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Spatially explicit trends in nitrogen use efficiency and partial profits in Tanzania, 2008-2020

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Abstract

Amidst concerns of global agricultural productivity growth slowdown, there is an emerging consensus that crop productivity growth in some African countries has either been stagnant or slow in the past decade. This slowdown is attributed to degrading soil health and volatile weather patterns resulting in low partial productivity especially of nitrogen—hereafter nitrogen use efficiency (NUE) and falling profits. We contribute to this literature by using plot level nationally representative panel data (2008-2020) for Tanzania to examine if indeed NUEs and profits have been on a downward spiral. We combine a causal random forest model for heterogeneous treatment effects and a regional market economic surplus model to explore the economic implications of the NUE trends. We find that NUEs differ not only across years, but also spatially. Additionally, the whole crop response curve differs across seasons and regions which poses enormous complexity when understanding NUEs using observational data implying that complex processes operate in low input farms that make it difficult to pin down the major challenges causing any slowdowns or increases in NUEs. We do not find any evidence of falling NUEs in Tanzania. Conversely, NUEs have increased as compared to 2008 (9 kg maize per kg of N) by about 10% in 2010, 18% in 2012, 18% in 2014 and 14% in 2020. Nonetheless, the profits and economic surpluses from nitrogen use are too low to incentivize farmers to use nitrogen fertilizers at the prevailing input and maize output price ratios. To address food insecurity concerns while incentivizing farmers to apply modest amounts of nitrogen fertilizer, this paper argues for increasing NUEs through proper crop management decisions and minimizing the fertilizer-maize grain price ratios.

1. Introduction

Agricultural productivity slowdown has been observed in developed countries for several decades now (Alston et al 2009, Suri and Udry 2022). While this is worrisome, if these countries are on the frontier, then one would think that global food security will still be guaranteed by the developing countries. This trajectory has however been compromised in that there is a growing evidence showing a slow down in agricultural productivity even for developing countries due to climate variability and degraded soil health (Wollburg et al 2024a, Wollburg et al 2024b). This amidst high potential yield gains from experimental trials (McCullough et al 2022; Falconnier et al 2023, Laalaj et al 2020).

Among the countries with the productivity slowdown is Tanzania. Yields of major crops have been stagnant in Tanzania as shown in appendix figure 1. For the major cereals (i.e., maize and rice), Tanzania had more growth in area (five-fold for maize and fifteen-fold for rice) than in yields (two-fold for both maize and rice). This implies that these crops may have moved to less favorable places across time.

The main limiting factor to agricultural production in the country is nitrogen. The use rates of nitrogen are much lower than global average. Attempts to increase the use rates are hampered by increasing fertilizer prices and slowing down of profitability of N use (Bonilla-Cedrez et al 2021).

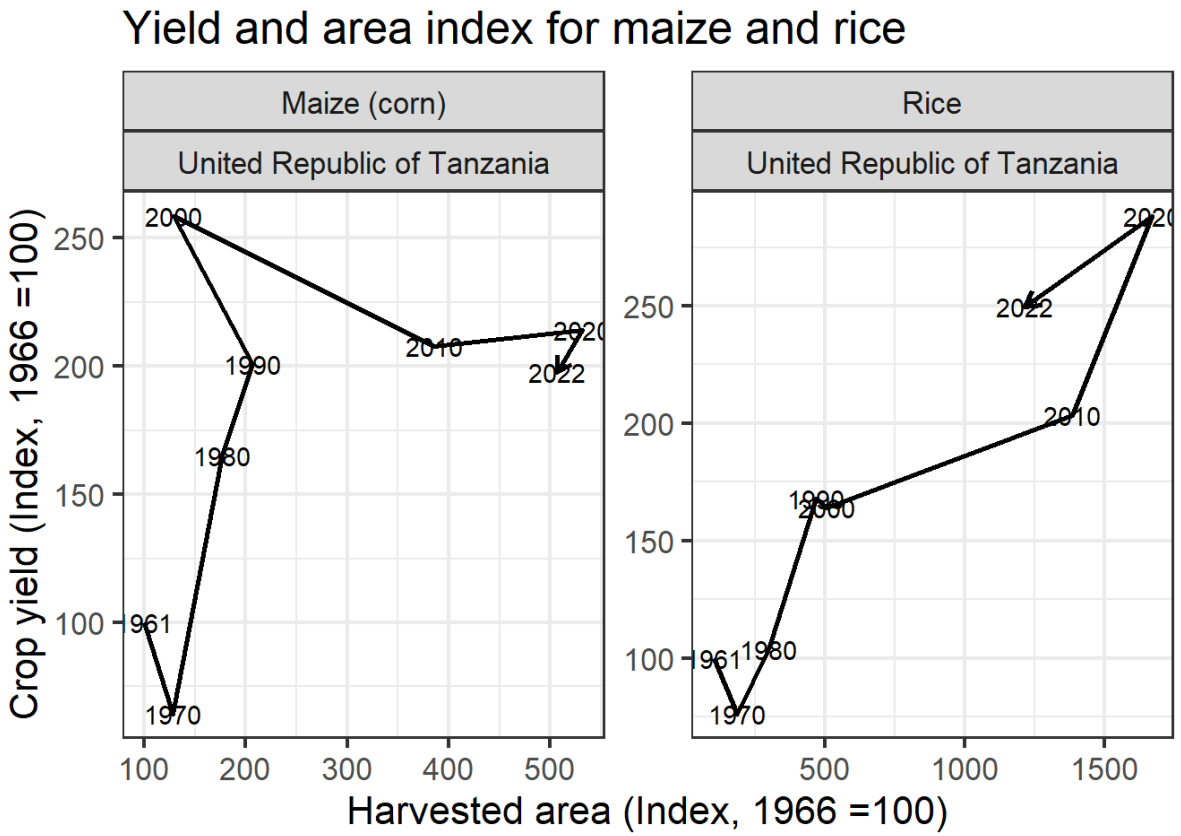

Figure 1: Harvested area and yield growth of maize and rice in Tanzania (source: authors using FAOSTAT)

Figure 2 shows the trends in importation and use of fertilizers across the years in Tanzania. On average, farmers are using about 9kg per ha. This is very low. According to Amankwah et al (2024), the main reasons cited by farmers in Tanzania for not using fertilizer are: that they do not need it and that it is too expensive for them. These sentiments by the farmers are consistent with the claims that the low use of fertilizer because its not profitable for the farmers to apply due to low nitrogen use efficiencies and unfavorable maize-fertilizer price ratios.

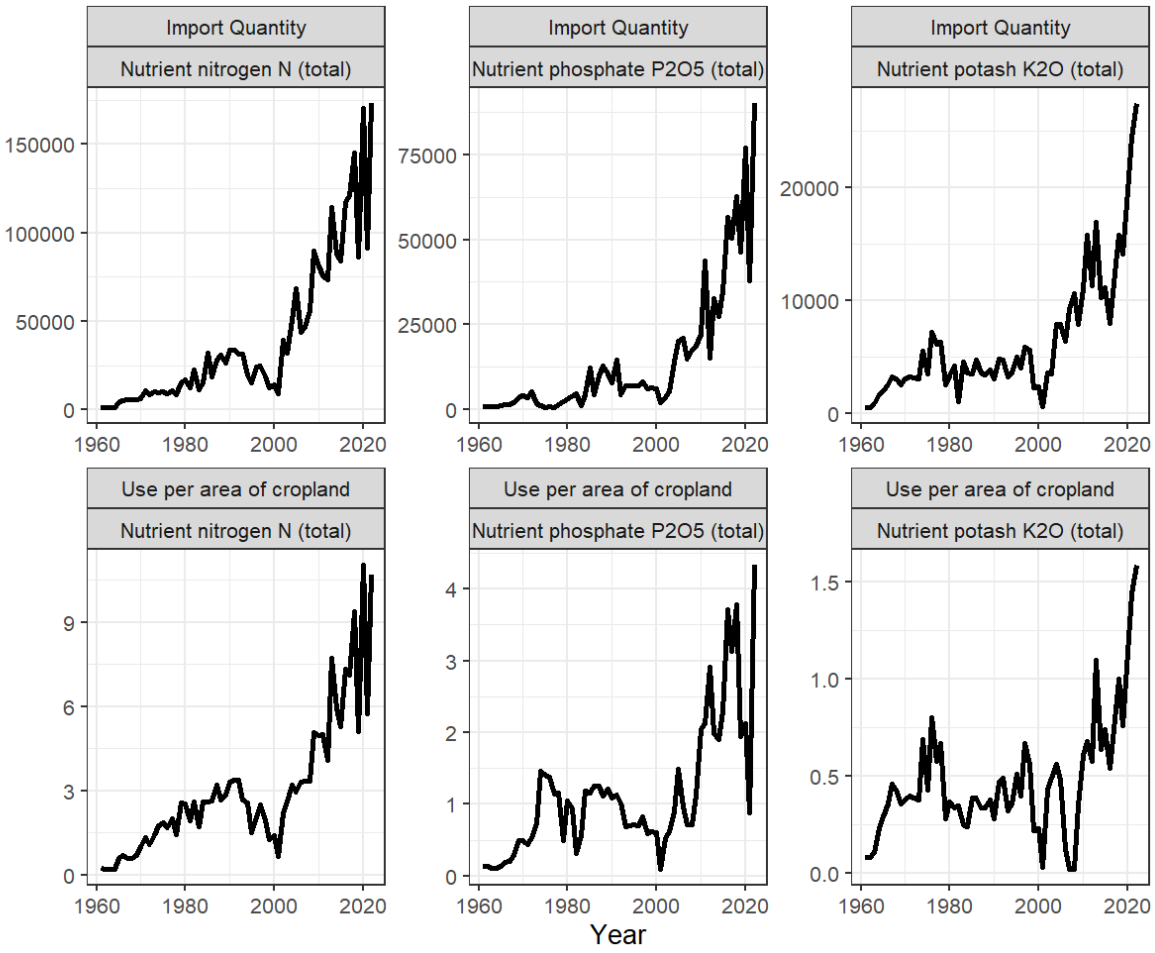

Figure 2: Fertilizer imports (tons) and use (kg per ha) in Tanzania, 1961-2022. (source: authors using FAOSTAT)

The existing evidence on the trends of nitrogen use efficiency (NUE) and fertilizer partial profits compare across disparate studies that were conducted using different methods (e.g., surveys, experiments) with different available technologies (e.g., varieties) and locations (e.g., differing in elevation). We therefore pose the following research questions: Are NUEs (and partial profits due to nitrogen fertilizer use) changing across time in Tanzania? On average? In particular areas? What are the characteristics of areas with decreasing NUE? What are the implications for understanding profitability? To address these questions, we use nationally representative panel household surveys covering over a decade of crop responses in Tanzania [2008-2020].

We contribute to two strands of literature. The first is on defining regions for assessing NUE trends. The conventional approach is to define regimes based on soil organic matter (Marenya and Barrett, Burke et al 20, Chamberlin et al 2021) or another soil quality measure (e.g., soil acidity). We instead use causal machine learning to identify zones that have different NUEs across time as this allows defining regions on multiple soil quality attributes. We then identify characteristics of these areas and policy recommendations. This allows us to identify zones of concern in terms of falling NUEs. The second strand of literature is on economic surplus assessment of returns to existing agricultural innovations in agricultural policy analysis (Alston et al 1995, Li et al 2014, Gemessa 2021).

