi of 2.1 t ha<sup>-1</sup> in 2013 (FAO, 2016), although yields in Malawi display a wide range. For example, Tamene et al. (2016) report yields in Dedza range from 0.4 t ha<sup>-1</sup> to 12 t ha<sup>-1</sup> and range from 0.8 t ha<sup>-1</sup> to 2.65 t ha<sup>-1</sup> for the national average. The average household applied 51 kg [N] ha<sup>-1</sup> of fertilizer to maize plots, where [N] represents nitrogen. Sheahan and Barrett (in press) reported 53 kg [N] ha<sup>-1</sup> of fertilizer applied to maize among fertilizer users in Malawi. Mungai et al. (2016) reported that farmers in Dedza who used fertilizer applied approximately 61 kg [N] ha<sup>-1</sup>. This indicates our surveyed fertilizer rates are like rates among other smallholders in Malawi. The average household cultivated approximately 0.6 ha. Maize occupied on average 58% of arable land and legumes occupied the remaining 42%. In 2013, legumes occupied approximately 30% of arable land in Malawi (FAO, 2016). The average household and owned one adult breeder goat, had 4.8 members living on the farm, and generated US \$ 155 year<sup>-1</sup> in off-farm income.

To examine food consumption, we categorized food consumption goods into the groups used by Ecker and Qaim (2011), with the full list of foods in our study listed in the Appendix. The proportion of total calories consumed in our survey coming from cereals was 79%, for pulses was 10%, for fruit and vegetables was 4%, for animals was 3%, and for meal complements was 4%. This compared to 73%, 11%, 3%, 3%, and 9% reported in Ecker and Qaim (2011), who analysed nationally-representative household data from Malawi.

### 2.2. Modelling approach

We used a Dynamic Agricultural Household Simulation Model (DAHBSIM) to examine the ex-ante effect of changes in the price of fertilizer on different indicators for the household. Indicators included average yearly fertilizer use (kg household<sup>-1</sup>), area of maize (ha) and legumes (ha), maize production (kg household<sup>-1</sup>), legume production (kg household<sup>-1</sup>), total income (US \$ household<sup>-1</sup>), and the proportion of

calories consumed from maize (%). Field-level indicators included maize grain yield ( $\text{kg ha}^{-1}$ ) and crop absorbed nitrogen ( $\text{kg [N] ha}^{-1}$ ).

DAHBSIM is a non-linear, programming model that optimizes an intertemporal objective function subject to a set of constraints, given the prevailing market conditions and historical precipitation (Flichman et al., 2016). The model design benefited from the development of earlier models such as FSSIM (Janssen et al., 2010) and FSSIM-Dev (Louhichi and Gomez y Paloma, 2014). Janssen et al. (2010) and Louhichi and Gomez y Paloma (2014) provided the implementation framework for modelling alternative scenarios of households using a static approach. Our model used a dynamic recursive approach similar to Mosnier et al. (2009), Louhichi et al. (2010), and Belhouchette et al. (2012). Our model maximizes the net present value of household net income for a specified number of years, subject to constraints on resource use by linking modules related to household crop production, food consumption, and economic and resource-use factors. The model allocates land, labour, and cash to different crops given a set of constraints. In the model the household determines its crop production, household food consumption, and labour allocation decisions simultaneously. The Appendix contains additional information on our modelling approach, as does Flichman et al. (2016).

### 2.2.1. Crop module

We followed the logic of Vanuytrecht et al. (2014) and Adam et al. (2012) when developing the crop module. This involved simplifying the cropping systems according to the aspects that were relevant to the objective of the study and the availability of data. The nitrogen content of soil is a major factor limiting yields in Malawi (Carr, 2014). We used simplified functions to simulate the effect of crop management on yield (Appendix). Flichman et al. (2016) provides a full description of the crop module. We integrated the summary functions into a household-scale analysis that focused on the behavioural consequences of different scenarios.

The crop module simulates cropping systems for multiple years and multiple crops using a monthly time step. It simulates, in a summary manner, soil water (including water use and drainage) and nitrogen budgets and their effect on crop yields. The nitrogen budgets include, if an option for the studied household, crop residue production and its decomposition, and livestock manure. The module has a generic crop simulator that enables the simulation of different crops and crop rotations using a single set of parameters. Precipitation, soil properties, crop characteristics, and crop management options including rotation, cultivar (variety) selection, irrigation, and nitrogen fertilization all affect crop growth. The module simulates crop cycles on a single parcel of land with uniform soil, precipitation, crop rotation and management, at the whole-plant level. This study used Dedza-specific monthly precipitation data from Harris et al. (2014). Crop input parameters used in the crop module were extracted from Doorenbos and Kassam (1979), calculated from the household survey, or calculated during the module calibration. Soil organic matter, soil water holding capacity, and initial soil water and nitrogen contents for different soil types were extracted from the Dedza-specific studies of Ollenburger (2012) and Ollenburger and Snapp (2014). We held the proportion of crop residues retained in the field at a constant 20% in our simulations. The module determines an unstressed (potential) yield based on crop potential evapotranspiration. The module then adjusts this potential yield for water and nitrogen limitations, if any, to determine actual yield (Appendix). The module takes the actual yield for specific years as the minimum of the yield limited by water and by nitrogen, as suggested by Stöckle et al. (2003).

We divided crops into two management intensities: extensive and intensive. The activities associated with the two management intensities were defined based on data collected in the household survey. Defining these activities involved three steps. First, we selected factors that we believed could explain yield variability: soil type (reported by households as either clay, loam, sand, or other), crop variety (local or

improved) and input quantities (seed, fertilizer, and labour). In our study, cropping was rainfed and mechanization was limited. Second, we clustered the management activities (crop variety and input quantities) for different soil types to derive, for a specific crop, a potential yield. In the study sites, soil types differ in their texture, water holding capacity, and initial organic matter (Flichman et al., 2016). Third, we performed a Principal Component Analysis and subsequent Hierarchical Cluster Analysis based in the intensification factors for each soil type and crop. From this analysis we defined the list of activities associated with different management intensities (extensive and intensive). An example showing differences in yields and inputs used for different maize management intensities is shown in Table A1. For most soils and crops there were two intensities, however for some crops and soils there was only one. Yields differed based on management intensity and varied according to soil type (Table A1).

