Increased mineral fertilizer use on maize can improve both household food security and regional food production in East Africa

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ABSTRACT

CONTEXT: Despite recent improvements in living standards, a substantial proportion of farm households in sub-Saharan Africa (SSA) is food insecure, and increasing crop productivity could help address this problem.
OBJECTIVE: We estimated the effect of increasing maize yields with mineral fertilizer on household food security and on regional and national maize supply in two East African countries - Uganda and Tanzania.
METHODS: We estimated maize yield response to nitrogen (N) fertilization with a machine learning model trained on 15,952 observations of maize responses to fertilizer across SSA. Together with spatial price data, we used this model to quantify the profit-maximizing N fertilizer input for a nationally-representative sample of 4188 agricultural households in the two countries. We computed a food availability indicator for all households.
RESULTS AND CONCLUSIONS: The mean profit-maximizing N input was 82 kg/ha in Tanzania, but it was much lower in Uganda (24 kg/ha) mostly because of less favorable prices. The profit-maximizing N input was above the reported N input for 95% of the households in Tanzania and for 43% of the households in Uganda. It was predicted to increase the food availability ratio of food insecure maize growers by 95% in Tanzania, and by 25% in Uganda. The administrative regions where maize supply could increase most were not the same as the regions where the increase in household-level food security was largest. With increased fertilization, food insecure maize growing households (35% in Tanzania and 42% in Uganda) could only contribute about 20% of the overall increase in maize supply, whereas the 20 to 30% food secure households that have a larger area planted with maize could contribute >60%.
SIGNIFICANCE: Our study makes two key contributions: i) a substantial increase in national maize supply is more likely to come from already food secure households with relatively large farms, while food insecure households with small farms may nevertheless increase their household-level food security through maize intensification, and ii) high potential areas to increase maize domestic production do not necessarily match with areas where there is immediate scope to improve household-level food security.

1. Introduction

Over the past decade, living standards have improved substantially in some countries of sub-Saharan Africa (SSA). This has been associated with high growth in agricultural gross domestic product (GDP) (Jayne et al., 2018a), improved health (Masters et al., 2018) and better nutrition (Beal et al., 2017). Despite these positive trends, food security remains a critical issue, and more than a third of rural households across 17 countries in SSA was found to be food insecure (Frelat et al., 2016). Food production has not kept pace with population growth (FAO et al., 2022; Luan et al., 2013) and the majority of countries in SSA are net food importers (Mendez del Villar and Lançon, 2015; Rakotoarisoa et al., 2011; van Ittersum et al., 2016),

Increasing staple food production on current agricultural land is necessary to improve household and national food security, while limiting biodiversity loss and carbon dioxide emissions associated with agricultural land expansion (van Loon et al., 2019; van Ittersum et al., 2016). Yet, crop yields in SSA are much lower than yields that are attainable with good agronomic management practices. A major reason for the low crop yields in SSA is that the average fertilizer use in SSA is low, that is 12, 2 and 3 kg ha^{-1} for nitrogen (N), phosphorus (P) and potassium (K), respectively (FAOSTAT, 2018). It has, however, rapidly increased in some countries over the past decades (for example, N fertilizer use was 39 kg ha^{-1} in Zambia and 23 kg ha^{-1} in Ethiopia in 2018). The limited use of mineral fertilizer leads to widespread nutrient mining (Cobo et al., 2010). Therefore, a significant increase in nutrient inputs in the form of mineral fertilizer is required to sustainably increase crop productivity (ten Berge et al., 2019; Jayne et al., 2013). In combination with mineral fertilizer, the integration of legumes in crop rotations (Franke et al., 2018), the implementation of agroforestry practices (Kuyah et al., 2019), and the better use of organic resources such as manure (Vanlauwe et al., 2014) are key to improve nutrient use efficiency and avoid detrimental nutrient losses to the environment.

The biophysical environment can constrain the effectiveness of mineral fertilizer inputs. For example, fields that are already fertile, or, in contrast, lack secondary nutrients and micronutrients, can be unresponsive to NPK fertilizers (Nziguheba et al., 2021; Vanlauwe et al., 2010). Drought stress or excessive rainfall events can also lead to low fertilizer use efficiency (Affholder, 1997; Mapanda et al., 2012), which may discourage farmers to invest in fertilizer. These biophysical constraints vary spatially, owing to a combination of natural environmental variability and soil fertility heterogeneity associated with previous field management by farmers (Njoroge et al., 2017). Economic constraints also act as a barrier for investment in fertilizer to increase crop productivity. High prices of fertilizer and low prices of agricultural products can lead to unfavorable cost:benefit ratios (see Jayne et al., 2018 and Bonilla Cedrez et al., 2021 for recent estimates of cost:benefit ratios across SSA). These economic constraints vary spatially, as fertilizer price is usually higher in remote – poorly accessible – areas (Bonilla Cedrez et al., 2020a). In addition, farm household characteristics can constrain intensification of crop production to improve household-level food availability (Tittonell et al., 2010). For example, rural households with limited crop land do not directly benefit from an increase in crop productivity (Giller et al., 2021; Ritzema et al., 2017), and poor households may not have the cash to buy fertilizer, even if it would be profitable to do so. Farmers resource endowment also varies spatially, with local variations as important as country-wide variations (Wichern et al., 2018). The current literature falls short in determining the spatial interaction between biophysical, economic and household-level factors that drive the contribution of maize intensification to food security in the diverse contexts of SSA. In their most optimistic scenario, Ritzema et al. (2017) investigated how a 100% increase in cereal yield would impact household food security of 1700 households in seven countries of East and West Africa. But the increase in cereal yield could be much stronger, e.g. maize yield can be quadrupled in some areas with favorable soil and climate in SSA (https://www.yieldgap.org/gygaviewer/index.html). Moreover, the authors relied on site-specific household surveys that possibly did not cover the full span of existing biophysical conditions and famers' context. Palmas and Chamberlin (2020) investigated the biophysical and economic constraints to the use of mineral fertilizer on maize in Tanzania. Their study brought crucial insights into the spatial determinants of fertilizer profitability, but did not consider the household dimension. Yet, household characteristics (e.g. land per capita) can strongly influence the contribution of intensification of cereal production to improved food security.

Maize is the most important staple food crop in SSA, especially in Eastern Africa (OCDE and FAO, 2016). Tanzania and Uganda are ideal case study countries for several reasons. Firstly, Tanzania and Uganda are in the top-ten maize producing countries in SSA, with 6.2 and 2.7 Mt yr^{-1} (2017–2018 average), respectively (FAOSTAT, 2018). Secondly, both countries have diverse agro-ecological conditions allowing the analysis of a wide range of maize growing conditions that also prevail elsewhere across SSA: there are six “maize mega-environments” (Hartkamp et al., 2000) in Tanzania: dry lowland, dry mid-altitude, highland, wet lower mid-altitude, wet upper mid-altitude and wet lowland, and five of these also prevail in Uganda (no wet lowlands). Thirdly, maize yield and fertilizer use in the two countries is low, as it is the case in most countries in SSA: the average maize yield in 2018 was 2.6 t ha^{-1} in Uganda, and 1.7 t ha^{-1} in Tanzania (FAOSTAT, 2018); Nitrogen fertilizer use on cropland was 1.2 kg (N) ha^{-1} year^{-1} in Uganda and 9.1 (N) kg ha^{-1} year^{-1} in Tanzania in 2018 (FAOSTAT, 2018). Fourthly, arable land per capita, a crucial indicator of how agricultural intensification can contribute to improve food security (Giller et al., 2021), is more constrained in Uganda than in Tanzania: land per capita is 0.16 ha in Uganda, close to the first quartile of 0.15 ha for SSA countries, and 0.24 ha in Tanzania, close to the third quartile of 0.25 ha per capita for SSA countries (World Bank, 2021a). Lastly, the two countries allow to explore the impact of variable mineral N fertilizer costs, as these are greater in Uganda than in Tanzania (Bonilla Cedrez et al., 2020a).

In this study we estimate the potential contribution of maize intensification with mineral fertilizer to increase maize production and household food security in Uganda and Tanzania. Using existing datasets across SSA on maize fertilizer trials (Bonilla Cedrez et al., 2021; Kihara et al., 2017; Kihara et al., 2016), fertilizer and maize price (Bonilla Cedrez et al., 2020a, 2020b), and nationally representative household surveys in Uganda and Tanzania (Kilic et al., 2015), we explore the spatial variation in maize response to nutrient inputs, maize prices and fertilizer costs, and household characteristics. We estimate the contribution to national food security, that is, the amount of surplus production that farm households can produce, to be sold and consumed by others. We explore the three following research questions: i) What is the potential increase in household-level food security by intensification of maize production? ii) What is the relative importance of increasing maize production in already food secure and currently food insecure maize growers for national maize production? and iii) Are the regions where household-level food security would benefit most, also the regions where national-level production would increase most? In line with the recent finding that small farms contribute only marginally to global food production (Lowder et al., 2021; Ricciardi et al., 2018), our leading hypothesis was that an increase in national maize production will be achieved mostly by large farms that are already food secure, while food insecure small farms will contribute less to this increase. We also hypothesized that despite their low contribution to national food security, food insecure small farms benefit from maize intensification to improve their food security.