In the context of Tanzania's fertilizer policy, this paper particularly builds on work by Palmas and Chamberlin (2020) and Chamberlin et al (2021) who analyze the spatially explicit profitability of fertilizer application in Tanzania. We depart from these studies in several ways. First, these studies relied on a small sample survey in specific geographies and short periods (624 households for 2016 and 2017) while we use nationally representative sample surveys covering over a decade of data (2008-2020). Second, these studies did not focus

on the trends in nutrient use efficiencies as we do in this paper. They focused on applying random forest estimator in computing spatially explicit NUEs and profits (Palmas and Chamberlin 2020) and in using panel data methods (Mundlak correlated random effect model) to address endogeneity concerns (Chamberlin et al 2021). Methodologically, we also extend from panel data methods and random forest models to using causal random forest models that focus on generating heterogenous treatment effects.

Third, these studies focused on evaluating the individual farmer expected profits and value-cost ratios (whether as marginal effects or average effects) to using nitrogen fertilizer without considering the equilibrium consequences of such supply shifts on prices. In this respect, we follow Komarek et al (2018), who combined crop simulations results with observational data on input and output prices in Tanzania to estimate the producer and consumer surplus of adopting different fertilizer policies using the economic surplus framework (Alston et al 1995). By using crop simulations from one region in Tanzania (Mbeya region), Komarek et al (2018) provides NUEs and profit gains that are beyond what is plausible in smallholder settings in Tanzania. We specifically follow the approach of combining causal treatment effect estimation and economic surplus model as in Zeng et al (2015), Kassie et al (2017), and Wossen et al (2018). These studies however focus on average treatment effects across the whole sample (mostly at national scale) yet treatment effects to agricultural practices are expected to vary by weather, soil types and elevation.

We instead use a causal random forest estimation framework which provides heterogeneous treatment effects. Using this approach (and consistent with ordinary least squares and non-parametric estimates), we do not find any evidence of falling NUEs in Tanzania across all regions of the country. Conversely, NUEs have increased as compared to 2008 (9 kg maize per kg of N) by about 10% in 2010, 18% in 2012, 18% in 2014 and 14% in 2020. The associated partial profits and value-cost ratios are very low (ranging from 0.8 to 3.2) to incentive fertilizer adoption but not falling. To ascertain if the supply shocks due to adoption of fertilizer are welfare improving to farmers, we computed producer surpluses across some of the years. Assuming a closed economy model, we found that the supply shocks given the current levels of fertilizer use levels are not enough to substantially affect maize output prices as such farmers can increase fertilizer use without getting price induced welfare losses.

2. Materials and Methods

2.1. Overall approach

The goal of the paper is to analyze the trends in N use efficiencies and the associated partial profits across the years so as to understand the economic welfare implications of these trends for the smallholder farmers. To address this comprehensive goal, we have developed an integrated quantitative workflow (see figure 3) which ingests soil attribute information, household survey data, administrative data and estimates from the literature (particularly demand and supply elasticities) to assess if farmer welfare has been going down over the years.

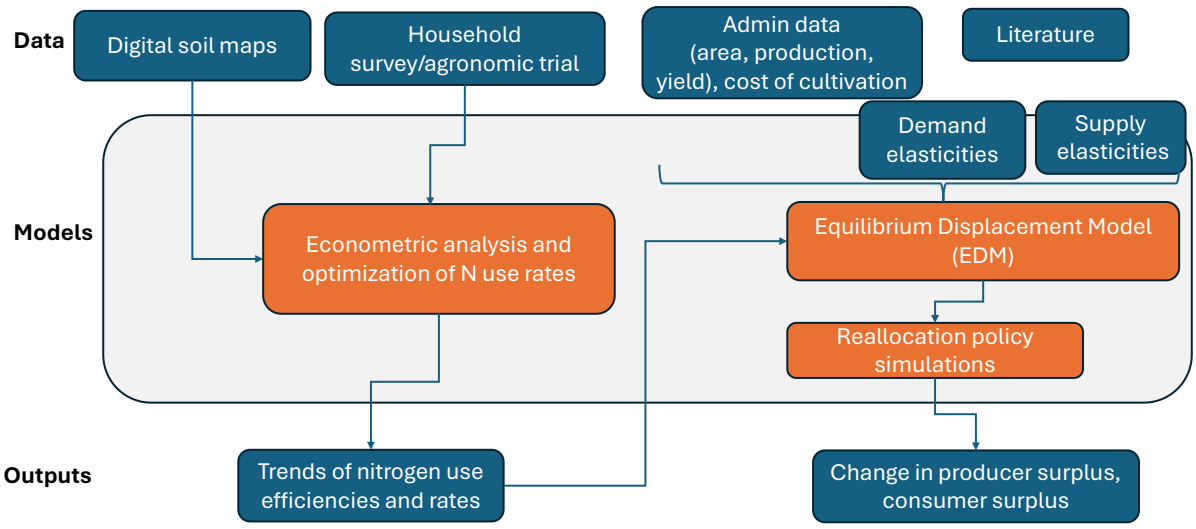

Figure 3: Comprehensive spatially explicit ex ante framework for targeting nitrogen use management

The approach combines the power of causal inference, machine learning and equilibrium displacement modelling (economic surplus approach, Alston et al 1995) to simulate the implications of the changes in spatially differentiated nitrogen use efficiencies. The approach is similar to that of Zeng et al (2015) and Wossen et al (2018) who combined the potential outcomes framework for quasi-experimental analysis to the conventional economic surplus approach (Alston et al 1995) of evaluating the returns to investments in agricultural innovations like hybrid seeds. Our use of causal machine learning instead of a parametric causal model extends these approach to spatially and contextually differentiated applications.

2.2. Theoretical Model

We assume the farmer's goal is to maximize profits (π) per unit of land (e.g., hectare) by producing maize output per hectare (y) which is sold at price, p using N fertilizer per hectare bought at the price of r. Mathematically, the objective function can be defined as:

$$\pi = Max_N \; py\,(N, X) - rN$$

where π is the partial profit, y is the maize yield as a function of management variables including nitrogen fertilizer (N), soil attributes, weather, e.t.c (represented by X), N is the nitrogen amount applied, r is the price of nitrogen fertilizer and p is the price of maize. Using this framework, the economically optimal amount of fertilizer a farmer needs to apply is found by solving $\frac{\partial y}{\partial N} = \frac{r}{p}$. If the marginal nitrogen use efficiency $\frac{\partial y}{\partial N}$ is falling overtime, then the farmer will end up operating at a loss. We present next approaches of estimating nitrogen use efficiency across space and time.

2.3. Empirical approach

2.2.1. Parametric approach and non-parametric approaches

We consider specifications of a linear, quadratic and non-parametric production functions for each of the years (t) (2008, 2010, 2012, 2014 and 2020). The specifications are as shown below:

Linear

$$y = \alpha_0 + \alpha_{1t} N + \tau X + \epsilon$$

Quadratic

$$y = \alpha_0 + \alpha_{1t}N + \alpha_2 N^2 + \tau X + \epsilon$$

Flexible functional form (using geo-additive regression)

$$y = f(N, by = t) + \tau X + \epsilon$$

where y is maize yield (kg per ha), N is the applied nitrogen (kg per ha). $f(N)$ is a flexible nonparametric function of nitrogen by year.

2.2.2. Causal machine learning framework

The parametric and non-parametric approaches presented above provide a restricted set of interactions that one may include in the model. Nitrogen efficiency is known to interact positively and negatively with several variables including soil organic matter (Chamberlin et al 2021), precipitation, and phosphorus. Therefore, by restricting the interactions to a few variables may lead to biases when considering the changes across time in which any of these interactions may be operating strongly. A machine learning framework has therefore been advocated to address this challenge (Kakimoto et al 2022). In our context, we are using observational data as such we need to consider the selection biases that may bias the results in that the farmers may have applied particular amounts of nitrogen due to their knowledge, preferences, and socioeconomic status. In this paper, we use the causal random forest estimator computed using *grf* R package (Athey et al 2019).

Table A1 in the appendices shows based on the calibration tests that the causal random forest specification is correctly specified.

2.2.3. Market level implications of the yield gains

Given the yield gains and added costs to N responses across space, we can then use the equilibrium displacement model (also called economic surplus) framework to determine the net present values of the targeted investments based on the response gains following a procedure by Zeng et al (2015), Kassie et al (2017) and Wossen et al (2018). We first compute the supply curve shift ($k - shift$) which incorporate the changes in yields and input costs as follows:

$$k_t = a_t \left[\frac{\left(\frac{\tau_y}{Y_t}\right)}{\epsilon} - \frac{\frac{\tau_c}{C_t}}{\left(1 + \frac{\tau_y}{Y_t}\right)} \right]$$

Where a_t is the adoption rate of nitrogen fertilizer in year t, τ_y is the estimated yield gain to fertilizer application, τ_c is the estimated cost change due to nitrogen fertilizer, ϵ is the supply elasticity. Assuming that that Tanzania is a small and closed economies (which is a plausible assumption given the export and import bans imposed on maize production), and linear demand and supply functions, we calculate the producer surplus changes (ΔPS), consumer surplus changes ($\Delta \mathrm{CS}$) and total surplus changes (ΔTS) as:

$$\Delta PS_t = P_{ct} Q_{ct} (K_t - Z)(1 + 0.5 Z\eta)$$

$$\Delta CS_t = P_{ct} Q_{ct} Z (1 + 0.5 Z\eta)$$

$$\Delta TS_t = \Delta PS_t + \Delta CS_t = P_{ct} Q_{ct} K_t (1 + 0.5 Z\eta)$$

where P_{ct} is the counterfactual price, Q_{ct} is the counterfactual quantity, η is the own price demand elasticity, and $Z = \frac{K\epsilon}{\epsilon + \eta} = \frac{P_{ct} - P_t}{P_t}$. The counterfactual price (P_{ct}) is computed as $P_{ct} = P_t \left(\frac{\epsilon + \eta}{\epsilon + \eta - K\epsilon}\right)$. The counterfactual quantity is computed as $Q_{ct} = Q_t - \Delta Q$ where $\Delta Q = \tau_y \times A_t \times a_t$ where A_t is the area of maize in the specific year.

With these producer, consumer and economic surplus measures, we can understand the welfare implications of the trends in N use efficiencies and fertilizer adoption rates over time. If the N use efficiencies are falling over

time while keeping all other variables constant, farmers are expected to lose economically but if price adjustments are favorable they can end up benefiting.

2.4. Data

We use the Tanzania Living Standards Measurement Survey (LSMS) panel data covering five waves (2008-2020) with total observations of about 1500 households in each wave (table 1). We also added geo-variables including: soil attributes (soil carbon, soil pH, sand, soil nitrogen), weather, elevation, and population density. We use the household survey data and geographical data to estimate the nitrogen use efficiencies.

In implementing the equilibrium displacement model, we used demand elasticity of -0.4 computed for poorest income quartile by McCullough et al (2024[1], supplemental table 13) and the elasticity of maize supply of 0.38 also used by Komarek et al (2018) which they obtained from the IMPACT model (Robinson et al 2015). Earlier studies (Danielson 2002) reported a short run supply elasticity of maize of 0.1.

3. Results and discussion

3.1. Descriptive statistics

Table 1 shows the summary statistics for the main variables considered in the econometric analyses. Maize yields have increased from around 750kg per ha to around 925kg per ha. In term of farmers using nitrogen fertilizers has hovered from around 16% in 2008 to 19% in 2020. For these farmers, they use around 40kg per ha with the average from full sample at around 7kg per ha. For farmers who use fertilizer, appendix figure A1 shows the spatial distribution of the use rates.

Table 1: Household survey descriptive statistics for Tanzania

Variable	2008	2010	2012	2014	2020
Average maize yield (kg/ha)	753.45	811.3	754.82	907.44	925.49
Share of nitrogen users	0.16	0.18	0.17	0.16	0.19
Nitrogen average use rate (N kg/ha) for users	39.42	39.2	37.23	43.01	40.4
Nitrogen Average use rate (N kg/ha) for full sample	6.48	7.24	6.15	6.71	7.59
Phosphate (kg/ha)	0.99	1.58	1.9	2.18	2.98
Average plot size (ha)	0.90	0.90	0.94	1.01	0.96
Number of crops	1.84	1.76	1.8	1.99	1.69
Household size	5.42	5.76	5.79	5.7	6.1
Average rainfall (mm)	1022.57	1020.69	954.68	1147.81	1443.24
Number of plots	**1557**	**1934**	**2368**	**1704**	**1863**

[1] We also compared the results using -0.75 following Komarek et al (2018).