We compared predicted grain yields for a range of crops, soils, and management intensities with farmer-reported grain yields for the same crops, soils, and management. For each crop, this involved calculating the normalized root mean squared error and examining the scatter plots of predicted and farm-reported grain yields (Appendix).

### 2.2.2. Food consumption

The model allows for potential non-separability between production and consumption decisions. A Linear Expenditure System calculates human food consumption, as used in Louhichi and Gomez y Paloma (2014). In this system food and non-food expenditures are increasing in income, and food and non-food consumption quantities are decreasing in own price. The system describes household expenditures for a set of 31 food items and a non-food bundle (Appendix).

### 2.2.3. Economics and resources

Our model combines aspects of biophysically-based limitations of yield potential with an examination of the economic trade-offs that households might face when trying to maximize their welfare subject to the limits of material resources and a household budget constraint that takes full income into account. Fig. 1A, below, shows the main biophysical and socio-economic components of the model, and their linkages. In this study the term income is used to capture the economic activity of the household. These income values represent total household income. This equals the sum of net crop income (sales value minus incurred financial costs), off-farm earnings, and the value of the household's food consumption from on-farm production (Appendix). Our income values are designed to provide an indication of the economic value of household activities.

Our model has a dynamic recursive structure that optimizes across a set of specified years (Fig. 1B). The model explicitly accounts for dynamic interactions across the years by using the end values of the previous year as the starting values in the current year. The model updates the water content of soil, soil organic matter, and the nitrogen content of soil each year by considering the previous crop and its management. Soil conditions of nitrogen and organic matter are the key dynamic variables that are updated and re-initialized between years, as well as the carryover of seed stocks. The model maximizes the net present value of net household income (which includes the value of home-consumed foods) over an intertemporal planning horizon of  $Y$  years. The model repeats the intertemporal optimization for  $Z$  successive periods, with dynamic variables updated recursively. We examined the results of the first year of each intertemporal loop, as capturing how the farm-household behaves over  $Z$  successive periods. For example, if there were 2 years in the intertemporal optimization horizon ( $Y = 2$ ) and 5 periods ( $Z = 5$ ), the model would run for 5 recursive steps (years), taking the planning horizons of 2005–2007, 2006–2008, 2007–2009, 2008–2010 and 2009–2011 into account during the intertemporal optimization phase. In this case, we would report the results in  $t_{1,1} = 2005$ ,  $t_{1,2} = 2006$ ,  $t_{1,3} = 2007$ ,  $t_{1,4} = 2008$ , and  $t_{1,5} = 2009$  (Fig. 1B). In each intertemporal optimization step, there