2. Material and methods

2.1. Overall approach

Our study assessed the contribution of the intensification of maize production to food security in three main steps. First, we trained a statistical model with fertilizer trial data to predict maize grain yield responses to N, P and K fertilizer application for the soil and climate conditions prevailing across SSA, and predicted the spatial variation in maize grain yield response to N, P and K fertilizer in Uganda and Tanzania. Then, we computed a simple food security indicator at household level (the food availability ratio, FA, see below) for a nationally representative set of farm households in Uganda and Tanzania. In a last step, we used the predicted maize yield responses to N, and spatial data on fertilizer and maize prices, to estimate i) the profit-maximizing N fertilizer input for each household, ii) the additional maize production from using this amount of fertilizer, and its effect on the household food availability ratio, and iii) the increase in the overall regional and national maize grain supply. We also performed a sensitivity analysis to evaluate the impact of changes in maize prices, N fertilizer costs, and maize yield responses to N on our estimates.

2.2. Maize yield response to mineral fertilizer

2.2.1. Experimental data from maize fertilizer trials

We combined data from 15,952 maize fertilizer trials conducted at 1352 locations in SSA from 1969 to 2017 (see Appendix 1 in Supplementary materials for details on the composition of the dataset). The dataset included information on trial location (longitude, latitude), maize grain yield, N, P and K fertilizer application rates, topsoil (0–30 cm) characteristics such as soil organic carbon, sand, available P, exchangeable K, Ca and Mg contents and pH, and climate variables such as growing-season rainfall, rainfall intensity and temperature, and number of consecutive dry days over the maize growing season. The trials were rainfed, implying that there may have been water stress in some growing seasons and/or in some locations. Environmental variables that were not reported with the trial data were estimated from spatial data bases (see Appendix 1 in Supplementary materials for details). Soil characteristics varied greatly, allowing the analysis of a wide range of maize growth conditions (Fig. S1). The trial locations spanned all maize-mega-environments (Fig. S2A), and covered a large range of seasonal rainfalls and temperatures (Fig. S2B).

2.2.2. Spatial prediction of maize response to N, P and K fertilizer

We used a Random Forest (RF) algorithm to predict maize grain yield as a function of nutrient inputs (N, P, K), soil properties (soil organic carbon, sand, available P, exchangeable K, Ca and Mg content and pH), and climatic factors (seasonal rainfall, average growing season temperature, number of consecutive dry spell during the season and daily rainfall intensity during the season). We tuned three hyperparameters (parameters that are calibrated during the learning process of the RF algorithm, i.e. the number of trees, the number of candidate predictor variables at each node and the minimum number of samples necessary to split a nonterminal node) based on 70% of the dataset (randomly selected) and an 8-fold cross validation with two replicates. We explored 30 combinations of the hyperparameters obtained by maximizing the coverage of the parameter space. The criterion maximized during the training procedure was the cross-validated proportion of the explained maize yield variance (R^2) averaged over the two replicates. The performance of the best RF model (with optimal combination of hyperparameters) was then evaluated on the 30% hold-out test dataset. Feature analysis (i.e. partial dependence plot and variable importance) was performed on the model fit with the full dataset. Variable importance values were calculated based on a metric that captures the increase in mean squared error (MSE), calculated from out-of-sample predictions, after randomly permuting the values of the respective predictors (Breiman, 2001), using the R package *vip* (Greenwell et al., 2020). Functional relationships between predictors and maize yield were analyzed through partial dependence plots using the *pdp* R package (Greenwell, 2017). A partial dependence plot shows the marginal effect of one input on the model prediction, averaged across the values taken by the other inputs. In order to test the contribution of climate factors, we built one model that included climate variables, and another model that did not include these, and compared the predictive capacity of the two models.

The RF model was then used to predict maize control yield (0 N, 0 P, 0 K) in Uganda and Tanzania at a spatial resolution of 250 m using soil data (topsoil organic carbon, sand, available P, exchangeable K, Ca and Mg content and pH) from Africa SoilGrid (Hengl et al., 2015, 2017). Effects on yield of incremental additions of N (i.e. 20, 40, 60, 80, 100, 120, 160, 180 and 200 kg ha^{-1}) were then investigated. Though the model was built to deal with the interactions between N, P and K inputs, for this spatial exploration we focused on the impact of N and assumed for all N additions an input of 20 kg ha^{-1} of both P and K, i.e. the P and K amounts that a compound basal fertilizer application would bring.

2.3. Food security analysis

2.3.1. Farm household survey data

We used the Living Standard Measurement Study – Integrated Surveys on Agriculture (LSMS-ISA) of 2010–2011 for Uganda and Tanzania (Kilic et al., 2015). These household surveys are nationally representative and cover the main regions of Uganda (World Bank, 2021b) and Tanzania (World Bank, 2021c). These surveys included 2716 households in Uganda and 3440 in Tanzania. Households reporting no crop production and households with missing location coordinates were excluded from the analysis, leading to a reduced sample of 1753 farm households in Uganda and 2435 in Tanzania. We used the following variables: household location (with a 10-km offset), household composition, farmer-reported total cropped land and area for the different crops, farmer-reported total crop production and sales of crop production, mineral fertilizer use on crops, total livestock production (meat and milk), sales of livestock products, and off-farm income.

2.3.2. Food security indicator: the household-level food availability ratio

We adopted the food security indicator described in Frelat et al. (2016), also used in Ritzema et al. (2017), Wichern et al. (2017) and Wichern et al. (2019): the ratio of household-level food availability (expressed in potential food equivalent energy, kcal per day) to household energy need (in kcal per day). Household-level food availability was computed as the sum of (i) the energy from crop and livestock products consumed by the household and (ii) the energy that could be obtained from food purchases with the income earned with the sales of on-farm products (crop and livestock) and off-farm activities. Consumption of on-farm grown crop and livestock products was computed by subtracting the reported sold quantities from the reported produced quantities. Energy in consumed crop and livestock products was then computed using product-specific energy content. In order to compute (potential) household-level food availability, the income from the sales of on-farm products and from off-farm activities was converted into energy (assuming that all of it was used to purchase maize) and added to calories in consumed crop and livestock products produced on-farm. Household energy need was obtained by multiplying household size (expressed in adult male equivalent) with the assumed 2500 kcal d^{-1} energy need of a male adult (FAO, 2001). The food availability ratio was computed as the ratio of household-level food availability to household energy need. A food availability ratio of one indicates that potential calorie availability at household level (on-farm production plus the calories that could be obtained with the income from off-farm activities and sales of farm products) matches household needs. The food availability ratio corresponds to potential food availability, i.e. in reality households do not entirely use their on- and off-farm income to purchase the staple food (maize in our case), because of other consumptive needs and also disfunctional markets (Dillon and Barrett, 2017). It therefore quantifies the *potential* of a household to be food secure. Under land, market and/or production constraints, the food availability ratio has been shown to be well correlated to other food security indicators (Hammond et al., 2017), namely the Household Dietary Diversity Score (HDDS), the Household Food Insecurity Access Scale (HFIAS) (Coates et al., 2007) and the number of months in which households experience food insecurity (van Wijk et al., 2020). The food availability ratio increased with HFIAS and HDDS, up to a food availability ratio of two (Hammond et al., 2017). A food availability ratio of two indicates that potential calorie availability at household level is twice household needs. We considered households with a food availability ratio below two as "food insecure", and those with a food availability ratio above two as "food secure". We further classified households with a food availability ratio below one as "food deficient households", and those with a food availability ratio between one and two as "food fragile households". Depending on whether households cultivated maize (i.e. maize area on the farm above zero) or not, they were subsequently classified into "food insecure maize growers" and "food insecure non-maize growers".

In previous studies, farmer-reported maize yield was used to quantify the food availability indicator in Uganda and Tanzania (e.g. Wichern et al., 2017; Fraval et al., 2019). For our analysis we used the maize yields predicted by the model for the N, P, K application reported by the farmer in the survey. Fields with missing information on N, P and K inputs, that is, for 99 fields in Uganda (out of 3603 surveyed fields) and 844 fields in Tanzania (out of 2125 surveyed fields), were assumed to have received median mineral fertilizer application (of all informed fields per country), which was zero in Tanzania and Uganda. Wichern et al. (2017) and Fraval et al. (2019) used the median of the reported maize prices per region to calculate the income from sold maize. In this study, we used the spatially interpolated maize price as in Bonilla Cedrez et al. (2020b). Similar to the farmer-reported prices in the LSMS surveys, they were higher in Tanzania than in Uganda (Fig. S3A, Fig. S4).