3.2. Parametric estimates of year specific regressions

Figure 4 shows the linear crop response function for each of the survey years. The marginal effect of N on yield was 8.67 in 2008, 7.09 in 2010, 11.51 in 2012, 13.02 in 2014 and 9.96 in 2020. These results are consistent with prior evidence across Africa as summarized by Chamberlin et al (2021, p. 2686). In their estimates for Tanzania, they found estimates between 10.04 to 12.60 depending on the econometric specifications.

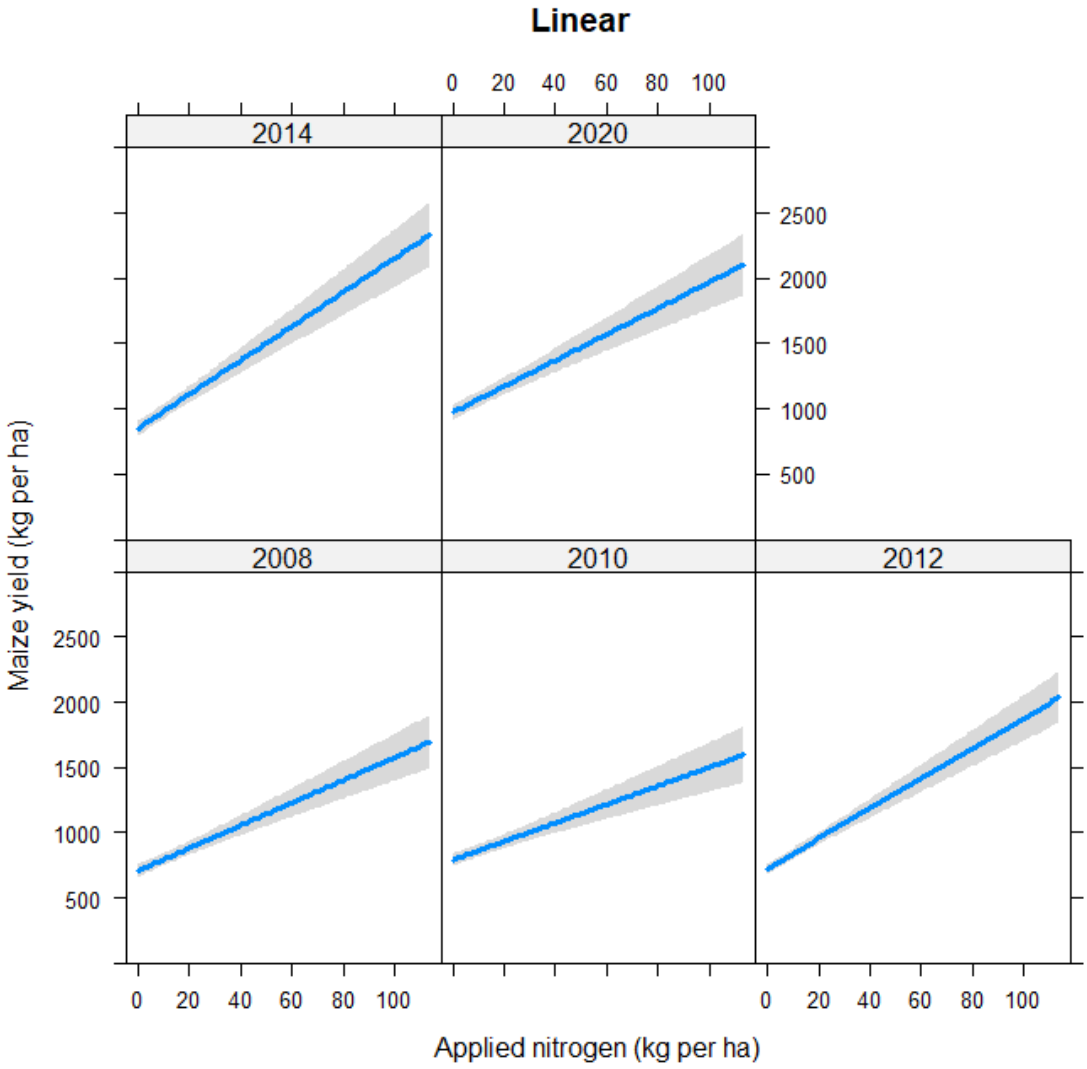

Figure 4: Linear yield response model

Figure 5 shows the quadratic crop response curves. Theoretically, one would expect a negative quadratic term, yet this was only observed in 2010 and 2012. In the appendices, we show the interactive effect between nitrogen, rainfall and soil organic carbon.

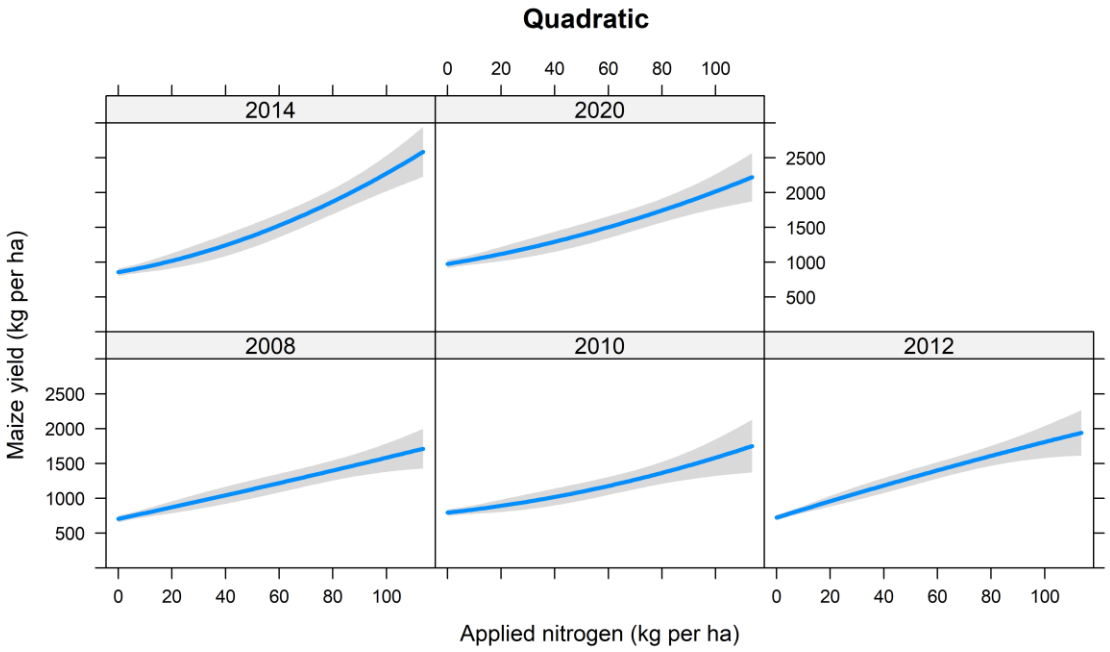

Figure 5: Quadratic yield response model

3.3. Non-parametric geo-additive regression model

The results above have demonstrated that the functional form may be different across years and sites. To understand if this is the case, we use a flexible approach that allows estimation of nonlinear functional forms using Bayesian geo-additive regression models (Umlauf et al 2018). Using the same set of controls as the previous estimators, figure 6 shows non-linear effects of nitrogen use on yields across the years. It is apparent from the figure 6b that the functional forms differ across years. The patterns differ markedly at higher levels of N use (i.e., above 60 kg per ha) with higher yields for these in 2014 and 2020 as compared to 2008 and 2010 (figure 6a). Falconnier et al (2023) found that the mean profit maximizing N input using agronomic trial data in Tanzania was 82kg/ha. In the years with curvature, our results are consistent with this agronomic evidence.

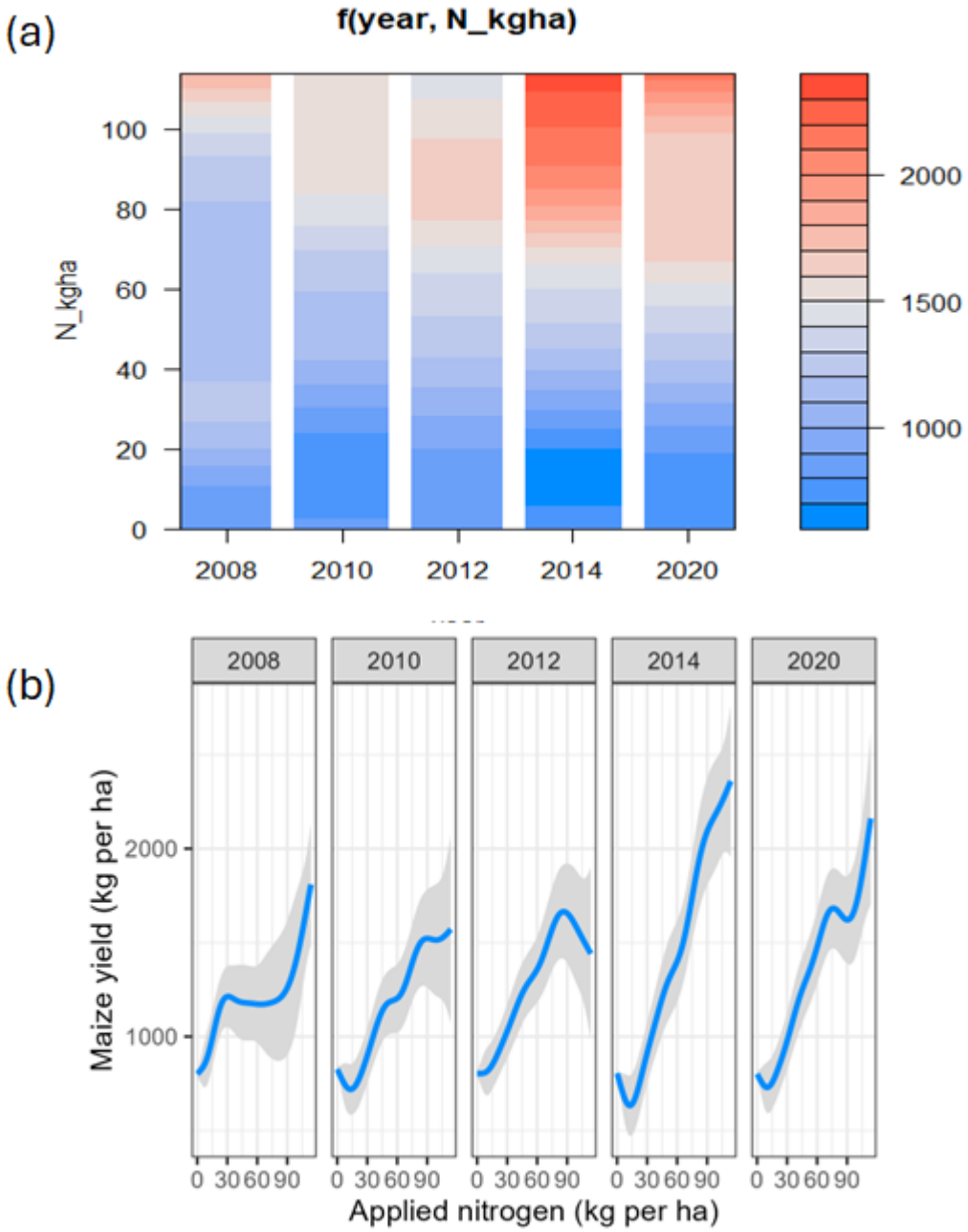

Figure 6: Impact of N use on yield by N use level and year

3.4. Causal random forest heterogenous NUEs and partial profits

Figure 7 shows the distribution of maize yield gains (kg) to a unit (kg) of nitrogen applied across all plots and years (panel a) and for each year (panel b). The NUEs range from -0.02 to 22 kg of maize for a kilogram of nitrogen with a median and mean of about 10. It is apparent in figure 7b that NUEs have not declined but rather there has been a slight increase from about 8.9 kg per kg of N in 2008 to 9.9 kg per kg of N in 2010, 10.4 kg per kg of N in 2012, 10.6 kg per kg of N in 2014 and 10.11 kg per kg of N in 2020. These estimates are almost half of what are reported in agronomic trials (e.g., Falconnier et al 2023 reported median nitrogen agronomic efficiency of 20 kg maize grain per kg of N with N inputs of 40kg/ha) consistent with evidence from Malawi (Mkondiwa et al 2024) and other parts of Africa (Anderson 1992).