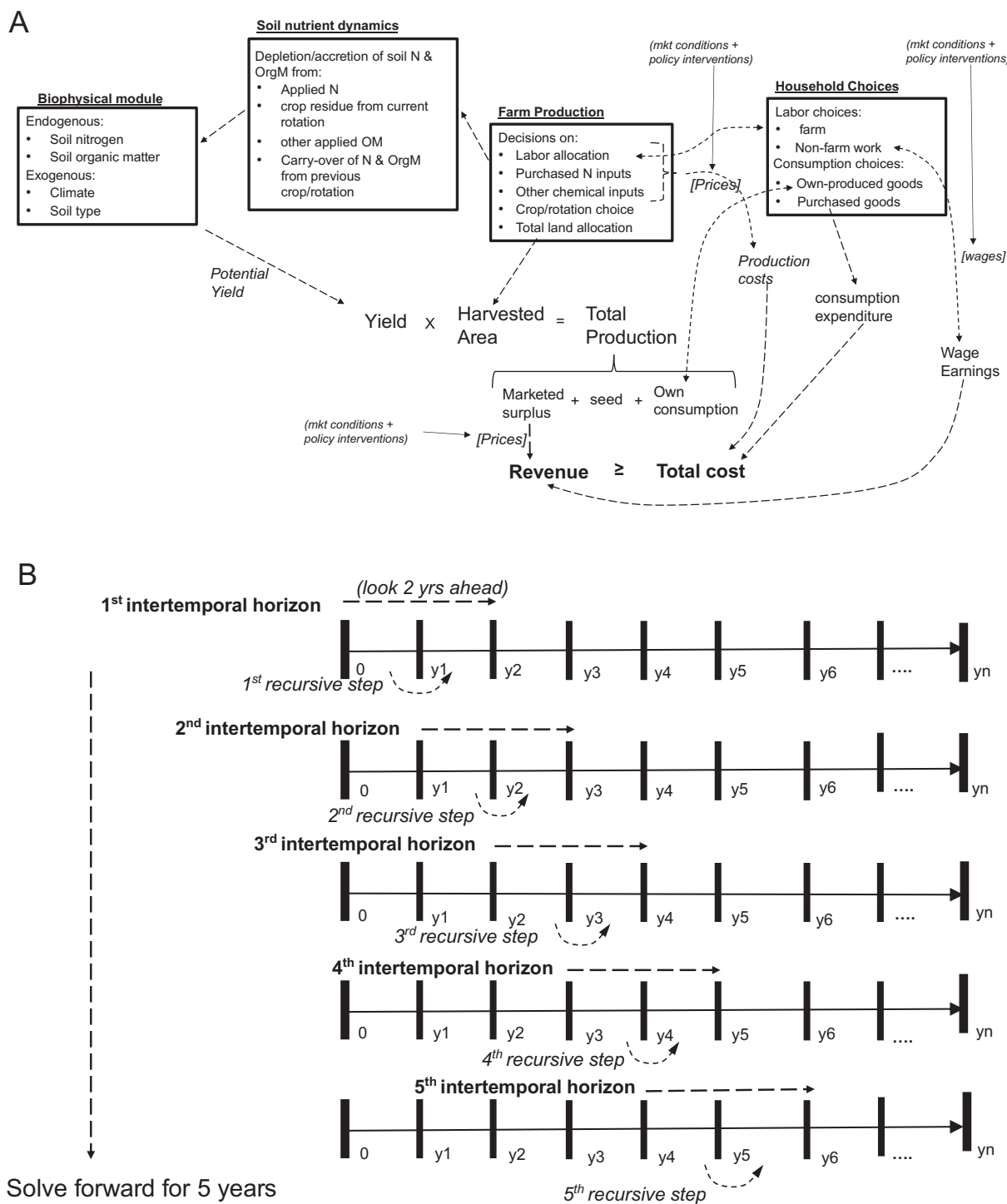


Fig. 1. A. The general structure of DAHBSIM. B. The intertemporal horizon over which DAHBSIM is solved.

is perfect foresight regarding prices and precipitation at the start of the decision-making period.

Model calibration involved using a variation of the mean-standard deviation approach of Hazell and Norton (1986) for risk analysis. Semaan et al. (2007) and Blanco-Gutiérrez et al. (2011) also used this approach to calibrate their model. Our Appendix contains details on the risk module formulation.

### 2.3. Simulation scenarios

We examined two scenarios: 1) a base-case scenario and 2) a

scenario for a change in the price of fertilizer. The base-case scenario intended to replicate current household livelihoods based on observed prices, costs, and household resources. The base-case scenario maintained all prices as observed in the survey. Prices were fixed in the base-case scenario and precipitation varied based on the observed historical data. We compared our base-case results to the farmer-reported data.

The second scenario examined changes in the price of fertilizer. The FISP has been providing farmers with discounted fertilizer. This subsidy was 64% in 2005 and 93% in 2012 (Chibwana et al., 2012; Chirwa and Dorward, 2013; Arndt et al., 2015). In 2012 a 50 kg bag of fertilizer cost 6536 MWK (Malawian Kwacha) on the open market and 500 MWK with

**Table 2**  
Household-scale simulated (model predicted) vs. farmer-reported (observed) indicators.

Indicator	Observed	Predicted	PAD (%)
Maize production ( $10^6$ kcal)	2.29	2.43	6.24
Legume production ( $10^6$ kcal)	0.49	0.45	9.12
Caloric consumption from cereals (% of total)	73.5	74.4	1.20

Notes: the percent absolute deviation (PAD) for an indicator is the absolute deviation between predicted and observed indicator levels per unit of observed indicator level, expressed as a %.

a FISP redemption voucher (Chirwa and Dorward, 2013), a 93% subsidy. In our study site, farmers reported paying an average of 130 MWK  $\text{kg}^{-1}$  for a bag of ammonium nitrate in 2012. This price closely matched the unsubsidized price for a bag of chemical fertilizer in 2012 (Chirwa and Dorward, 2013). Even though many farmers in Malawi receive subsidized fertilizer, in our study site this was not prevalent. Not all farmers have access to subsidized fertilizer because of the FISP design and its implementation. For example, Arndt et al. (2015) outline that the FISP recipients should be the productive poor, but identifying the productive poor is challenging and eligibility is often determined by local leaders. The local leaders do not always use a consistent criterion. Shee et al. (2016) support this finding, they find that the most important agricultural challenge reported by surveyed farmers was the high price of agricultural inputs. We explored what could happen to farm-household indicators if fertilizer prices fell to zero or increased by 100%, relative to the current observed price of 130 MWK  $\text{kg}^{-1}$  for a bag of ammonium nitrate. These price changes would alter production costs and this may have implications for the farm and household system. Our simulations started in each year from 2008 to 2013 and included a two-year horizon for each intertemporal optimization.

To inform the FISP, we simulated relatively large changes in fertilizer prices, i.e., a 100% increase and a total removal of prices. In addition, we calculated the own-price elasticity of fertilizer demand, defined as the percentage change in the quantity of fertilizer used by the household if fertilizer prices increased by 1%. We calculated this elasticity for incremental 1% changes in the observed price of fertilizer, and examined 5 incremental changes both above and below the observed price of fertilizer.

#### 2.4. Benefit-cost ratios

Government can induce changes in the price of fertilizer paid by farmers through providing subsidies, which are complex and controversial in Malawi (Jayne and Rashid, 2013). Earlier studies have mainly used statistical and economy-wide models to calculate the benefit-cost ratio (BCR) of Malawi's FISP (Lunduka et al., 2013; Arndt et al., 2015). We complement these existing BCRs with our own back-of-the-envelope BCR calculations to provide an additional perspective on understanding the potential cost effectiveness of fertilizer policies. We calculated the BCR for providing free fertilizer using a household-scale simulation model. We calculated an income-based BCR as the increase in total household income divided by the cost of providing free fertilizer to the household. We calculated a production-based BCR as the increase in the value of maize production divided by the cost of providing free fertilizer to the household. We calculated the increases in total household income or value of maize production as the difference in either total household income or value of maize production between the base-case scenario and the scenario with a price of fertilizer set to zero. We calculated the cost of providing free fertilizer to the household as the quantity of fertilizer used by the household if prices were zero multiplied by the open-market price (the base-case price of fertilizer).