2.3.3. Computing profit-maximizing N input

Using the N response predicted by the RF model at the household locations, we computed the partial gross margin (i.e. not including the cost of other inputs that are left unchanged) for incremental additions of fertilizer N: 20, 40, 60, 80, 100, 120, 160, 180 and 200 kg ha^{-1}:

$$gm_i = (Y_{0N} + NAE_i \times i) \times maize\ \mathrm{price} - i \times N\ cost \tag{1}$$

where gm_i is the gross margin for N input rate *i*, Y_{0N} is maize grain yield with no N fertilizer input predicted by the model at a given household location, N-AE_i is the agronomic efficiency of N predicted by the model at a given household location, *i* is the N input rate, *maize price* is the predicted maize price at a given household location, and *N cost* is N fertilizer cost at a given household location. Profit-maximizing N input was the N input rate with the highest gross margin at a given household location. Additional labor cost for increased fertilizer application was not considered because of lack of reliable data.

N-AE was computed as follows (Vanlauwe et al., 2011):

$$\mathrm{NAE_i} = \frac{(\mathrm{Y}i - \mathrm{Y0N}\ )}{i} \tag{2}$$

where Y*i* is the maize grain yield with N input rate *i* and Y_{0N} is the maize grain yield with no N fertilizer input.

The market maize price and N fertilizer cost at a given household location was extracted from the spatial dataset of Bonilla Cedrez et al. (2020a, 2020b) (Appendix 2 in Supplementary materials describes the model development procedure of these two studies).

2.3.4. Change in food availability ratio and increase in regional and national maize supply

When profit-maximizing N fertilizer input was above the currently reported N fertilizer input by farmers, we computed the corresponding potential additional maize production ΔP:

$$\Delta \mathrm{P} = (\mathrm{Y}_{new1} - \mathrm{Y}_{current1}) \times \mathrm{area}_{s1} + (\mathrm{Y}_{new2} - \mathrm{Y}_{current2}) \times \mathrm{area}_{s2} \tag{3}$$

where Y_{new1} and Y_{new2} are the predicted maize yields with profit-maximizing N input for the short and long growing seasons, respectively, $Y_{current1}$ and $Y_{current2}$ are the corresponding predicted maize yields with the N input as reported by the farmer in the survey, and $area_{s1}$ and $area_{s2}$ are the maize areas in, respectively, short and long season, as reported by the household head in the survey (depending on household location, there may be only one growing season and $area_{s2}$ was therefore equal to 0). We assumed equal maize responses to N for the two seasons at a given household location. When profit-maximizing N fertilizer input was equal or below the currently reported N fertilizer input, ΔP was set to 0. ΔP was converted to energy and used to compute the household food availability ratio adjusted for the use of profit-maximizing N input (FAprofmax). A relative change in the household food availability ratio (ΔFA) was then computed as follows:

$$\Delta FA = FAprofmax/FAbaseline \quad (4)$$

Where FAprofmax is the food availability ratio with profit-maximizing N input and FAbaseline is the food availability ratio with current reported N input on maize.

The impact of N-AE and farm characteristics (per-capita maize area, total cropland, livestock and off-farm income) on ΔFA was explored by classifying farms in three classes with regard to these variables: class one below the 33th percentile of all farms for the considered variable, class two between the 33th and 66th percentile, and class three above the 66th percentile.

Then ΔP was aggregated for all surveyed household at the level of the administrative region and country, to compute the relative increase in maize grain supply, assumed to be a proxy for the relative increase in regional/national maize production. The contribution of food insecure and food secure households (further disaggregated by classes of per-capita maize area) to this potential increase in maize grain supply was also calculated.

2.3.5. Sensitivity analysis

The impact of variations in N-AE, maize price and N cost on i) the profit-maximizing N input, ii) the share of food insecure maize growers who would increase their food availability ratio with the use of profit-maximizing N input, iii) the median ΔFA of food insecure maize growers, and iv) the relative potential increase in national maize grain supply, was explored through sensitivity analysis. N-AE, maize price and N fertilizer cost varied between 0.25 and 2 times their baseline value.

3. Results

3.1. Maize grain yield predictions

The inclusion of climate-related predictors (seasonal rainfall and mean temperature over the maize growing season, number of consecutive dry days over the season, and daily rainfall intensity over the season) only marginally improved the predictive capacity of the model; R^2 increased from 0.82 to 0.87. For this reason, we used the RF model without climate variables. The model predicted maize grain yield (for hold-out data) with a Root Mean Square Error (RMSE) of 919 kg grain yield ha^{-1} (corresponding to a relative RMSE of 27%), and a Mean Absolute Error (MAE) of 657 kg grain yield ha^{-1} (Fig. 1). Uncertainty in model predictions increased with higher values of observed maize yield (Fig. 1). N and P fertilizer inputs contributed most to predict maize yield, followed by the soil sand content (Fig. S5). In contrast, the contribution of K fertilizer and that of the other soil properties (available P, exchangeable K, Mg, Ca, organic carbon and pH) was marginal (Fig. S5). Predicted maize yield increased with N applied in the range 0–150 kg N ha^{-1} and with P up to 50 kg P ha^{-1}, but decreased with coarser soil texture (higher soil sand content, Fig. S6).

3.2. Predicted maize yield in response to fertilizer in Uganda and Tanzania

Predicted maize grain yields with no fertilizer input ("control yield") ranged from 500 to >2500 kg/ha (Fig. 2A). Predicted control yield was generally smaller in sandy areas such as the coastal areas in Tanzania and somewhat higher in areas with high soil available P such as the volcanic soils in Eastern Uganda near Mount Elgon and in the northern highlands of Tanzania near Kilimanjaro (Figs. S7, S8). With the maximum fertilizer use considered (200 kg N ha^{-1}, 20 kg P ha^{-1}, 20 kg K ha^{-1}), predicted yield increased by up to five times the control yield (Fig. 2B). The largest predicted yield increase was in areas with the smallest control yields (for example, in the southwest Tanzanian highlands, south-eastern Tanzania, and the area around Lake Victoria in Uganda). Median N-AE (across locations) was 20 kg (grain) kg (N)$^{-1}$ with N inputs of 40 kg/ha, and decreased gradually with higher N fertilizer inputs (Fig. S9B). N-AE also significantly (P-value <0.001) decreased with higher control yields, lower sand content, and higher soil organic carbon (Fig. S10). As a consequence, the areas with the lowest control yields were generally areas of highest N-AE (Fig. 2A and Fig. S11).

3.3. Food security analysis with current fertilizer use

Fertilizer use reported by farmers in the 2011 survey was very low. In Tanzania, only 12% of the 3212 surveyed maize plots had received N, 3% had received P and 0.3% had received K, with a median application (for fields receiving mineral fertilizer) of 38 (N), 12 (P) and 7 (K) kg ha^{-1}. In Uganda, <1% of the 3553 surveyed maize plots had received mineral fertilizer, with median application of 1.0 (N), 1.4 (P) and 2.5 (K) kg ha^{-1}. Overall, predicted maize grain yield (with N use reported by farmers) was greater (median = 1207 kg ha^{-1}) than farmer-reported maize yield (median = 482 kg ha^{-1}), possibly because of weed/disease/pest stresses not accounted for by the RF model. Yet, in some cases, especially in Uganda, farmer-reported yield was greater than the predicted yield with the reported N use – possibly because of the uncertainty related to farmers' estimates of their maize production and area.