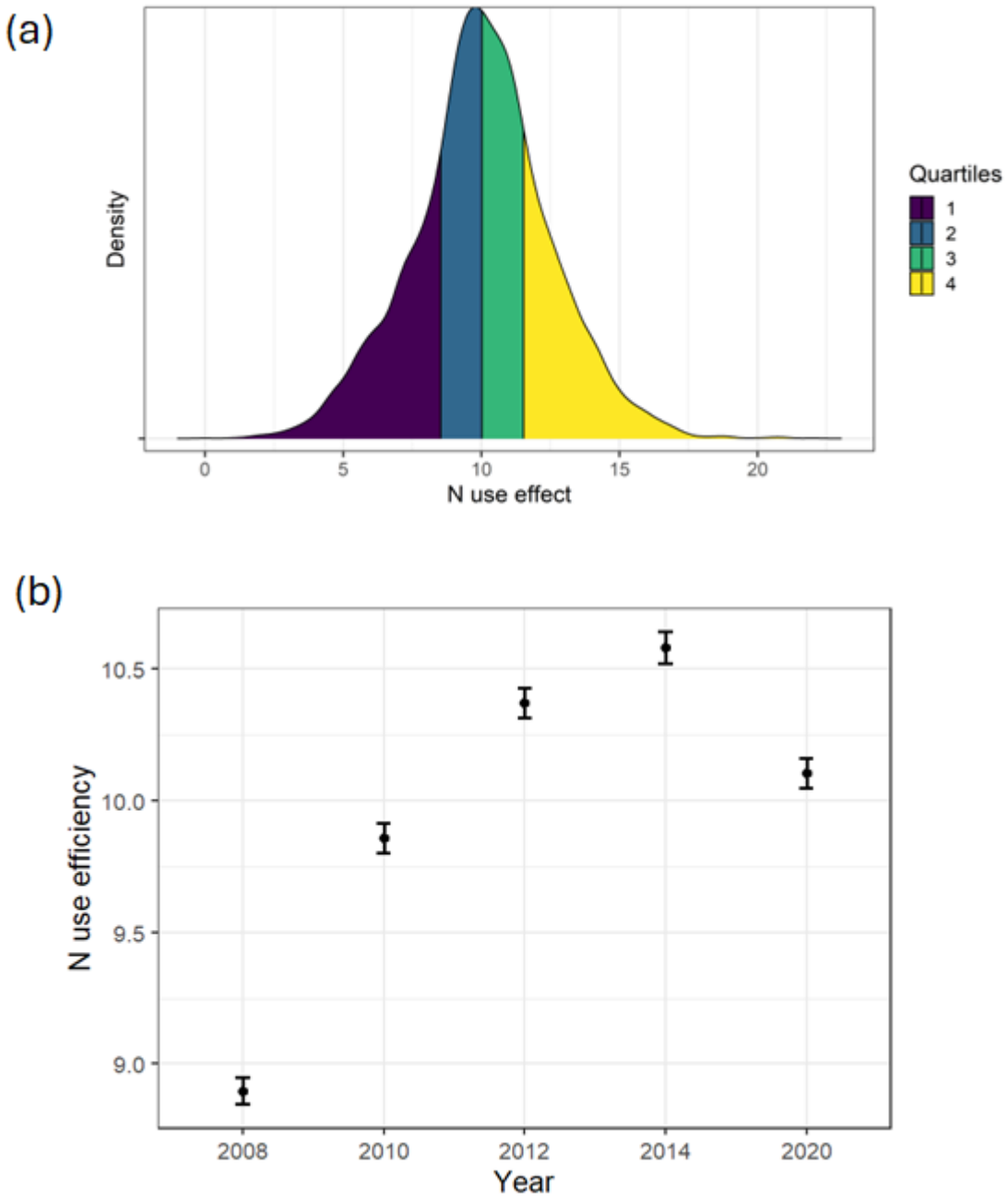

Figure 7: N use efficiency distribution across farms and across years

3.4.1. Continuous treatment effect estimates of N use efficiency

Figure 8 shows the spatial distribution of nitrogen use efficiencies (NUEs) computed from the continuous treatment causal random forest model. Figure 8a show the individual plot NUEs across all the years while figure 8b shows the regional level averages across all the years. We find that NUEs are higher in the north-eastern regions and lower in the southern regions and north-western regions.

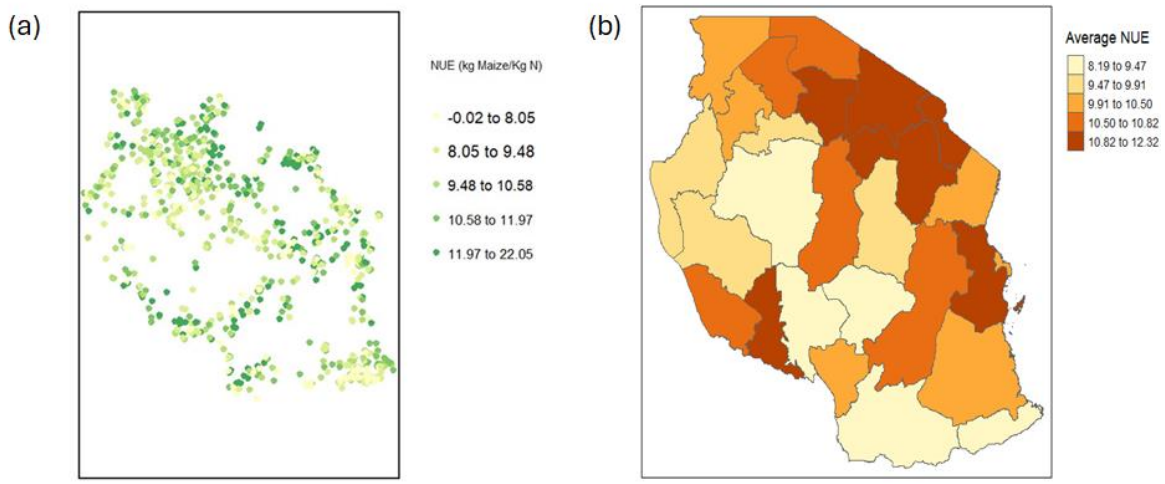

Figure 8: Average nitrogen use efficiency [2008-2020]

3.4.2. Differentiation by soil attributes, elevation and rainfall

The heterogenous estimates may vary by other factors other than space. We focus next on identifying the characteristics of these heterogeneities, especially focusing on factors that have been identified in the literature to be the major drivers of variability. These include soil organic matter (soil organic carbon), sand content, rural population density, elevation and rainfall.

Figure 9 shows the relationship between soil attributes and NUEs. NUEs are lower in sandy soils (figure 9a), in soils with low or very high soil electrical conductivity (figure 9b), in soils with low soil pH (figure 9c). Figure 9d shows that NUEs are higher for soils with high soil organic carbon. This is consistent with prior evidence by Chamberlin et al (2021). In the case of rainfall, Tanzania receives high amounts of rainfall such that places with more than 1500mm get less NUEs (see appendix figure A6).

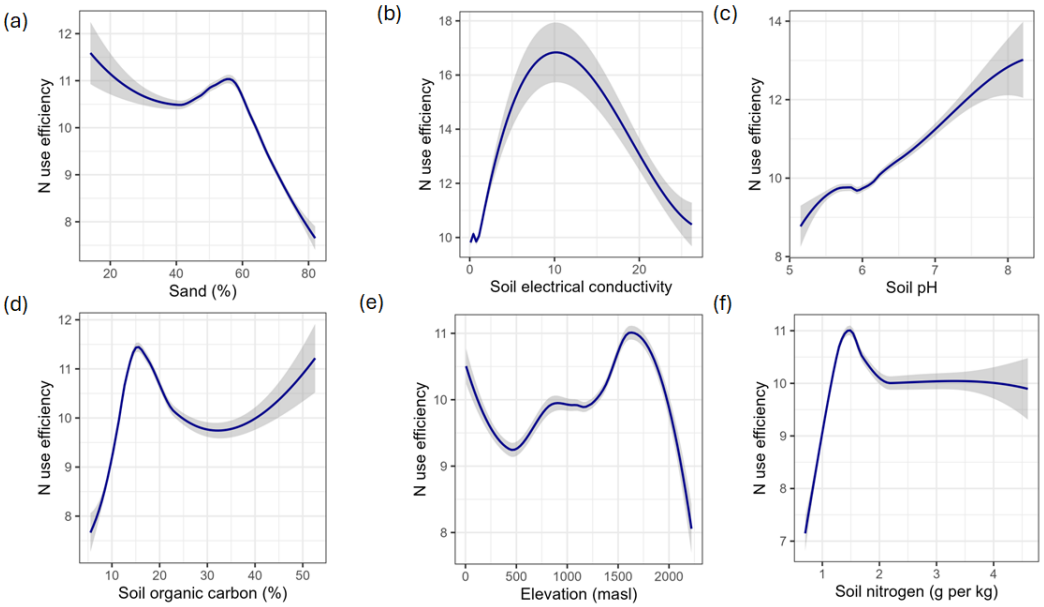

Figure 9: Relationship between nitrogen use efficiency, soil organic carbon, soil sand, soil pH, soil nitrogen, and elevation.

3.4.3. Are N use efficiencies in Tanzania falling?

Next, we assume that observed NUEs represent the crop response slopes. We are interested in the the trend of these slopes by state. Given that the local trends may be highly non-linear, we focus on comparing each years estimate to the base year. We focus on classifying if any of the regions have increasing or stagnant/decreasing NUE trends. Figure 10 shows the spatio-temporal patterns of NUEs. We see that across the years, NUEs have actually increased by small margins across all regions. As compared to 2008 (with NUE of 9 kg maize per kg of N), NUEs have increased by about 10% in 2010, 18% in 2012, 18% in 2014 and 14% in 2020.