### 3. Results and discussion

#### 3.1. Crop module comparison

We compared the grain yields of the crops simulated in our model to farmer-reported grain yields. This comparison involved examining how the model simulated the observed variation in yield across all crops from the household survey, as well as how maize yields responded to fertilizer. The normalized root mean squared error for bean (*Phaseolus vulgaris*) was 27%, for cowpea (*Vigna unguiculata*) was 32%, for groundnut (*Arachis hypogaea*) was 17%, for maize was 25%, and for soybean (*Glycine max*) 35% (Fig. A2). Our study highlights the nitrophilic nature of maize; with a positive association between yield and fertilizer applied, as has been shown regularly in Malawi (Snapp et al., 2010; Smith et al., 2016). The range of simulated yields differed based on farmer-reported soil types. For example, on sandy soils the yields for all crops ranged from 10  $\text{kg ha}^{-1}$  to 6077  $\text{kg ha}^{-1}$ , and on loam soils ranged from 69  $\text{kg ha}^{-1}$  to 7000  $\text{kg ha}^{-1}$ . The average yield for maize on a loam soil was 2804  $\text{kg ha}^{-1}$  and was 2555  $\text{kg ha}^{-1}$  on a sandy soil. The Appendix and Flichman et al. (2016) provides additional details on the procedure used to calibrate and evaluate the model.

#### 3.2. Household model comparison

Table 2 reports how our base-case scenario compared to observed indicators of household production and consumption, including the percent absolute deviation (PAD). The PAD for an activity is the absolute deviation between predicted and observed activity levels per unit of actual activity. The PAD for maize and legume production was below 10%. To calculate the proportion of caloric consumption from staples we multiplied average daily farmer-reported per person food consumption from the survey by the Malawi-specific calories in food reported in Ecker and Qaim (2011). Farmer-reported food consumption in the survey relates to average consumption of food over the week prior to the survey occurring. In our survey cereals comprised approximately 79% of total per person caloric intake, compared to the 73% reported in Ecker and Qaim (2011). The PAD for total caloric consumption was 9%.

#### 3.3. Simulation results and discussion

This section presents our assessment of how changes in fertilizer prices affected the simulated behaviour of the representative household. Table 3 presents the simulated household-scale effects of changes in fertilizer prices. We observed a negative association between fertilizer prices and the fertilizer used. If fertilizer had no cost to the household, fertilizer use would rise from 16.8  $\text{kg [N]}$  to 49.6  $\text{kg [N]}$ , whereas a 100% increase in fertilizer prices caused fertilizer use to fall from 16.8  $\text{kg [N]}$  to 14.9  $\text{kg [N]}$ . Looking at incremental changes in fertilizer prices around the observed price, we found that a 1% increase in fertilizer price led to a (on average) 0.92% decrease in the quantity of fertilizer used. This own-price elasticity of fertilizer demand of  $-0.92$  was similar to results in Chembezi (1990), who econometrically estimated an own-price elasticity of fertilizer demand for Malawian smallholders of  $-0.82$  (for a two-step procedure) and  $-1.08$  (using a single equation method).

As fertilizer prices increased the area of maize declined. Changes in fertilizer prices had the direct effect of altering fertilizer use and hence grain yields. The changes in fertilizer prices had the additional economic effect of altering the relative returns of different crops, and hence the areas of maize and legumes (Table 3). Applying fertilizer can help maintain and increase crop yields. Combining multiple practices can also help maintain and increase yields, for example, integrated soil fertility management advocates combining the use of appropriate germplasm, fertilizer, and organic resources with good agronomic

**Table 3**  
Simulated household-scale effects of changes in fertilizer prices.

	Zero price		Base price		100% increase	
	Mean	SD	Mean	SD	Mean	SD
Fertilizer price (US \$ [N] kg <sup>-1</sup> )	0	0	1.08	0	2.16	0
Fertilizer applied ([N] kg)	49.6	5.94	16.8	0.73	14.9	0.48
Maize area (ha)	0.44	0.013	0.34	0.0090	0.34	0.0090
Legume area (ha)	0.16	0.013	0.26	0.0090	0.25	0.011
Legume production (10 <sup>6</sup> kcal)	0.37	0.025	0.35	0.018	0.33	0.031
Maize productivity (kg ha <sup>-1</sup> )	2557.7	141.2	1642.0	184.4	1227.7	54.6
Maize production (kg)	1116.7	37.5	549.2	50.7	419.6	19.0
Total household income (US \$)	412.6	7.09	271.9	9.20	229.2	3.98
Caloric consumption from cereals (% of total)	73.5	0.035	74.4	0.076	74.8	0.038

Notes: all values are an average yearly value. SD represents standard deviation. The mean and SD are calculated using all simulation years. [N] represents nitrogen.

practices (Vanlauwe and Giller, 2006; Vanlauwe et al., 2015). Our findings showed that subsidizing fertilizer had a disincentive effect on using organic means of maintaining soil fertility because removing the price of fertilizer reduced the area of legumes—a source of biological nitrogen fixation.