We found that a large share of the surveyed farm households was food insecure when using the maize yield predicted with their reported N use: 44% of the households in Tanzania and 46% in Uganda had a food availability ratio of less than two, and 25% of household in Tanzania and Uganda had a food availability ratio of less than one (Fig. 3). When using farmer-reported maize yield, these percentages were greater in Tanzania, and similar in Uganda: 74% of the households in Tanzania and 45% in Uganda had a food availability ratio of less than two. In what follows we report results that used predicted maize yields. Crops produced and consumed on-farm were the largest contributors to household food availability for food insecure (FA < 2) households in Tanzania (Fig. 3a). Off-farm income and sales of livestock and crop products contributed more to the food security status of farm households in Uganda than in Tanzania (Fig. 3b). The majority of food insecure (FA < 2) households produced maize: 64% in Tanzania and 51% in Uganda. The majority of food secure (FA > 2) households also grew maize, 87% in Tanzania and 58% in Uganda. There were no obvious spatial patterns

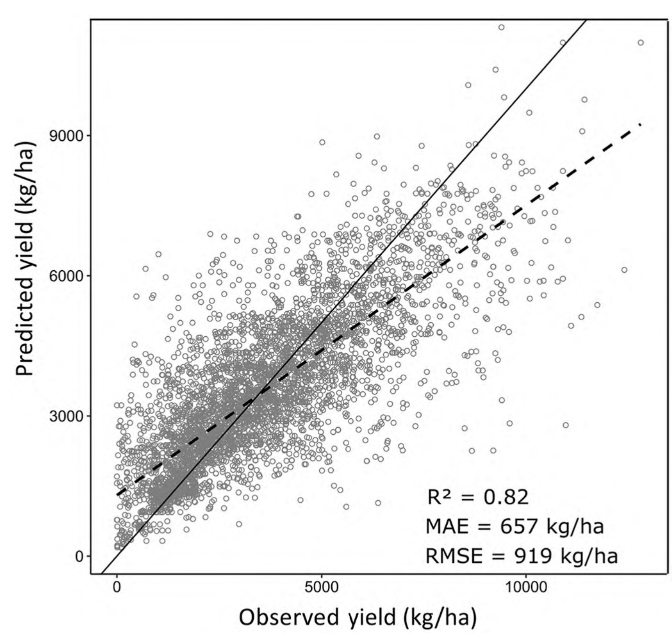

Fig. 1. Observed and Random Forest predictions of maize yield for the maize trials across sub-Saharan Africa used for model validation. The solid line is the 1:1 line, the dotted line is the regression line of predicted vs observed values.

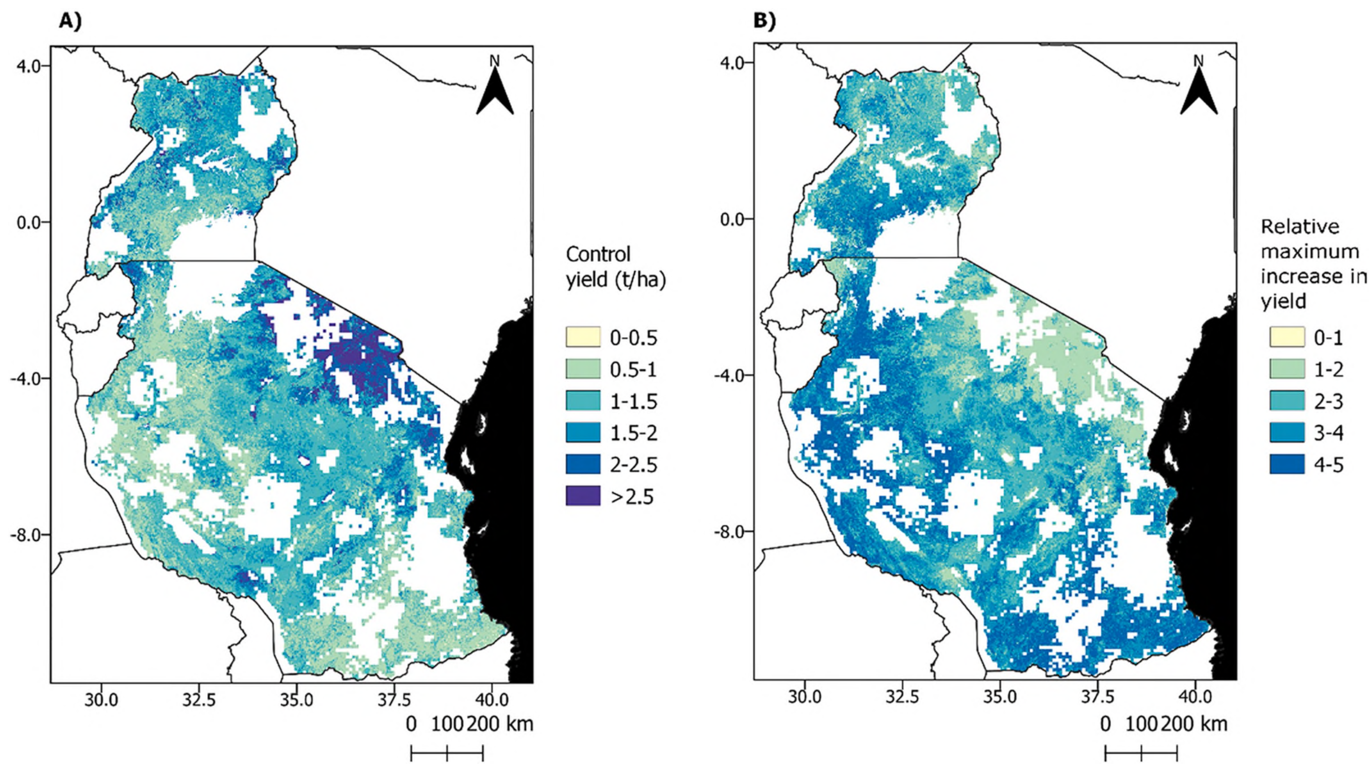

Fig. 2. A) Control maize yield (no fertilizer input) predicted by the Random Forest model and B) maximum relative increase in yield (i.e. yield with maximum (200 N/20P/20 K) fertilizer application divided by control yield). Areas in Uganda and Tanzania where maize is not grown (according to IFPRI, 2020) appear in white. In areas with two (short and long) cropping seasons per year, the model predicted the same yield because weather-related variables were not used as input to the Random Forest model.

in the locations of food insecure maize growers; Households were sampled and surveyed in the eastern, western, northern and southern parts of Uganda and Tanzania (Fig. S12A), and food insecure maize households could be found in almost all regionss where the survey was conducted (Fig. S12B). The scope for intensifying maize production (that is, the maximum relative increase in maize yield, Fig. 2B) varied greatly across the locations where food insecure households were found, in both countries (Fig. S12B).

3.4. Impact of additional N input on household food security

Based on model prediction and spatial price data, the mean profit-maximizing N input was 82 kg (N) ha^{-1} in Tanzania, and only 24 kg (N) ha^{-1} in Uganda (Fig. S13). The difference between countries was mostly attributed to lower maize price and higher N cost in Uganda (Fig. S4). For 90% of maize growers in Tanzania (95% of the food insecure maize growers), profit-maximizing N input was above the current reported N use, and their food availability ratio was predicted to increase when using the profit-maximizing N input. In Uganda, this was the case for only 41% of the maize growers (43% of the food insecure maize growers). Households for which profit-maximizing N input was above current reported use were spread all over Tanzania, and in Uganda around Lake Victoria (Fig. S13B), i.e. in areas with higher maize prices, lower fertilizer costs, and thus with a maize price: N fertilizer cost ratio compatible with profitable use of more fertilizer (Fig. S3).

The relative increase in the food availability ratio (with additional N input) decreased with the baseline food availability ratio: food insecure (FA $>$ 2) households benefited much more in relative terms, than food secure (FA $>$ 2) households (Fig. 4A). In addition, household with greater N-AE, larger per-capita maize area, and larger cropped land benefited most from the use of profit-maximizing N inputs (Fig. 4B, C and D). Off-farm and livestock income had only a marginal impact on the relative increase in food availability ratio (Fig. 4E and 5F).

With the additional - profit-maximizing - N input, the share of food insecure maize growers was predicted to drop from 28% to 13% of the total household population in Tanzania (Fig. 5A). In Uganda, the change was marginal, i.e. from 23% to 21% (Fig. 5A). The farm households who could reach food security had medium to large per-capita maize area (above 0.17 ha in Tanzania, and 0.03 ha in Uganda) (Fig. 5B). None of the households with small per-capita maize area could achieve food security with the additional profit-maximizing N input (data not shown).

3.5. Regional-level vs household-level food security

Though food insecure (FA $<$ 2) households benefited more from profit-maximizing N input for their food security than food secure (FA $>$ 2) households, they contributed only marginally to the overall increase in national maize supply. Food insecure households contributed $<$20% to the overall increase in maize supply in Tanzania and Uganda, though they represented around 40% of the total farm population in both countries (Fig. 6). In contrast, food secure households with large per-capita maize area, contributed $>$60% to the overall increase in maize supply in both countries, though they represented only 20 to 30% of total household population (Fig. 6).