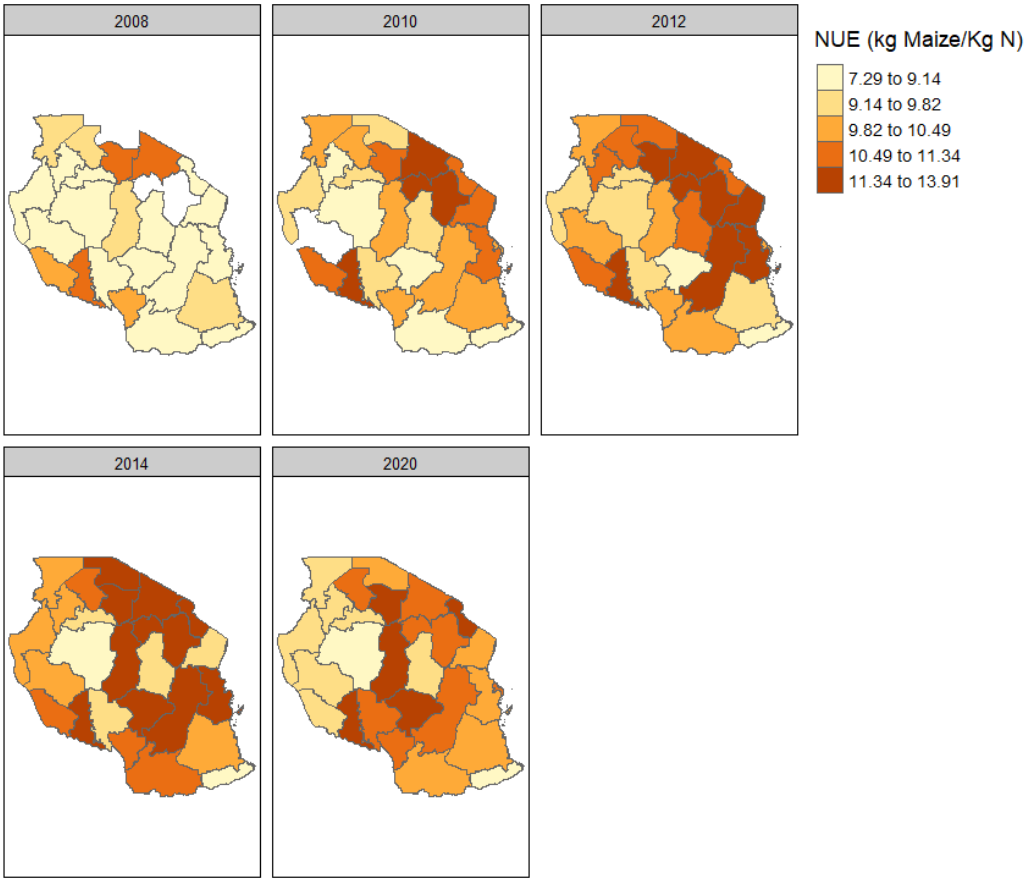

Figure 10: Spatio-temporal distribution of N use efficiencies

3.4.4. Are partial profits and producer surplus in Tanzania falling?

Figure 11 shows that partial profits have not declined in Tanzania during the period of interest. When using the same prices across the years, we find similar patterns. The partial profits have remained meagre to motivate farmers to use fertilizers with value-cost ratios hovering on average at 1.5 yet the general criteria is that VCR of at least 2 is worth to compensate the farmer for using fertilizers (Chamberlin et al 2021). In terms of partial profits and producer surpluses per ha, we find that farmers can get 0.5 to 3.4 US$ per ha in partial profits (figure A13) and compared to 0.11 to 0.24 US$ per ha in producer surpluses per ha of fertilized land (appendix table A3). These meagre net benefits (which despite not including labor and other costs) may explain the failure of most farmers to use inorganic fertilizers in Tanzania compounded by liquidity constraints poor farmers face at the start of or within the growing season.

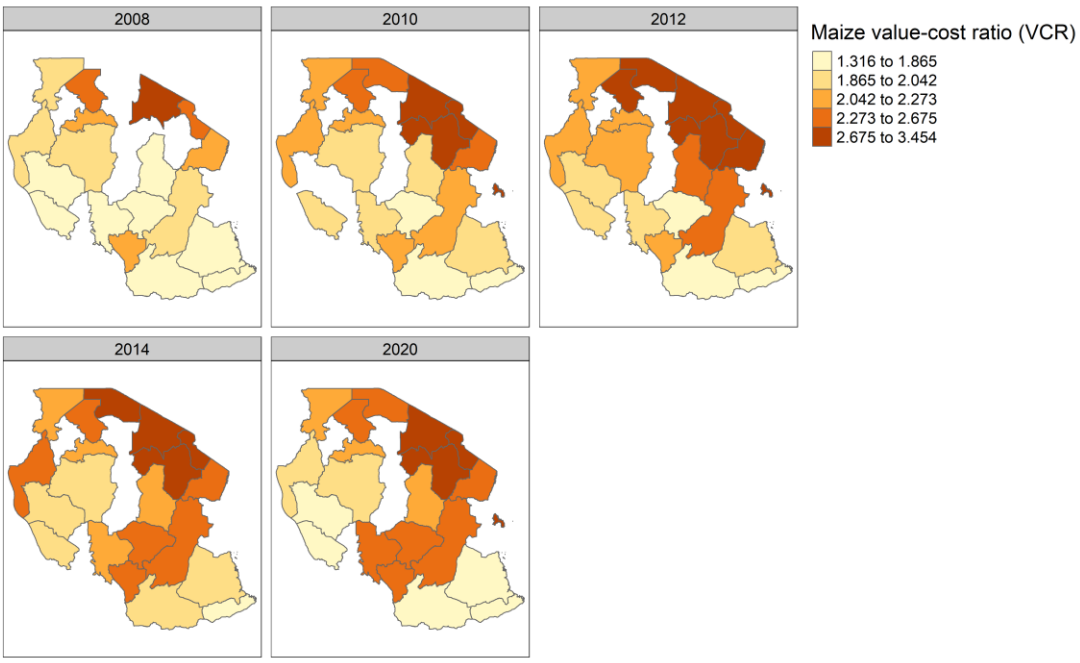

Figure 11: Spatio-temporal distribution of partial profits to N fertilizer application in Tanzania, 2008-2020.

4. Limitations and future research

The study has several limitations. First, the period that we are investigating spans about a decade yet the patterns may well investigated over a longer period following the same farms.

Second, we are using observational data which implies that there are many unobserved changes in the operations of the farms that affect the nitrogen use efficiency. Other studies have either used long term experiments and crop simulation modelling (e.g., Clarke et al 2024) or adjusted evidence from observational data using agronomic trials data (e.g., Laajaj et al 2020, Mkondiwa et al 2024).

Third, the economic assessment focuses on the on-farm gains but does not consider the overall farm income implications and there may be other structural transformation implications including employment and land markets. According to Harris et al (2024), the on-farm technology adoption including fertilizer are not enough to support a living income in Tanzania.

Relatedly, the analysis focuses only on inorganic fertilizer input adjustments yet there is evidence of substantial complementarity with improved variety use and irrigation. Further research should build on the equilibrium displacement approaches as in Awada and Phillips (2020), Awada and and Phillips (2023), and Li et al (2013).

5. Conclusion

The goal of this paper was to examine the trends in spatially explicit nitrogen use efficiencies and partial profits to nitrogen fertilizer in Tanzania—a country with very low use rates of nitrogen fertilizer. We used parametric, non-parametric and causal random forest estimation approaches to estimate NUEs. We then subject these to a partial equilibrium displacement model to assess the potential price and quantity changes and associated economic surpluses.

We find that the N use efficiencies are low (8-15) but that they have not been falling over the years. In fact, the N use efficiencies rose marginally from about 9kg of maize per kg of N in 2008 to about 10kg of maize per kg of

N. The NUEs are higher for areas with less sandy soils, and with high soil organic carbon. In the case of rainfall, Tanzania receives high amounts of rainfall such that places with more than 1500mm get less NUEs.

To address food insecurity concerns while incentivizing farmers to apply modest amounts of nitrogen fertilizer, this paper argues for increasing NUEs through proper crop management decisions.

Acknowledgements

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Supplementary materials

The data and code to reproduce the analyses in this paper are available of EiA exante github repository: https://github.com/MaxwellMkondiwa/TZ_Spatial_NUE_Trends_Causal_AI.

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Appendix

Tables

Table A1: Linear maize yield response model

Parameter		2008	2010	2012	2014	2020
Intercept	Estimate	930.96	856.56	710.11	998.39	1087.99
	Lower CI	753.70	693.67	587.15	843.95	930.41
	Upper CI	1108.23	1019.44	833.06	1152.84	1245.56
Nitrogen (kg/ha)	Estimate	8.67	7.09	11.51	13.02	9.96
	Lower CI	6.80	5.14	9.74	10.78	7.82
	Upper CI	10.53	9.04	13.28	15.27	12.10
Plot size (ha)	Estimate	-124.18	-171.66	-128.07	-101.81	-117.39
	Lower CI	-160.89	-204.65	-152.51	-133.67	-148.14
	Upper CI	-87.46	-138.67	-103.62	-69.95	-86.64
Phosphate (kg/ha)	Estimate	15.45	9.68	0.16	7.46	7.93
	Lower CI	10.79	6.33	-2.36	3.62	4.60
	Upper CI	20.10	13.04	2.69	11.29	11.27
Number of intercrops	Estimate	-98.65	-89.22	-33.34	-106.47	-74.39
	Lower CI	-139.16	-131.95	-67.50	-146.47	-116.89
	Upper CI	-58.14	-46.50	0.82	-66.48	-31.88
Household size	Estimate	17.37	17.91	9.37	14.98	12.20
	Lower CI	3.89	6.00	0.16	2.38	1.07
	Upper CI	30.85	29.82	18.58	27.58	23.32
Female head	Estimate	-83.92	-81.27	-45.70	-107.50	-112.98
	Lower CI	-172.08	-165.92	-117.32	-199.00	-199.07
	Upper CI	4.24	3.37	25.92	-15.99	-26.90
Education (years)	Estimate	67.08	20.83	38.89	63.41	37.54
	Lower CI	-0.62	-43.01	-7.44	5.69	-16.83
	Upper CI	134.79	84.66	85.21	121.13	91.92
Average rainfall (mm)	Estimate	-0.05	0.11	0.11	0.04	-0.06
	Lower CI	-0.18	-0.02	0.02	-0.05	-0.14
	Upper CI	0.09	0.24	0.20	0.14	0.01

Table A2: Calibration tests for the causal random forest model

	Estimate	Std.Error	P-value
Mean forest prediction	0.997	0.102	<0.001
Differential forest prediction	1.253	0.268	<0.001

Note: A significant estimate of close to 1 means that the model is correctly specified.

Table A3: Producer surplus, consumer surplus and economic surplus

2008								
Region	K	Z	Price_2008	Counterfactual price	PS(USD)	CS(USD)	Economic Suplus	PS per ha
Arusha	0.07	0.04	0.37	0.39	3004.20	2853.99	5858.19	0.22
Dodoma	0.00	0.00	0.32	0.32	196.68	186.84	383.52	0.14
Iringa	0.20	0.10	0.33	0.36	13199.76	12539.77	25739.52	0.15
Kagera	0.01	0.00	0.32	0.33	146.09	138.78	284.87	0.16
Kigoma	0.03	0.01	0.32	0.33	519.99	493.99	1013.98	0.16
Kilimanjaro	0.27	0.13	0.39	0.45	8654.15	8221.44	16875.60	0.20
Lindi	0.01	0.00	0.28	0.28	66.62	63.29	129.91	0.14
Mbeya	0.18	0.09	0.30	0.33	14635.63	13903.85	28539.48	0.15
Morogoro	0.12	0.06	0.32	0.34	4877.19	4633.33	9510.51	0.16
Mtwara	0.03	0.01	0.27	0.27	243.73	231.54	475.27	0.11
Mwanza	0.03	0.01	0.38	0.38	1444.35	1372.13	2816.49	0.19
Rukwa	0.06	0.03	0.27	0.28	3005.19	2854.93	5860.12	0.15
Ruvuma	0.21	0.10	0.26	0.29	7138.12	6781.22	13919.34	0.12
Shinyanga	0.02	0.01	0.34	0.34	2385.41	2266.14	4651.55	0.16
Tabora	0.14	0.07	0.32	0.35	8942.35	8495.24	17437.59	0.15
Tanga	0.01	0.01	0.36	0.36	1148.78	1091.34	2240.13	0.17
2022								
Region	K	Z	Price_2020	Counterfactual price	Producer Surplus (USD)	Consumer Surplus	Economic Suplus	PS_USDper_ha
Arusha	0.10	0.05	0.38	0.40	4272.73	4059.10	8331.83	0.24
Dar es Salaam	0.29	0.14	0.38	0.44	8937.43	8490.56	17427.99	0.24
Dodoma	0.01	0.00	0.32	0.32	437.65	415.77	853.42	0.17
Iringa	0.40	0.19	0.32	0.40	24500.51	23275.48	47775.99	0.22
Kagera	0.01	0.01	0.33	0.33	354.40	336.68	691.09	0.17
Kigoma	0.24	0.12	0.33	0.37	7398.23	7028.32	14426.55	0.17
Kilimanjaro	0.32	0.15	0.39	0.46	13591.53	12911.95	26503.48	0.27
Lindi	0.02	0.01	0.27	0.27	143.72	136.54	280.26	0.15
Mara	0.13	0.06	0.36	0.39	4905.96	4660.67	9566.63	0.21
Mbeya	0.37	0.18	0.32	0.39	25055.32	23802.56	48857.88	0.20
Morogoro	0.21	0.10	0.33	0.36	8960.38	8512.36	17472.74	0.20
Mtwara	0.09	0.04	0.27	0.28	1003.06	952.91	1955.97	0.12