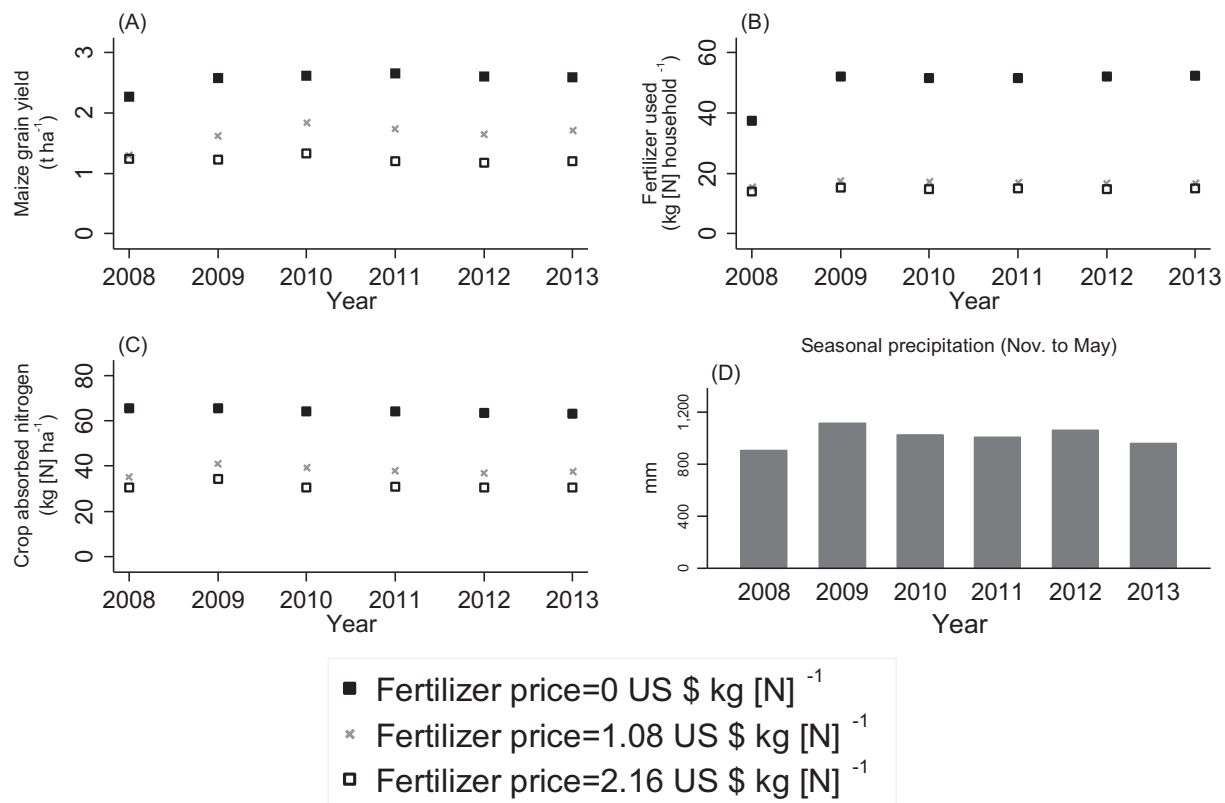
As fertilizer prices increased maize production declined (Table 3), explained by less maize acreage and lower yields due (in part) to less fertilizer applied. With a zero price for fertilizer the average maize yield was 2.56 t ha<sup>-1</sup>—1117 kg produced on 0.44 ha. This is the average of yields across all maize plots; the household has different soil types and management intensities. With a zero cost of fertilizer the household shifted towards higher-yielding maize activities (the intensive manage-

ment option in Table A1). These activities also required more labour and financial costs for other maize-specific inputs. We saw the expected relationship between fertilizer cost and fertilizer use, maize productivity, and maize area. Household fertilizer use appears sensitive to reductions in the cost of fertilizer.

Fig. 2 presents the evolution of maize yields (panel A), fertilizer used by all crops (panel B), nitrogen absorbed by all crops (panel C) over time, and seasonal precipitation (panel D). Yields did not vary greatly over time as seasonal precipitation was relatively constant. Water is often less of a limiting factor than nutrients for crop growth in Malawi (Carr, 2014). Fig. 2 shows the linkages between the fertilizer price and the yield of maize. At higher fertilizer prices the household applied less fertilizer (panel B) and this translated into crops absorbing less nitrogen (panel C). Consequently, maize yield declined (panel A).

Higher fertilizer prices had a negative effect on total household income (Table 3). If fertilizer had no cost, the household's income each year rose by an average 52% from US \$ 272 to US \$ 413, whereas a 100% increase in fertilizer prices caused a 18% decline in income from US \$ 272 to US \$ 229. In other similar studies, a 50% subsidy on the cost of buying fertilizer in Ethiopia had a limited effect on simulated crop area and production, with cheaper fertilizer increasing simulated incomes by an average 1%, although some individual farmers experienced income gains of over 40% (Louhichi et al., 2016). Specifically in Malawi, Lunduka et al. (2013) summarized multiple studies on the income effect of fertilizer subsidies for smallholder farmers. In general, evidence suggests modest gains in income from exposure to fertilizer subsidies, for example, an 8% increase in annual per person expenditure for households receiving fertilizer subsidies.

Fertilizer price changes did not have a sizeable effect on the simulated proportion of total calories consumed derived from cereals, which remained at approximately 75% in all scenarios (Table 3). Maize made up almost all the cereal calories consumed. As fertilizer prices rose incomes fell and total consumption changed. There were no



**Fig. 2.** Simulated effect of fertilizer price changes on maize yields (A, kg ha<sup>-1</sup>), fertilizer used (B, kg [N] household<sup>-1</sup>), nitrogen absorbed by crops (C, kg ha<sup>-1</sup>), and precipitation (D). [N] represents nitrogen.

changes in the relative importance of different food groups to total consumption.

In our study, the income-based benefit-cost-ratio (BCR) was 2.6 and the production-based BCR was 2.9. Other studies on the BCRs of the FISP in Malawi exist. Lunduka et al. (2013) highlighted that BCRs ranged from less than one to over ten. The BCRs in Malawi are contingent on, among others, the price of fertilizer, price of grain, the responsiveness of maize production to fertilizer applied (nitrogen-use efficiency), and the methodology used (Lunduka et al., 2013). For example, prices for maize grain (US \$ kg<sup>-1</sup>) ranged from 0.14 to 0.21 between 2005 and 2008. In our study, the price of maize grain was US \$ 0.27 kg<sup>-1</sup>. Using the average price of maize grain from 2005 to 2008 from Lunduka et al. (2013), our production-based BCR became 1.8. Arndt et al. (2015) find a production-based BCR of approximately 1, and an economy-wide BCR of 1.62.