The relative increase in regional maize supply with N fertilizer use was predicted to vary between one (i.e. no increase) and three, across administrative regions in Tanzania and Uganda (Fig. 7A). In some regions, this increase in total maize production concurred with an increase in the household-level food availability ratio for food insecure maize growers. For example, in the Mtwara Region in southern Tanzania (#23 in Fig. 7), regional maize supply was predicted to increase three times, and the food availability ratio for food insecure households by almost 2.5 times. However, there were regions where despite a small predicted increase in total maize supply, the predicted increase in household-level food availability for food insecure maize growers was substantial. For example, in the Iringa Region in central Tanzania (#8 in Fig. 7), total

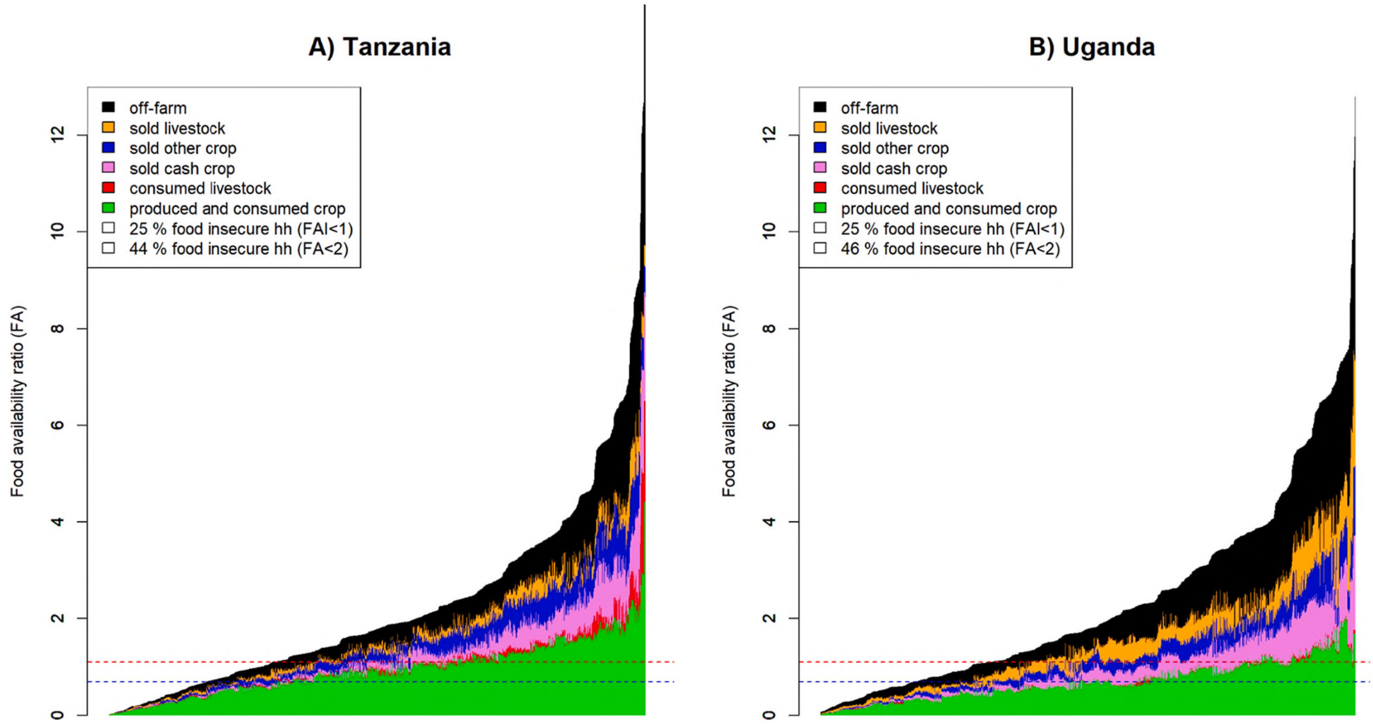

Fig. 3. Household (hh) food availability ratio (FA) for 2435 households in Tanzania (A) and 1753 households in Uganda (B). The y-axis was log-transformed so that y = log (FA +1). Households were ordered by increasing food availability ratio (i.e the ratio of available food to the required food) along the x-axis. A bar is one household. The red dashed line is the 5000 kcal cap^{-1} day^{-1} food security threshold (i.e. food availability ratio = 2), and the blue dashed line is the 2500 kcal cap^{-1} day^{-1} food security threshold (i.e. food availability ratio = 1). A rolling average was applied with subsets of 30 households to smooth the curves for easier interpretation. Different colours indicate the source of the food, be it produced on-farm or purchased. Crops were considered as cash crops when >90% of the annual production was sold. Large values of sold and consumed crop on the right side of the plots correspond to potential bias in survey data rather than to real consumption values. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

maize supply was predicted to increase 1.8 times, while the household-level food availability ratio for food insecure maize growers was predicted to increase 2.3 times. Regions where the potential for increasing total maize supply was highest did not necessarily match with regions with the largest potential for improving household-level food security.

3.6. Impact of changes in N-AE, maize price and N fertilizer cost

The profit-maximizing N input, the share of beneficiaries (i.e. food insecure maize growers who increased their food availability ratio with additional N fertilizer use on maize), and the relative national increase in maize supply were all sensitive to changes in maize prices, N-AE and N fertilizer costs (Fig. 8). Changes in N-AE had the same effect as changes in maize prices on the output variables of Fig. 7, which is not suprising as both variables play a similar role in the equation that determines profitability of N fertilizer use (see Section 2.3.3). On the other hand, the median relative change in food availability ratio for food insecure maize growers was not sensitive to changes in maize prices, N-AE and N fertilizer costs, because it was also influenced by the share of beneficiaries (i.e. this share fluctuated in the different scenarios on maize prices and N fertilizer costs) (Fig. 8C).

4. Discussion

4.1. Potential and obstacles of maize intensification to improve household food security

Our analysis showed that a substantial share of food insecure maize growers in Tanzania and Uganda could increase their household food availability in the short term with additional N fertilizer use on maize. This finding matches the results of an analysis in East, West and Southern Africa (comprising 1024 households in total) of Giller et al. (2021), who estimated that closing the yield gap of major crops would allow >50% of farm households to become food secure.

Soil properties influence the opportunity for farm households to improve their food security. Largest benefits were obtained in areas with large N-AE values, that is, on sandy soils with low soil organic matter and therefore low maize yields when no fertilizer was used. On the other hand, smaller N-AE values were achieved on clayey soils on which maize yields in the absence of fertilizer were relatively high because these soils tend to have more organic matter that can mineralize and provide substantial amounts of N to the crop in the absence of fertilizer. Some characteristics of the farm households were also important in enhancing food security at household level. We found that the opportunity to achieve food security through intensified fertilizer use increased with farm size and maize area per capita, similar to the findings of Giller et al. (2021) for small farms sizes in Ethiopia, Ghana and Malawi. However, in addition to intensification of crop production, off-farm income is key for enhanced food security at household level. Agricultural intensification may, however, help spur a thriving rural non-farm economy that can generate alternative income sources for households (Haggblade et al., 2010). In this context, rural to urban migration, the so-called “natural Malthusian population control” (Demont et al., 2007) can restrain further farm fragmentation in rural areas and provide at the same time key remittances for the development of the rural economy.

Although additional N fertilizer use could substantially contribute to improved household food security, this strategy was not profitable for farm households in locations where the maize price and N fertilizer cost were unfavorable; the estimated profit-maximizing N input was null in Western, Northern and Eastern Uganda in particular, corroborating the low current use of mineral fertilizer by farmers. An increase in the price: cost ratio could be achieved with input subsidy programs for maize