Mwanza	0.07	0.03	0.36	0.38	2477.44	2353.57	4831.01	0.21
Rukwa	0.10	0.05	0.27	0.29	5563.83	5285.64	10849.47	0.14
Ruvuma	0.23	0.11	0.27	0.30	20311.57	19296.00	39607.57	0.15
Shinyanga	0.07	0.03	0.33	0.34	1789.08	1699.63	3488.71	0.17
Tabora	0.15	0.07	0.33	0.35	10004.75	9504.51	19509.25	0.15
Tanga	0.13	0.07	0.35	0.37	7148.42	6791.00	13939.42	0.19

Figures

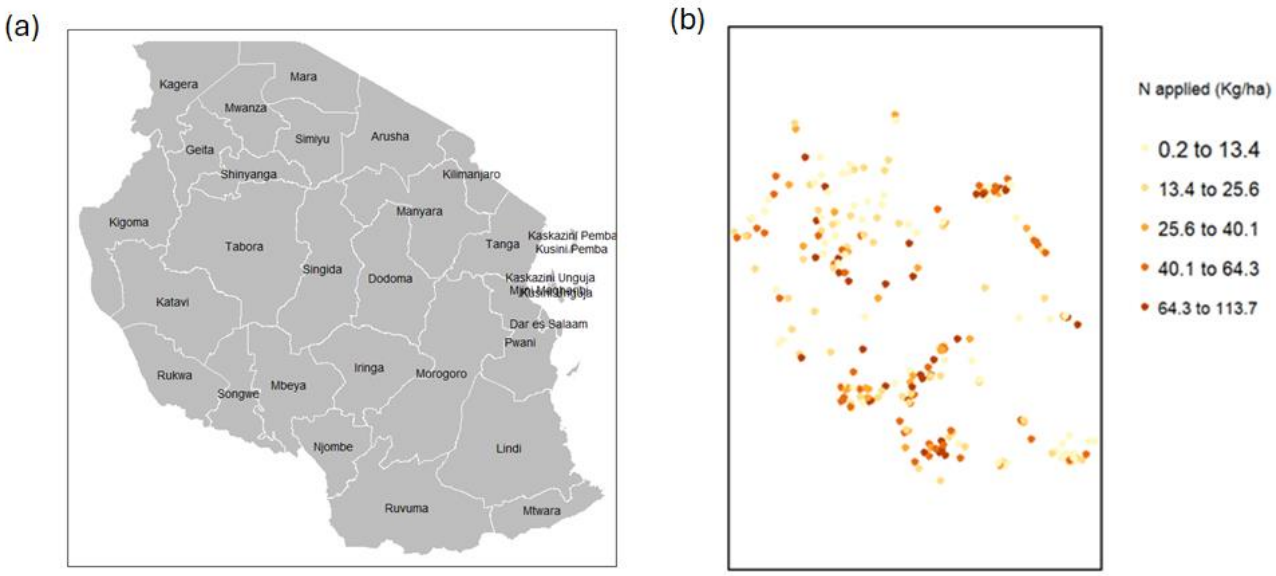

Figure A1: Regions in Tanzania and N use rates (kg per ha)