Our BCRs (reported above) do not consider the administration costs of a fertilizer policy, political economy issues, or possible changes in maize prices resulting from the increased supply of maize associated with lower prices of fertilizer. The method we used to calculate the BCR of the fertilizer policy used a farm-household simulation model, this method complements other statistical and structural, model-based economy-wide approaches that have been used to evaluate fertilizer policies in Malawi. Examples of contrasting methods include how nitrogen-use efficiency was used. Our model calculates this, while other studies use values from the literature, for example in Dorward and Chirwa (2011), and Lunduka et al. (2013) indicate that nitrogen-use efficiency can be calculated statistically or taken from household survey data. Nitrogen-use efficiency varies depending on, among other factors, management ability and agroecological conditions. In addition, to calculate the production-based BCR we use the same formula as in Arndt et al. (2015). Our simulated change in production was based on a household-scale analysis which incorporates farm-specific constraints on key financial and physical relationships that define both consumption and production possibilities. The change in production simulated in the analysis of Arndt et al. (2015) was based on a national-scale model which uses reduced-form relationships that capture the overall macro-scale, market equilibrium among the various sectors of the economy, and the flows of payments between the different economic agents of the macro-economy. The behavioural differences between this macro-scale, general-equilibrium framework and the farm-scale, partial-equilibrium approach we use would account for the differences in the BCR ratio. The year of reported data in individual studies is crucial to the BCR as prices for maize and fertilizer vary each year (Lunduka et al., 2013).

To put the results into a different context, other options to achieve lower fertilizer prices exist through exploiting economies of scale in transportation and removing marketing inefficiencies. IFDC (2013) report approximately 40% of the inland fertilizer cost structure from seaports to Malawi relate to transport, 45% relate to middleman marketing margins, with the remainder related to loading costs. Investments in infrastructure and other policy-driven interventions that

## Appendix A

This Appendix contains the main elements of the model used in our study.

### Objective function

Based on the mean-standard deviation analysis, Eq. (1) specifies the objective function of the individual household modelled in this study:

$$\text{Max } U = \text{NPV} - \phi \times \sigma \quad (1)$$

where  $U$  is expected household utility, NPV is the net present value of (net) household income,  $\phi$  is the risk aversion coefficient (set at 0.45), and  $\sigma$  is the standard deviation of the net present value of income. The household must have non-negative activity levels, for example, non-negative crop areas, fertilizer and seed quantities, and food consumption quantities. Eq. (2) specifies the net present value of income for the household:

can lower these costs would have benefits beyond just fertilizer use, and could also affect the markets for both inputs and outputs. Calculation of the implied benefits and costs for such a case are beyond the scope of our study, but would make an interesting comparison with the benefits and costs of a pure input subsidy policy such as the FISP, in future work.

## 4. Conclusion

This study simulated the effects of changes in inorganic fertilizer prices on different household indicators of performance and welfare. Our results provide useful insights into the barriers that farmers encounter when trying to increase their use of fertilizer. We showed that removing fertilizer costs had a positive effect on the area of higher-yielding (and higher-input) maize. Our results also add to earlier studies in Malawi on the benefit-cost ratio associated with fertilizer policies and earlier studies on the own-price elasticity of fertilizer demand by using an alternative method (i.e., a farm household model). We found that the benefit-cost ratios (BCRs) associated with fertilizer-support programs exceeded one, and here our findings complement the studies discussed in Section 3.3.

We emphasize two points, here. First, lower open-market fertilizer prices appear to benefit smallholder farmers, as shown in our simulations by the positive income effect of lower prices. Second, although surveyed households in our study grew legumes, owned livestock, and worked off-farm, maize production dominated their overall on-farm, livelihood strategy because it contributed the most to their food consumption. We recognize the important cultural and historical reasons why maize has become such a dominant crop for Malawian smallholder farmers – such as the long-standing food security policies that emphasized the importance of cultivating maize as the staple food crop, and the fact that maize grain can be stored more easily than other foods, given limited household-scale technologies. Exploring options to increase the diversity of household livelihoods, from an economic perspective, through improving legume and livestock productivity and better off-farm opportunities appears another avenue for further research, that a model like DAHBSIM can be applied towards. As was the case in this study, the structural nature of DAHBSIM can help point out potential constraints that limit diversification.

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$$NPV = \sum_{y=1}^Y \left( \frac{CI_y + OI_y + VFC_y}{(1 + i)^y} \right) \tag{2}$$

where  $y$  denotes a specific year of the simulation (indexed to the value of 1 for the first year, for example, 2008 = 1 and 2009 = 2, in which case  $Y = 2$ ),  $CI_y$  represents net crop income in year  $y$ ,  $OI_y$  represents off-farm income in year  $y$ , and  $VFC_y$  represents the household's value of food consumption from on-farm production in year  $y$ . In this study the term income is used to capture the economic activity of the household. The income values reported in this study are total household income and are the sum of the terms in the numerator of Eq. (2), i.e., in year  $y$  income =  $CI_y + OI_y + VFC_y$ . The household had a discount rate,  $i$ , of 4%. Net crop income is the value of all crop sales (based on their market price and quantity sold) minus all variable input costs that had an actual financial cost, for example seed, fertilizer, and hired labour. The household had a fixed amount of off-farm income each year, set at the amount observed in the household survey. Fig. A1 shows the evolution of prices over time.

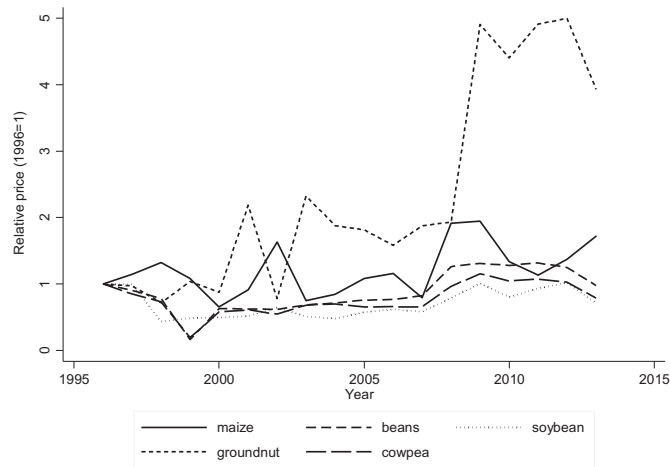


Fig. A1. Relative prices of the crops used in this current study. Source: FAO (2016)