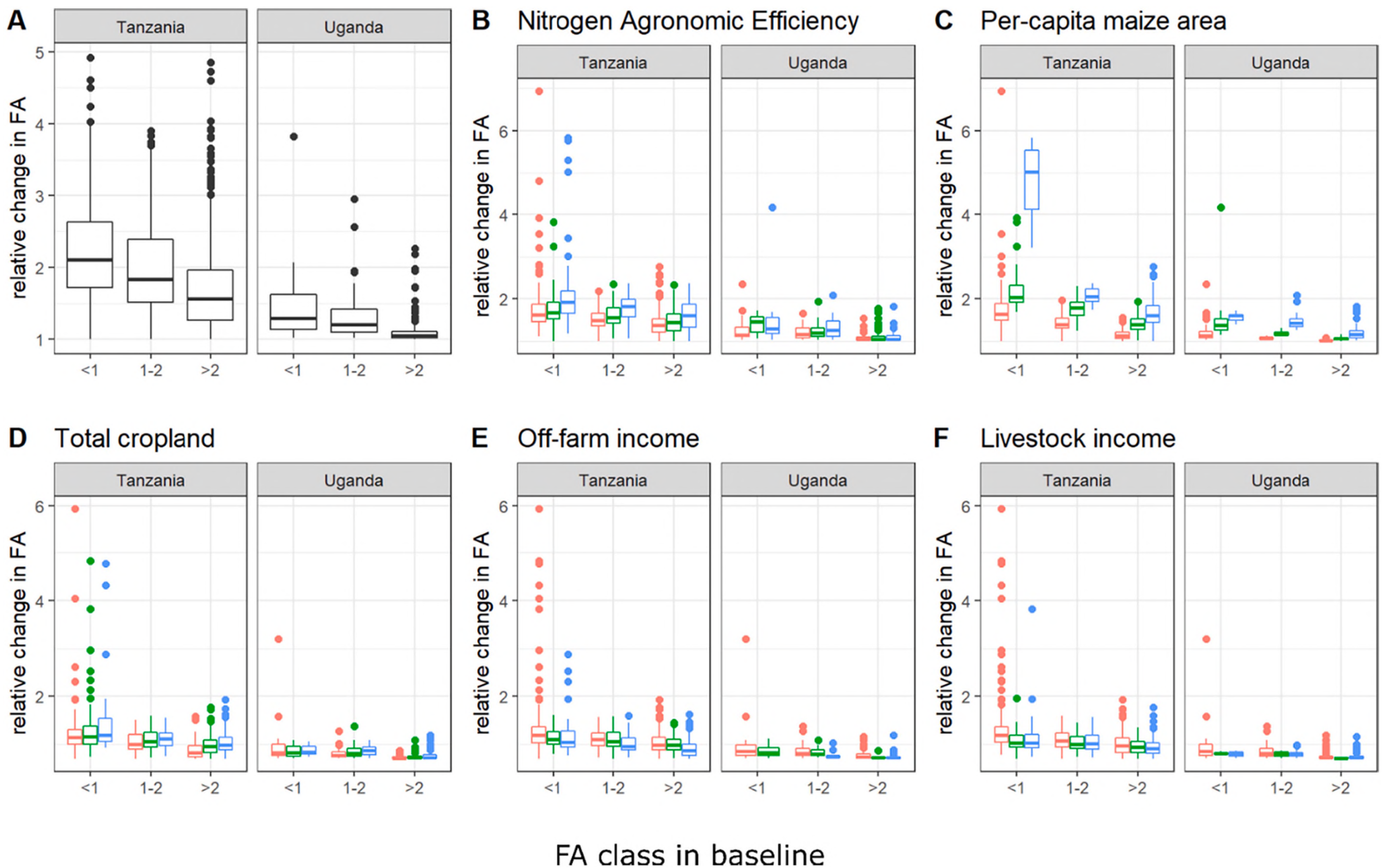

Fig. 4. Boxplots of relative change in Food availability ratio (FA) per FA class in baseline (i.e. with current reported N input on maize) in Tanzania and Uganda (A), and for three classes of nitrogen agronomic efficiency (N-AE) (B), per-capita maize area (C), total cropland (D), off-farm income (E) and livestock income (F). Red boxplot are households below the 33th percentile of the considered N-AE or farm characteristic, green boxplots are households between the 33th and 66th percentile, and blue boxplots are households above the 66th percentile. The y-axis was log-transformed so that y = log (relative change in FA +1). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

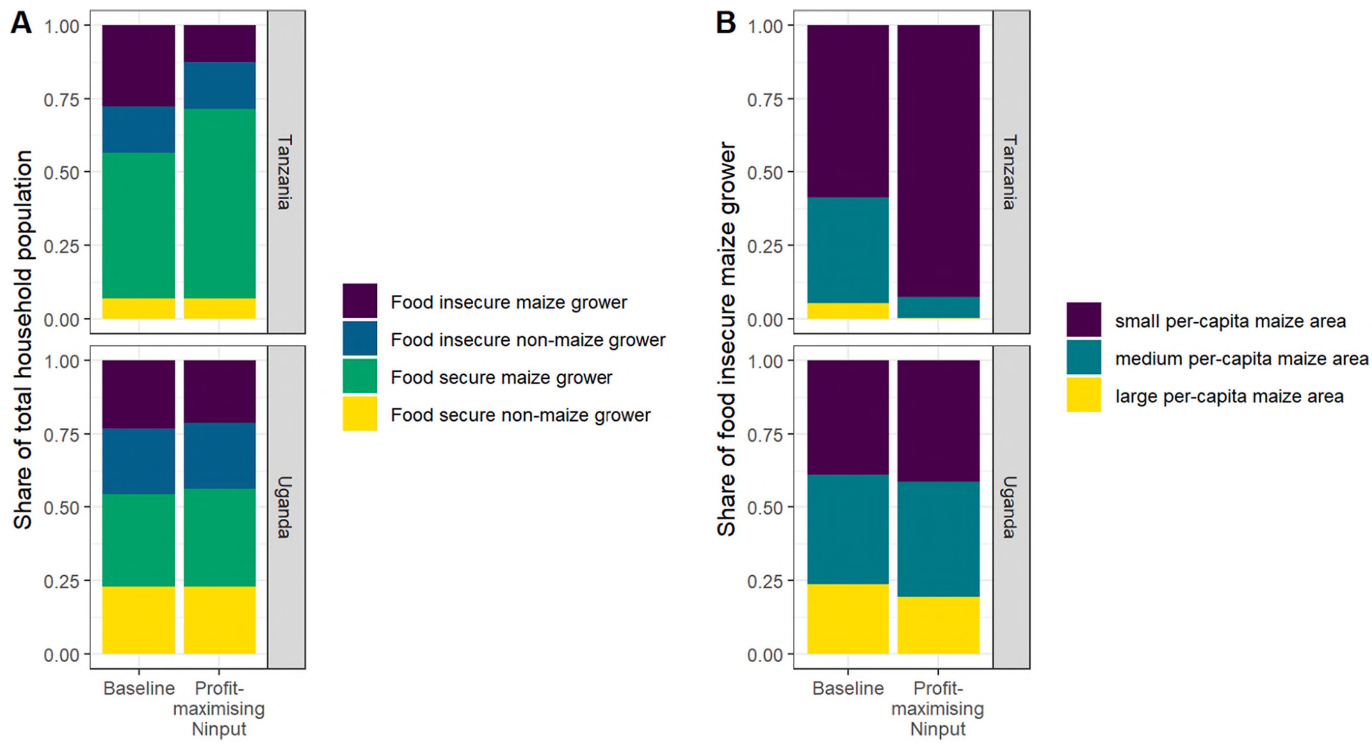

Fig. 5. (A) Share of food insecure maize growers in total agricultural household population in baseline situation (current maize yield) and with profit-maximizing N input on maize in Uganda and Tanzania and (B) share of these food insecure maize growers who have small per-capita maize area (<0.17 ha in Tanzania and < 0.03 in Uganda), medium per-capita maize area (0.17–0.38 ha in Tanzania and 0.03–0.07 in Uganda) and large per-capita maize area (>0.38 in Tanzania and > 0.07 in Uganda).

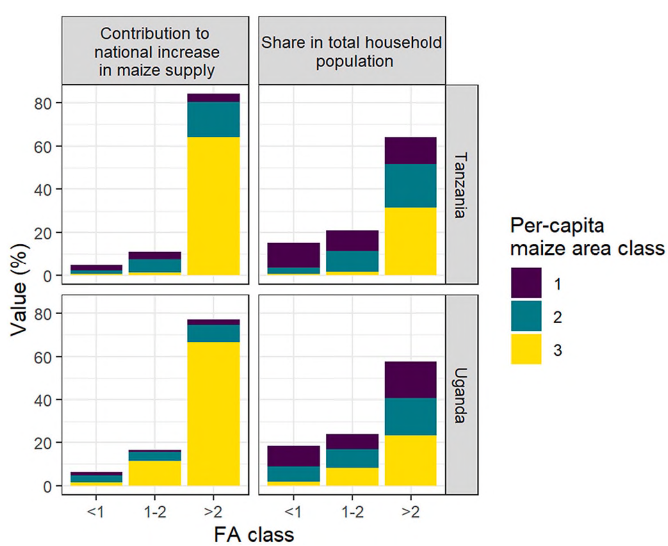

Fig. 6. Comparison between the i) relative contribution to national increase in maize supply and ii) share in total household population, for household of contrasting food availability ratio (FA) and maize area per capita classes in Tanzania and Uganda. Class 1 for per-capita maize area is <0.17 ha in Tanzania and < 0.03 in Uganda, class 2 for per-capita maize area is 0.17–0.38 ha in Tanzania and 0.03–0.07 in Uganda, and class 3 for per-capita maize area is >0.38 in Tanzania and > 0.07 in Uganda.

growers for whom fertilizer is currently not profitable. Input subsidy programs through which farmers can access fertilizer at below-market prices have been on the rise again since 2010 in several countries of SSA (Jayne et al., 2018b). Despite failing to target the poorer farmers in a number of instances (Pan and Christiaensen, 2012; Jayne et al., 2013), these programs have had a measurable impact on maize productivity. For example, the Farm Input Subsidy Program (FISP) in Malawi brought a 17% increase in farmers' gross margin (Karamba and Winters, 2015). Reducing transport costs (with e.g. improvements in road conditions) could also contribute to lower fertilizer cost and improve the profitability of fertilizer use (Guo et al., 2009). For example, the average N fertilizer price of 0.39 USD kg^{-1} in Illinois (USA) during 2001–2013 (Beckman and Riche, 2015) is about 17% of the estimated price across Tanzania and Uganda in this study (2.34 USD kg^{-1}). The much lower N cost reported by Beckman and Riche (2015) corresponds to the lower limit of N cost explored in the sensitivity analysis of this study; this boundary is therefore not unrealistic for prices elsewhere in the world. On the other hand, with a 75% increase in N fertilizer price, profit-maximizing N input in Tanzania was predicted to drop to zero, highlighting the drastic impact that the current rise in fossil fuel prices, and thus N fertilizer prices, is likely to have on food security in SSA. Seasonal variations in maize grain prices (Bonilla Cedrez et al., 2020b) can also impact fertilizer profitability. Poor households usually sell their production soon after harvest when prices are usually low, because they have no storage facilities and/or need cash. In our study, we considered annualized maize grain prices, while farmers who are equipped with adequate storage facilities and well connected to markets, may want to sell their extra produce during the lean season when maize prices are higher (Burke et al., 2020).