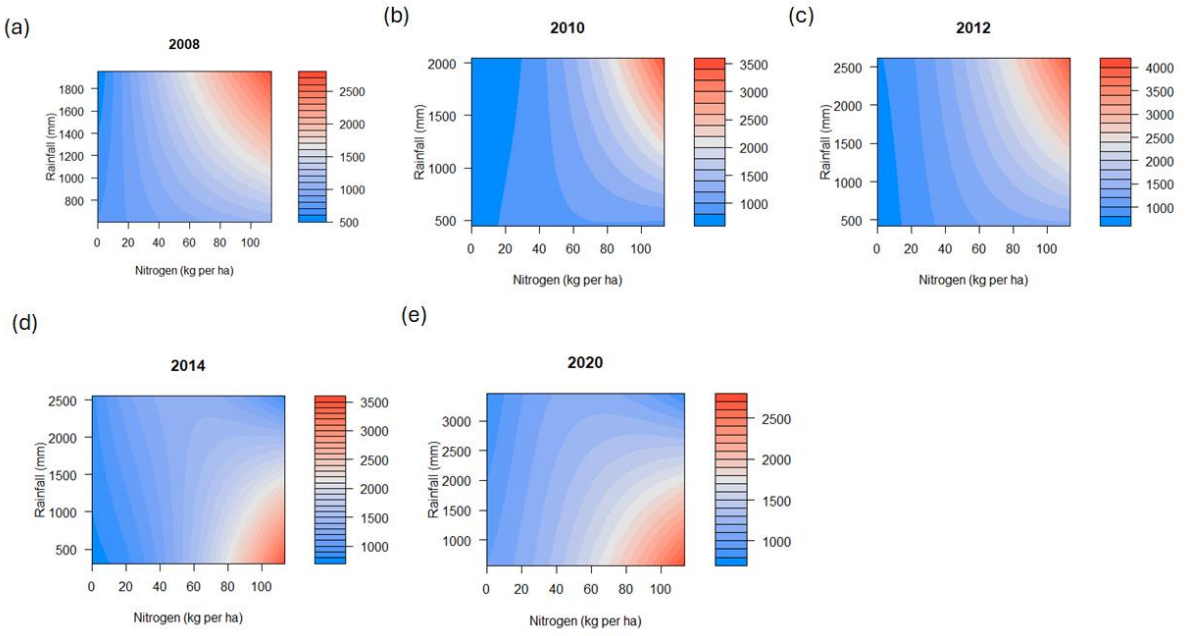

Figure A2: Rainfall and nitrogen interaction across years

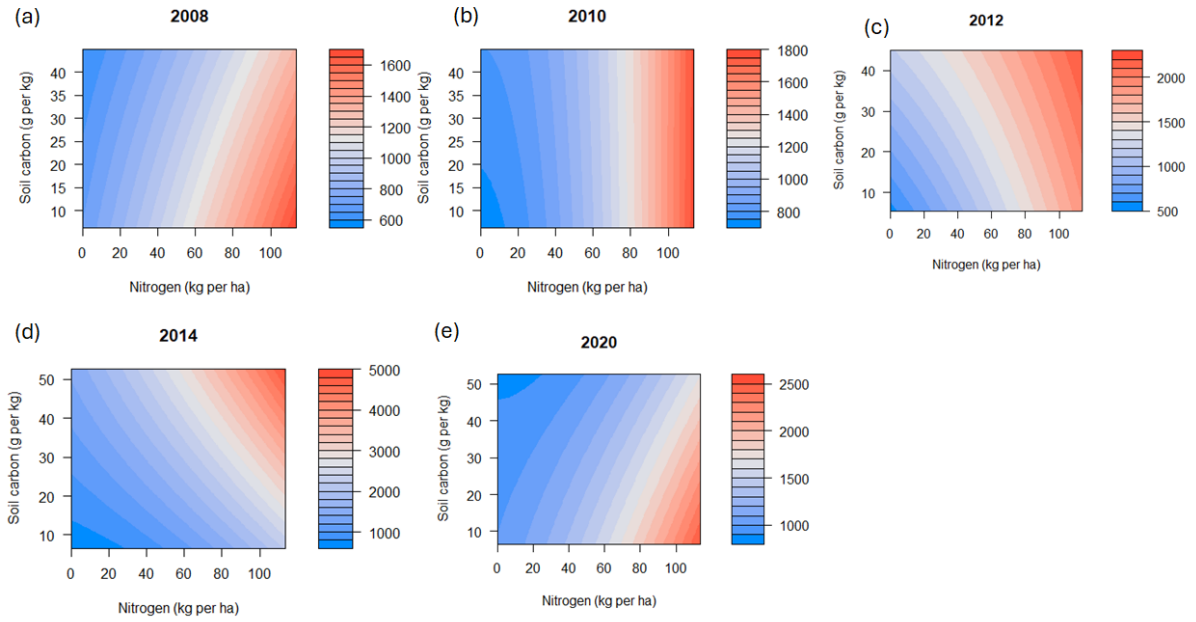

Figure A3: Soil carbon and nitrogen interaction

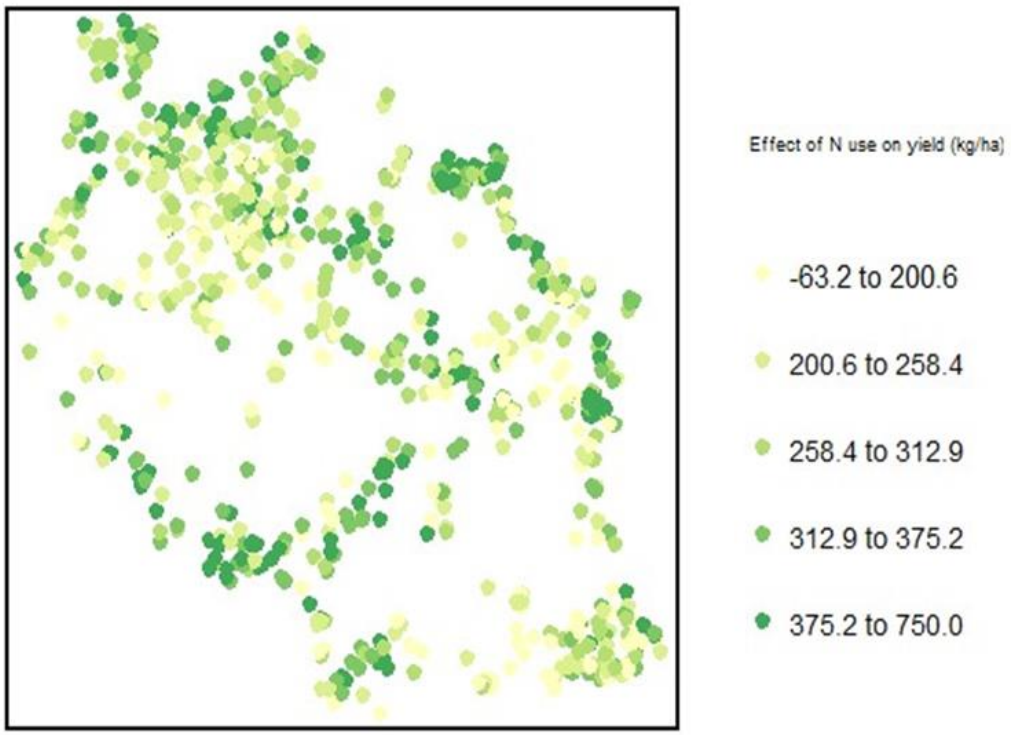

Figure A4: Binary treatment effect of fertilizer use

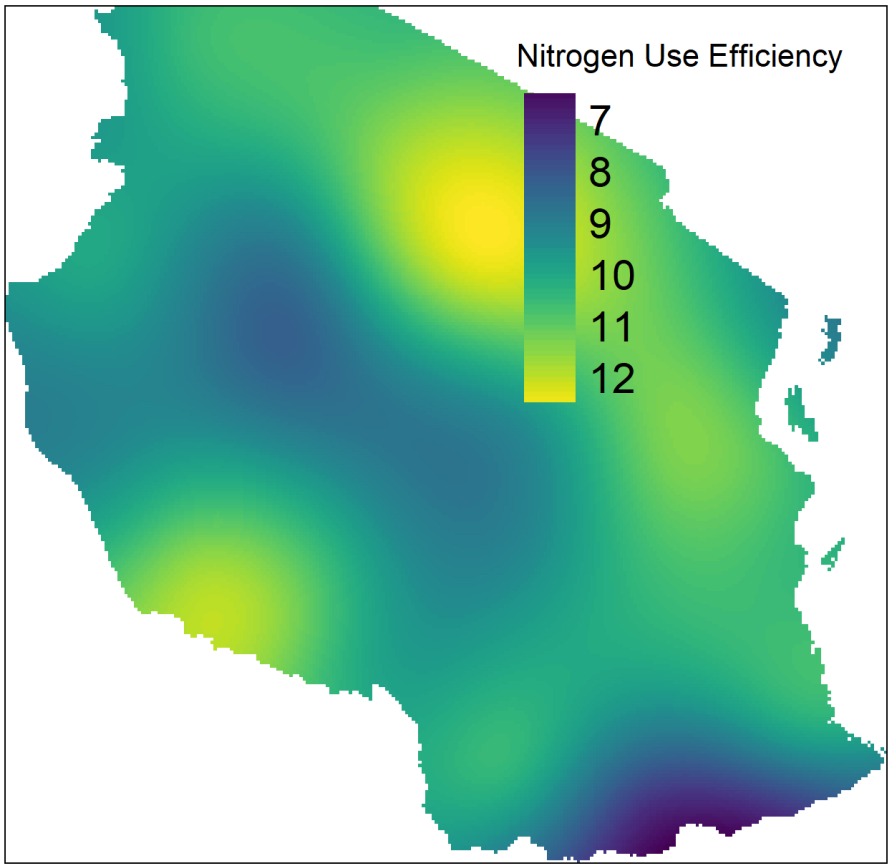

Figure A5: Causal ML interpolated estimates of nitrogen use efficiency

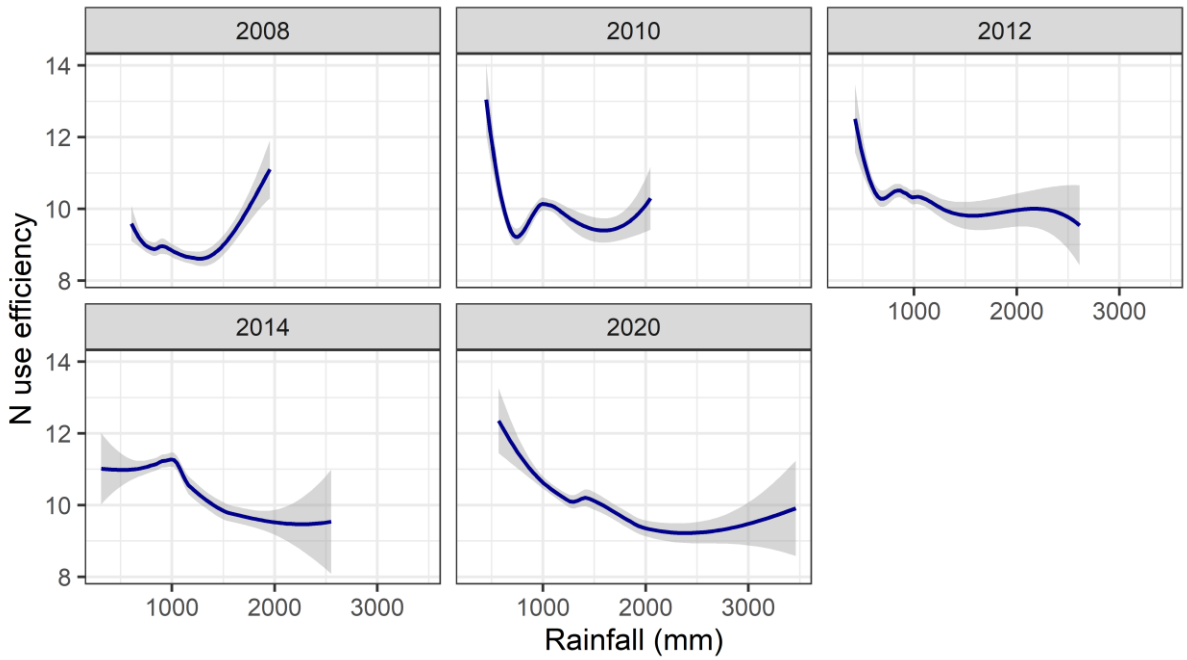

Figure A6: NUEs by rainfall and year

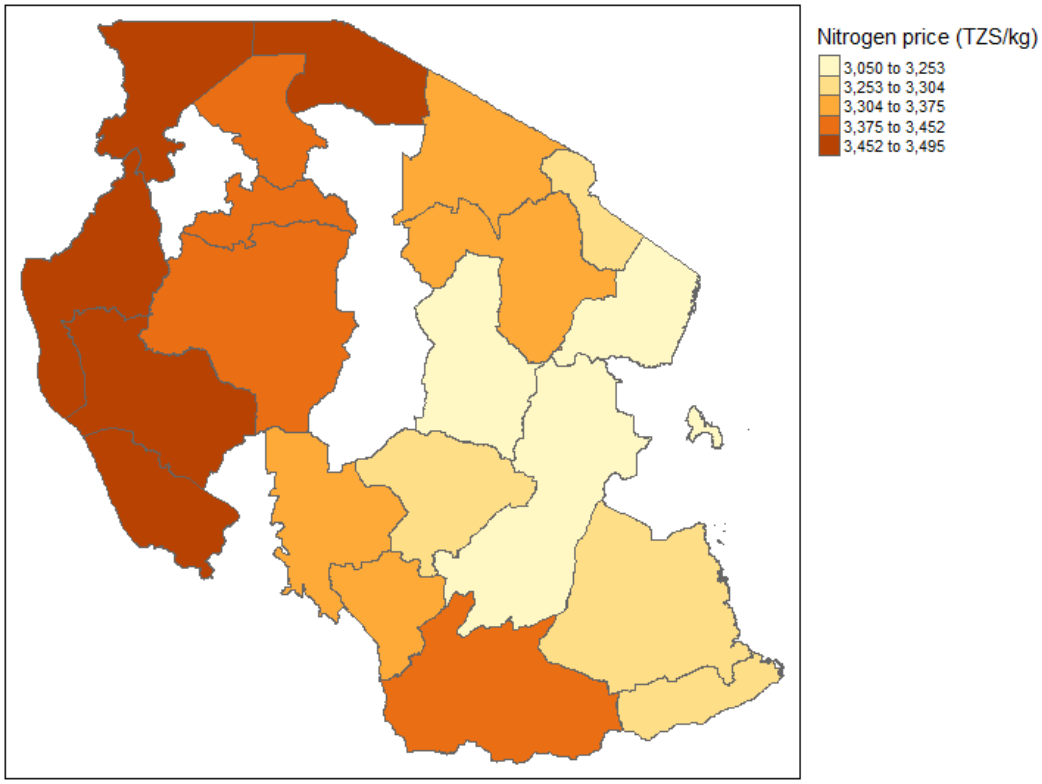

Figure A7: Regional nitrogen prices

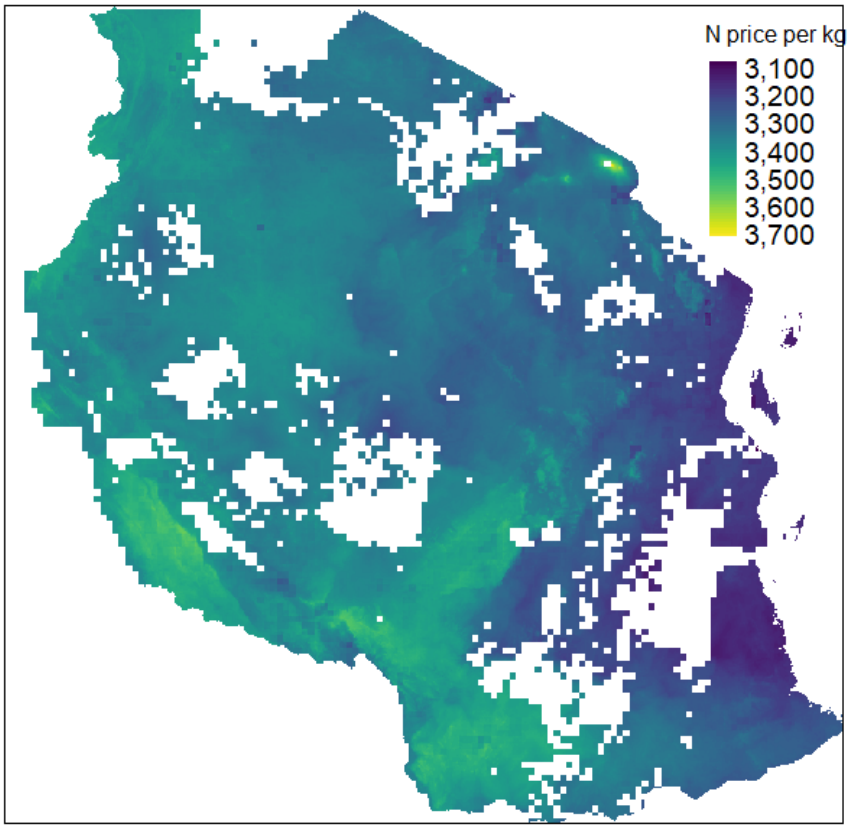

Figure A8: Price of nitrogen per ha (source: Authors)