This study used a set of states of nature for prices to calculate the standard deviation of the net present value of income. Our standard deviation calculation, as specified in Eq. (3), follows the approach taken by Blanco-Gutiérrez et al. (2011). The states of nature are defined by crop price variability, as defined in FAO (2016). The standard deviation from Eq. (1) equals:

$$\phi = \left[ \frac{(\sum_{sn} NPV_{sn} - NPV)^2}{SN} \right]^{1/2} \tag{3}$$

where  $NPV_{sn}$  is the net present value of (net) household income given a specific state of nature of prices ( $sn$ ) and actual modelled input and output quantities.  $NPV$  is the actual net present value of income based on observed prices and actual modelled input and output quantities.  $SN$  represents the number of states of nature, set at 50. To calculate  $NPV_{sn}$  we calculated a “price deviation” parameter for each crop in the model. To calculate this “price deviation” parameter we took nominal historical prices from FAO (2016) for each crop and calculated the difference between the average price and the maximum and minimum price. Fig. A1 shows the range of prices. The “price deviation” parameter for each crop equalled the absolute value of the difference between the average price and the maximum price or minimum price (whichever had the largest absolute value) divided by the average price and expressed as a percentage. We then generated a variable “price parameter<sub>sn</sub>” from this “price deviation” parameter for  $SN$  different states of nature for each crop and for each crop this parameter equalled, as specified in Eq. (4). To calculate  $NPV_{sn}$ , we multiplied modelled sales quantity by observed prices and the price parameter<sub>sn</sub> for different states of nature ( $sn$ ).

$$price\ parameter_{sn} = 1 + \left( \frac{uniform(-1, 1) \times \text{“price deviation” parameter}}{100} \right) \tag{4}$$

A Linear Expenditure System, as used in Louhichi and Gomez y Paloma (2014), calculates the quantity of food consumed by the household each year using Eq. (5):

$$p_i q_i = \gamma_i + \beta_i (I - \sum_j \gamma_j p_j) \tag{5}$$

with

$$0 < \beta_i < 1$$

$$\sum_i \beta_i = 1$$

$$q_i - \gamma_i > 0$$

where  $p_i$  is the price of good  $i$ ,  $q_i$  is the quantity of good  $i$  consumed by the household;  $I$  is household income from crops and off-farm activities.  $\beta_i$  and  $\gamma_i$  are the parameters in the Linear Expenditure System. This system considers  $\sum_j \gamma_j p_j$  as subsistence expenditure and  $I - \sum_j \gamma_j p_j$  as *supernumerary* income (Sadoulet and de Janvry, 1995). To compute  $\beta_i$  and  $\gamma_i$  we adapted the income elasticities of food demand from Ecker and Qaim (2011) and the Frisch parameter for Africa south of the Sahara from Aguiar et al. (2016). Our study considered a set of 31 food items and a non-food bundle: bean, soybean, beverage, bovine meat, cabbage, cassava, goat meat, groundnut, maize, mango, millet and sorghum, milk, nuts, oils and fat, other animal products, other cereals, other fruits, other meats, other pulses, other spices, other vegetables, pork, potato, poultry, rice, salt, spinach, starch, sugar, sweet potato, and non-food.



### Constraints

Here we present the main resource constraints for the household in our model.

**Land.** The cultivated area each year on a specific soil type cannot exceed potential arable land for that soil type. The model includes four soil types: clay, loam, sand, and other. The household cannot rent land in this model. The household cannot grow beans, cowpea, or soybean on the same plot of land, for a specific soil type, in two consecutive years.

**Labour.** The household must have enough labour from family sources and from hiring in labour to meet monthly labour requirements for agricultural tasks. Hired labour has a cost and this affects net crop income (the net value of crop production).

**Cash.** Spending on market purchases, for example, agricultural inputs and food items not produced on farm, cannot exceed the crop income plus off-farm income in any specific year.

**Supply and demand balances.** For each product, total consumption cannot exceed consumption from farm production plus consumption from market purchases. The household can save seed for future years to reduce the need to purchase seed from the market, so seed is a dynamic variable.

### Crop module

The household can grow bean, cowpea, groundnut, maize, and soybean. The module uses the logic of Doorenbos and Kassam (1979) to calculate water-limited yields for these crops (Eq. (6)):

$$\left(1 - \frac{Y_w}{Y_m}\right) = K_y \left(1 - \frac{ET_a}{ET_m}\right)$$

where:

$Y_w$  is water-limited yield (kg ha<sup>-1</sup>)

$Y_m$  is maximum yield (kg ha<sup>-1</sup>)

$K_y$  = yield response factor ( $K_y = 1$  if yield reduction is directly proportional to reduced water use,

$K_y > 1$  if crop response is sensitive to water deficits and,

$K_y < 1$  if crop is more tolerant to water deficit)

$ET_a$  = actual evapotranspiration (mm day<sup>-1</sup>)

$ET_m$  = maximum evapotranspiration (mm day<sup>-1</sup>)

(6)

The module uses the logic of Godwin et al. (1991) to calculate nitrogen-limited yield (Eq. (7)):

$$Y_N = Y_W \left(1 - \frac{NC_{crit} - NCONC_a}{NC_{crit} - NC_{min}}\right)$$

where:

$Y_N$  = nitrogen-limited yield (kg ha<sup>-1</sup>)

$Y_W$  = potential growth after water limitation considerations (kg ha<sup>-1</sup>)

$NC_{crit}$  = plant critical nitrogen concentration (kg ha<sup>-1</sup>)

$NCONC_a$  = plant nitrogen concentration after new growth (kg ha<sup>-1</sup>)

$NC_{min}$  = minimum plant nitrogen concentration at which point growth stops (kg ha<sup>-1</sup>)