Profit-maximizing N input rates increase with improved N use efficiency by maize (higher N-AE values), which can enlarge the share of beneficiaries from intensification of maize production, especially in Uganda. The average predicted N-AE for maize in our study was 20 kg

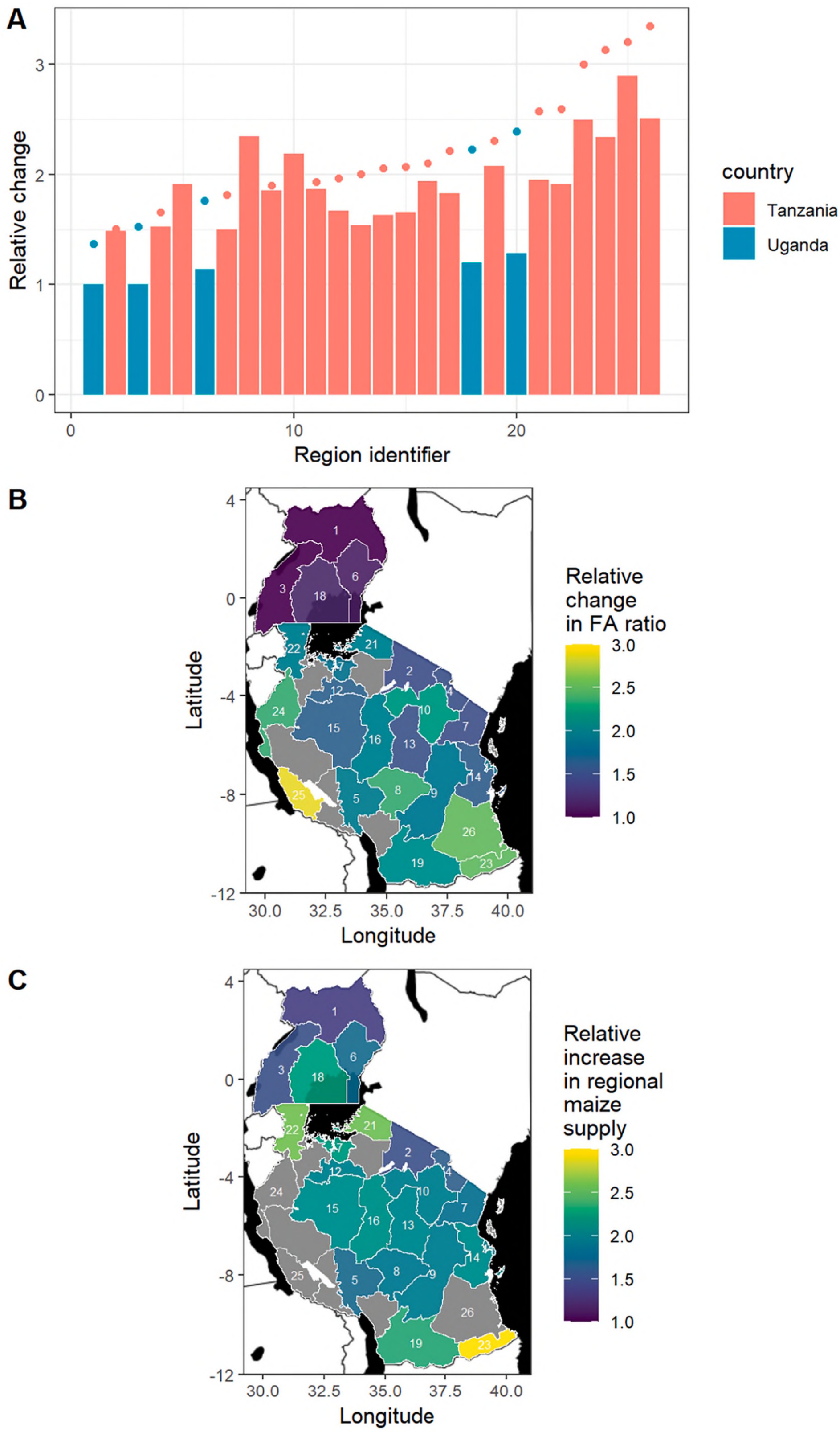

Fig. 7. A) Relative change in regional maize supply (dots) and median relative change in household-level food availability (FA) ratio for food insecure maize-growers (with the use of additional, profit-maximizing N input), in regions of Uganda and Tanzania (bars), B) map of regional median relative change in food availability ratio for food insecure maize-growers, and C) map of relative increase in regional maize supply. Numbers in the map are number of regions that correspond with the Region identifier along the x-axis of fig. A.

grain yield kg^{-1} N added (for a N input of 40 kg N ha^{-1}), which is well below the 32 kg kg N^{-1} or more that can be achieved in well-managed maize fields (ten Berge et al., 2019; Vanlauwe et al., 2011). Our model was trained with mostly on-farm data, with possibly sub-optimal weed, pest and disease management affecting N-AE. More generally, improving the synchrony between crop demand and N supply following the "4R" nutrient management framework ("using the **r**ight N source at the **r**ight rate, **r**ight time and in the **r**ight place", Udvardi et al., 2021) is also key to achieve greater N-AE.

Our analysis showed that for most farm households in Tanzania, the use of additional N fertilizer was profitable. Yet, the question remains why these farmers do not actually use (more) fertilizer. One reason could