(7)

The household module uses the minimum of the nitrogen-limited ( $Y_N$ ) and water-limited ( $Y_W$ ) yield as the actual yield in the simulations. The crop module updates parameters related to water stress, nitrogen stress, and organic matter each year based on farmer management and external conditions, for example, fertilizer application or precipitation. Both water and nitrogen affect yield. In our study, the main factor limiting yield was nitrogen. Total precipitation each year was often greater than 1000 mm (Fig. 2D). The previous crop affects the current crop yield through its effect on the nitrogen content of soil, as presented in Flichman et al. (2016). In the crop module, the final nitrogen content of soil for the current year equals the initial nitrogen content of soil (which equals the final nitrogen content of soil from the previous year) plus mineralization from organic matter for the current year plus nitrogen fertilization (which could be mineral or organic) plus nitrogen from previous crop residues minus nitrogen uptake from the crop minus nitrogen leaching.

For each activity, our crop module was evaluated in two steps. In the first step, we parametrized the module by calibrating the module for each activity cultivated with the extensive technique on a clay soil. In the second step, we evaluated the module for the same activity in step one but for different crop management (intensive technique) and soil types (loam, sand and other). By doing the above, the conversion of nitrogen to crop yield coefficient ( $K_n$ ) and the yield response factor to water stress ( $K_y$ ) were determined by calibration since the module was sensitive to these parameters under rainfed conditions. Values of  $K_n$  and  $K_y$  were adjusted within a reasonable range of variation based on previous research, knowledge, or experience to have the best model estimation of the yield observed for each activity from the survey. To ensure a good correlation between observed and simulated data, the adjustment process was stopped when further modification of crop parameters values generated little or no change in the normalized root mean square error. Specific parameters for crop phenology, water, nitrogen, and organic matter were taken from the literature (Doorenbos and Kassam, 1979; Ollenburger, 2012; Ollenburger and Snapp, 2014), calculated from the survey or calculated from the calibration. Flichman et al. (2016) provides more details on this procedure, including on the coefficient for nitrogen conversion to crop yield ( $K_n$ ).

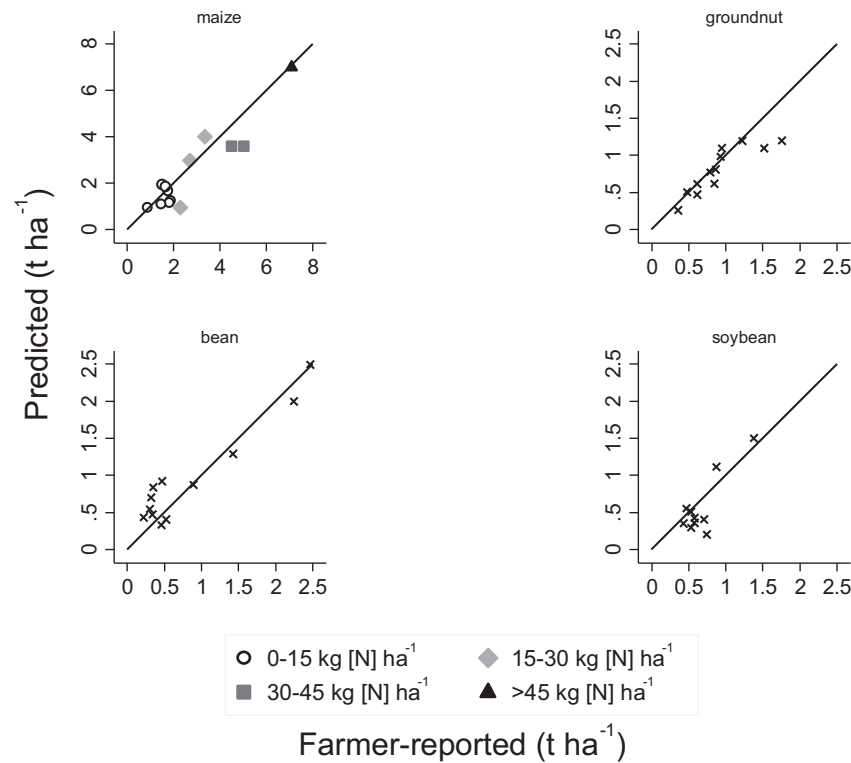


Fig. A2. Association between farmer-reported and predicted grain yields. Solid line is 1:1 line (the 45° line). Predicted refers to 2013 grain yields simulated in the crop module. Farmer-reported refers to farmer-reported grain yields in 2013 reported by the representative household. Non-cross markers represent different amounts of fertilizer applied to maize where [N] represents nitrogen.

Table A1

Observed maize yield and inputs use, and simulated areas by intensification level.

	Extensive	Intensive
Observed maize yield ( $\text{kg ha}^{-1}$ )	1648	4269
Observed fertilizer ( $\text{kg [N] ha}^{-1}$ )	37	131
Observed seed ( $\text{kg ha}^{-1}$ )	30	49
Observed labour ( $\text{days ha}^{-1}$ )	212	464
Observed costs of non-fertilizer, non-seed inputs ( $\text{US \$ ha}^{-1}$ )	0.5	3.6
Simulated maize area (fertilizer price = 0)	0.24	0.20
Simulated maize area (fertilizer price = 1.08 US \$ $\text{kg}^{-1}$ [N])	0.32	0.02
Simulated maize area (fertilizer price = 2.16 US \$ $\text{kg}^{-1}$ [N])	0.34	0

Note: [N] represents nitrogen. Yields in each intensity level are the average across different soil types (sand, loam, clay, or other) and seed varieties (local or improved) and range from 872  $\text{kg ha}^{-1}$  to 2299  $\text{kg ha}^{-1}$  for the extensive level and from 2687  $\text{kg ha}^{-1}$  to 7075  $\text{kg ha}^{-1}$  for the intensive level.

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