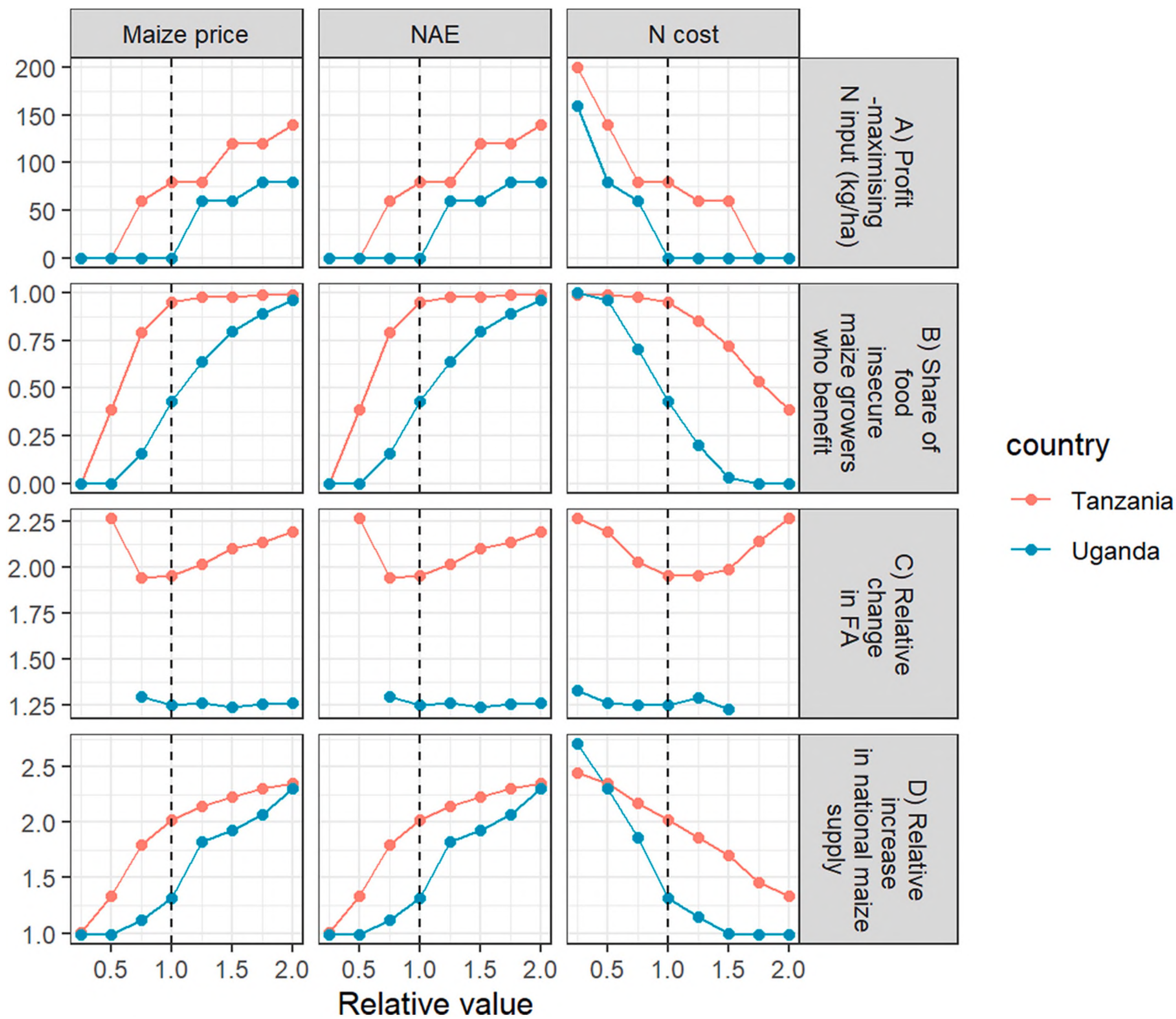

Fig. 8. Sensitivity analysis of the impact of a change in maize price, nitrogen agronomic efficiency (N-AE) and N cost on A) profit-maximizing N input, B) share of food insecure maize growers who increase their food availability ratio with the use of additional profit-maximizing N input on maize, C) median relative change in food availability ratio (FA) for food insecure maize growers, and D) relative increase in national maize supply due to the use of additional N input on maize, in Tanzania and Uganda.

be that farmers lack capital to buy fertilizer, possibly also because credit options to finance its purchase at the start of the season are scarce or do not exist. Another explanation could be the usual risk averse nature of farmers, associated with e.g. exposure to drought (Assefa et al., 2021; Jourdain et al., 2020). While fertilizer use might be profitable on average, in years with, for example, drought stress leading to poor yields, farmers would not break even (e.g. Bielders and Gérard, 2015). In addition, in our study we assumed that farmers would apply the profit-maximizing N fertilizer input. However, in reality farmers might only go for more N fertilizer if the increment in gross margin exceeds the extra N cost by a safety margin. A value:cost ratio of two is typically used as a basis for adoption of a technology (e.g. Jayne et al., 2018b). Lastly, the extra cost of labour for fertilizer application was not considered in our study; including it would also lower the estimated profitability of fertilizer use.

4.2. National food security vs household-level food security

The use of additional N fertilizer was predicted to substantially increase overall regional and national maize production. The food riots of 2008, the COVID-19 outbreak, and the recent war in Ukraine have emphasized the vulnerability of relying heavily on food imports to national governments and revived the idea of national and regional food self-sufficiency (d'Amour et al., 2016; Fontan Sers and Mughal, 2020). Building resilience in SSA's states to the consequences of such events, while meeting a growing food demand with population growth and avoiding further cropland expansion, requires drastic increases in cereal yields. Van Ittersum et al. (2016) calculated that cereal yields have to increase to close to 80% of their water-limited yield potential to feed the population in SSA by 2050, and this will require a 15-fold increase in nutrient inputs (ten Berge et al., 2019). Our study helps identify regions where the scope to increase maize production is greatest (see Fig. 7C). However, these priority regions in terms of national food security do not necessarily match with the regions where the scope to improve household-level food security is the strongest (see Fig. 7B). Policy interventions that prioritize national food security will require specific attention to this, ensuring that "no one is left behind" (United Nations, 2015).

4.3. Long-term sustainability of cropping systems

Although relatively small profit-maximizing N fertilizer inputs (80 kg N ha^{-1} in Tanzania, and 20 kg N ha^{-1} in Uganda) may yield immediate benefits for household food security, these inputs are unlikely to be sufficient to avoid soil mining and to guarantee long-term sustainability of maize-based systems. Ten Berge et al. (2019) calculated that on average a minimum of 140–150 kg N ha^{-1} must be available to maize crop to sustain yields compatible with SSA food self-sufficiency by 2050, i.e. far more than the profit-maximizing N fertilizer inputs computed in our study. Recycling of biomass, use of farmyard manure, rotating with grain legumes and use of leguminous trees in agroforestry systems can complement mineral fertilizer to provide the N required to sustain high maize yields in future. The increased N fertilizer input required to achieve household and national food security, while preserving long-term soil fertility, comes, however, at a cost for the environment in the form of N leaching losses and gaseous emissions. Narrowing the maize yield gap in SSA will undoubtedly increase N_2O emissions (Leitner et al., 2020). Yet, ten Berge et al. (2019) estimated that meeting the food demand in SSA by 2050 through intensification of cereal production with mineral fertilizer, assuming good agronomy and using the '4R'principles of nutrient management, would emit less greenhouse gases than through cropland expansion from deforestation. Large fertilizer inputs, if not retained in soils, can also contribute to eutrophication in lakes, inland and coastal waters, with direct threats to biodiversity and human health. The '4R' approach to nutrient management that is crucial for increasing nutrient use efficiency and profitability, will at the same time reduce leaching and run-off of nutrients causing eutrophication.

4.4. Opportunities to use and improve the proposed framework

Extending our analysis to other countries or regions with larger land holdings and possibly larger maize area per capita would be necessary to fully grasp the potential of maize intensification to contribute to improved food security throughout SSA, e.g. in the cotton basin in Mali the median cultivated land area per capita is 0.84 ha compared with 0.13 ha in central Malawi and 0.14 ha in the Ethiopian highlands (Giller et al., 2021). Besides, other crops than maize, e.g. traditional grains like sorghum and millet, rice, legumes (e.g. groundnut and cowpea), highland banana, root and tuber crops and vegetables, have to be considered to quantify the full potential of intensification and diversification of crop production to reduce food insecurity. It will however, be challenging to do this with an empirical model as there is less data available for these types of crops than for maize.

The accuracy of the RF model of our study ($R^2 = 0.82$) was better than that of a model trained on yields measured in 601 field trials in Tanzania ($R^2 = 0.24$, Palmas and Chamberlin, 2020), highlighting the importance of training the model on a large dataset. The main features of our model were in line with the findings of a meta-analysis of 71 studies across SSA that showed that soil texture, pH and exchangeable K were the main factors explaining variability in N-AE (Ichami et al., 2019). Soils can vary substantially in macro and micro-nutrient content at short distances – owing to past crop management by farmers (Falconnier et al., 2016). The variations of crop responses to nutrient inputs depending on rainfall season (short vs long in area with two growing seasons per year) would also deserve further analysis. With the current data, total rainfall, and other indicators related to its distribution, only marginally improved the ability of the RF model to explain maize yield variability. Process-based crop models could be used to simulate crop responses to fertilizer inputs. This type of models can be calibrated with data from a limited set of trials spread across representative locations and then used to make predictions at any location (see Deng et al., 2019 for an example). More specifically, process-based crop models can account for the impact of drought or excessive rainfall on fertilizer use efficiency, and are useful to determine the probability of yield failure and the risk of not breaking-even when using fertilizer (e.g. Ricome et al., 2017). Risk assessment will help to further distinguish areas where fertilizer use is a low-risk opportunity for farmers and those where its use is too risky and must be complemented with specific interventions [e.g. index-based insurance (Benami et al., 2021)].

Lastly, local variations in prices of maize and costs of fertilizer, due to e.g. transportation costs that are not included in the spatial price predictions, and uncertainty of farmer-reported crop areas are substantial sources of uncertainty in our analysis, as pointed out in our sensitivity analysis. Our study and the proposed framework could therefore guide national and regional priority settings of interventions around intensification of maize production with fertilizer, but should be complemented with place-based assessments of the local relevance of proposed interventions.

5. Conclusions

Intensification of maize production with mineral fertilizer can substantially improve the food security of food insecure households in Uganda and Tanzania. Households with relatively large per-capita maize area benefit most, as well as those located in areas where maize yields are low in the absence of fertilizer use and where yield responses to nutrients are high. In some areas, particularly in Uganda, profit-maximizing N fertilizer input is low, and the potential of maize intensification through fertilizers to reduce food insecurity is thus limited. Institutional commitment to smart input subsidies and investments in road networks could lower fertilizer price, and broader investments in agricultural research, development and extension to operationalize best-practices (better seed quality, timely planting, optimal plant density, and proper weed, pest and disease management) could help to improve nutrient use efficiency by crops. Our study brings important insights for priority setting as high potential areas for increased maize domestic production do not necessarily match with areas where there is immediate scope for improving household-level food security. These two impact levels should be coherently considered when articulating policy and research priorities that aim at improving food security at household level and regionally.

Declaration of Competing Interest

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

Data availability

Data will be made available on request.

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