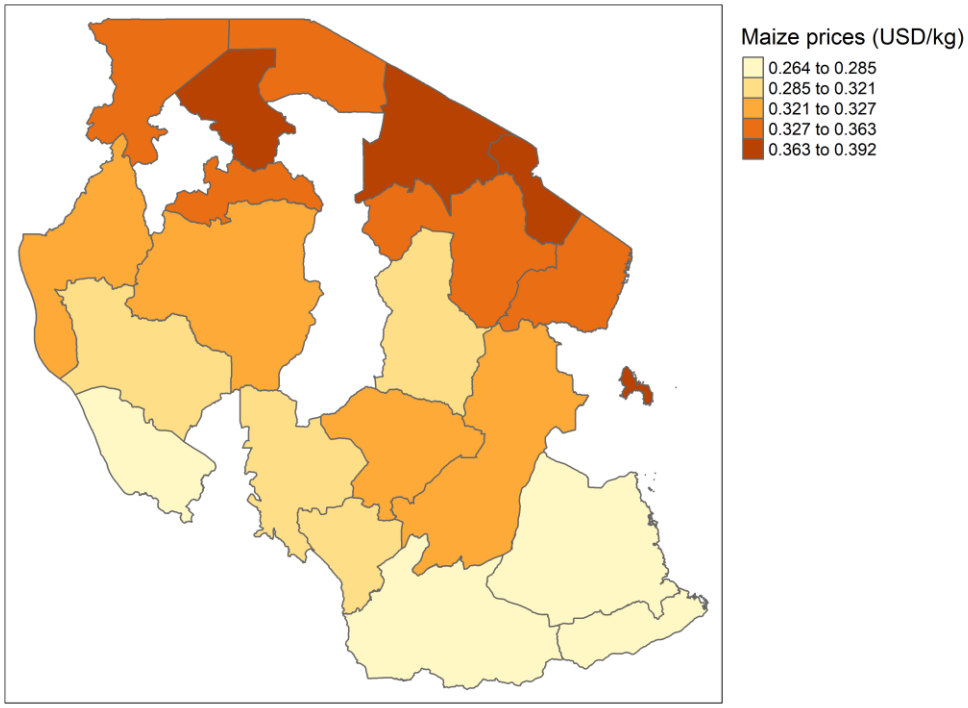

Figure A9: Survey maize prices

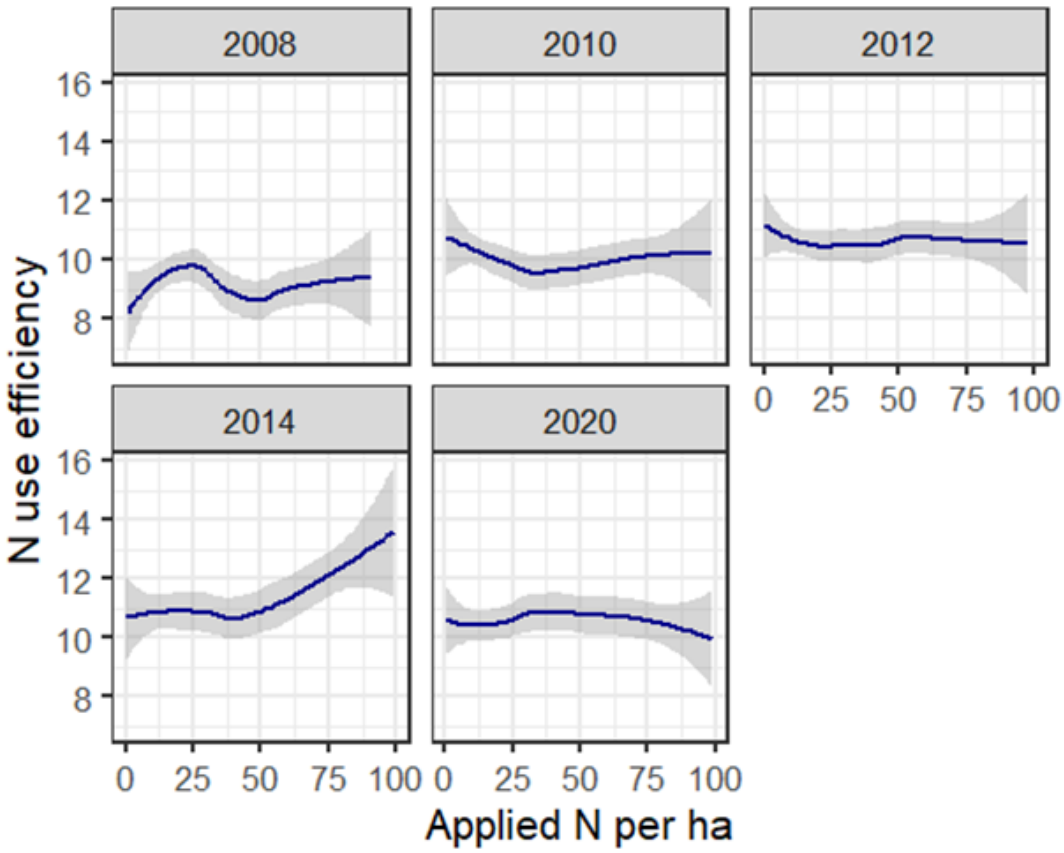

Figure A10: Nitrogen use efficiency by year

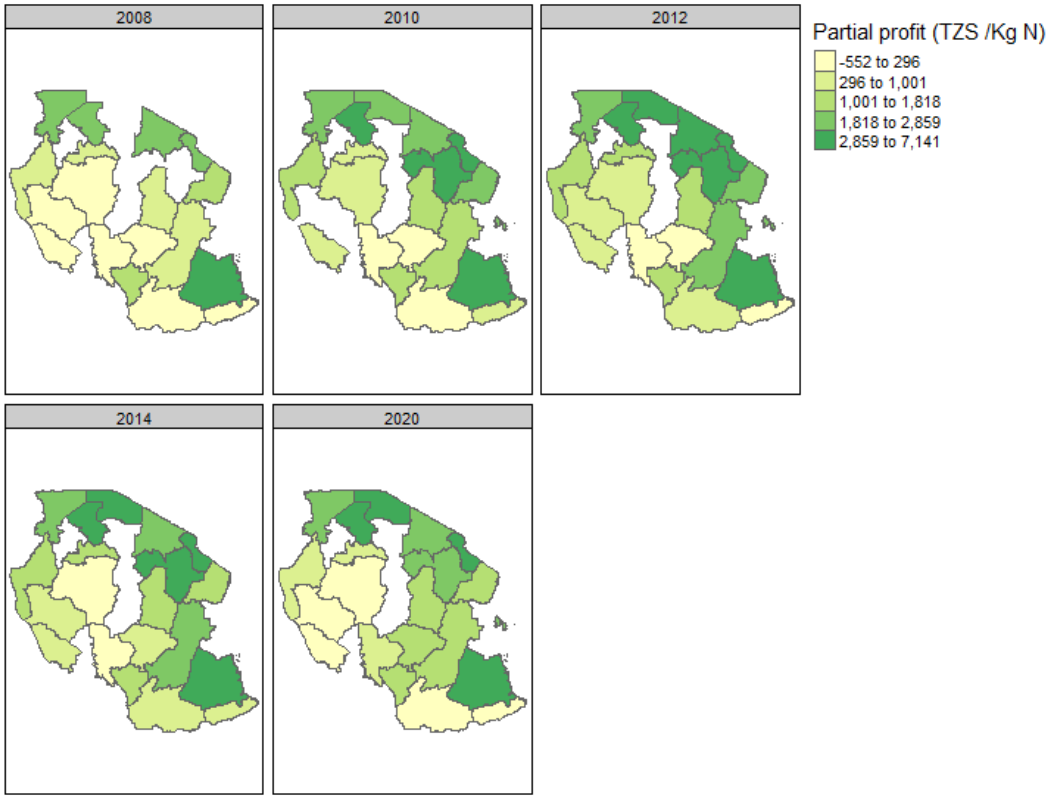

Figure A11: Partial profits from using nitrogen fertilizer

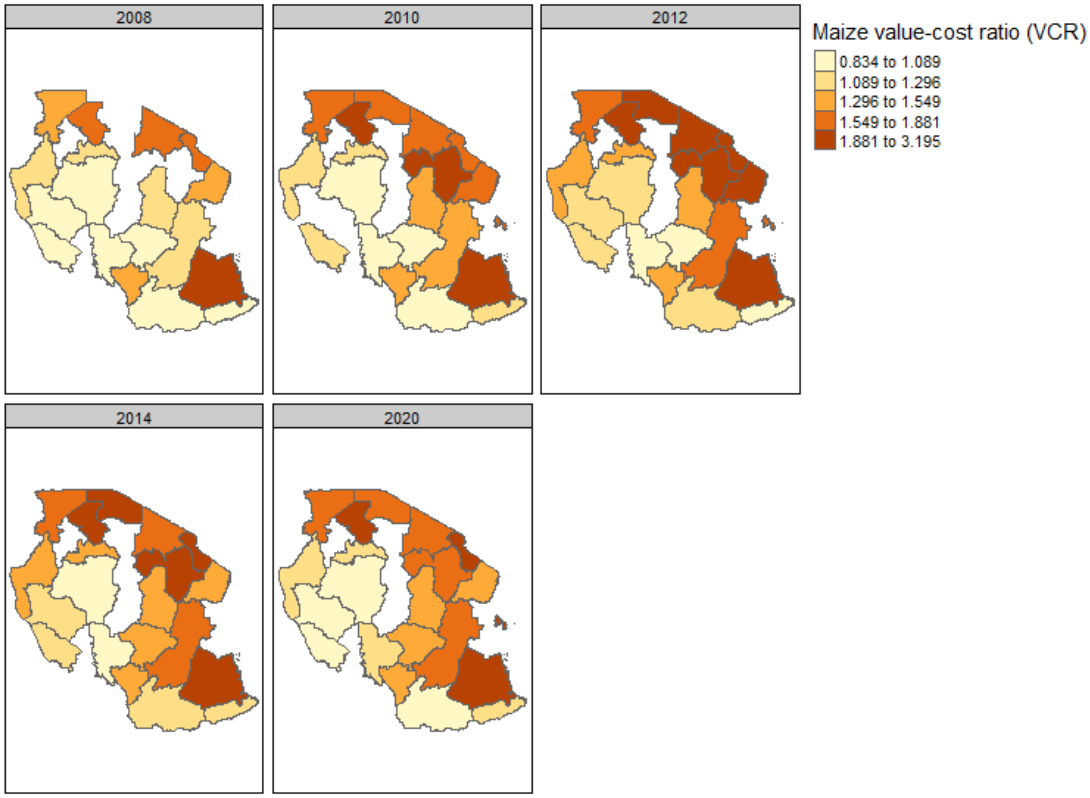

Figure A12: Value cost ratio (using 2021 regional maize prices)

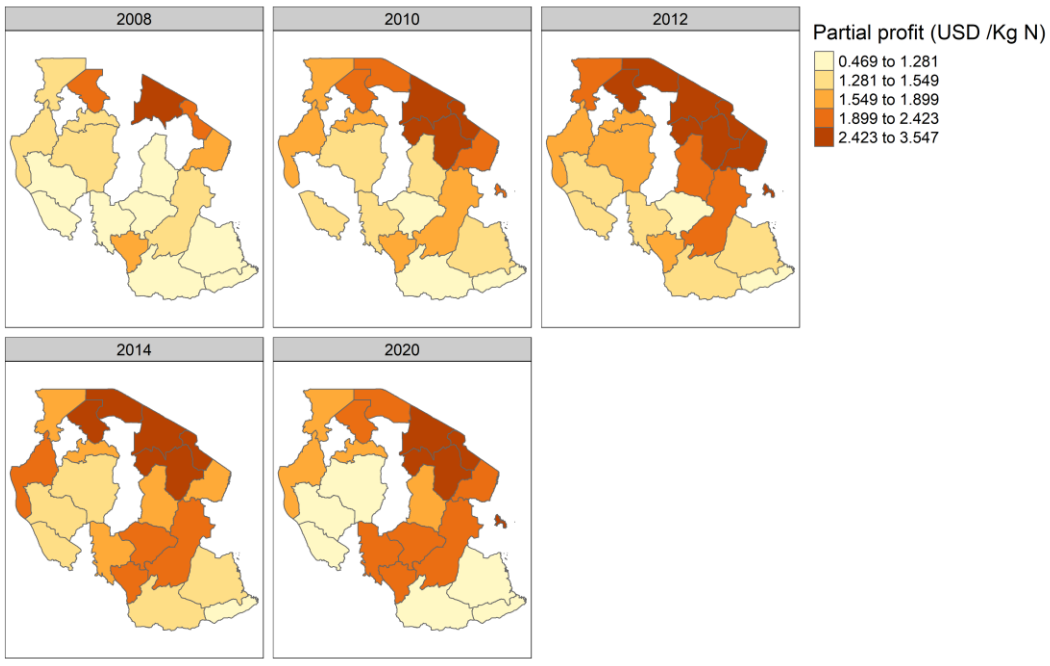

Figure A13: Partial profits (using USD prices for maize output and nitrogen)

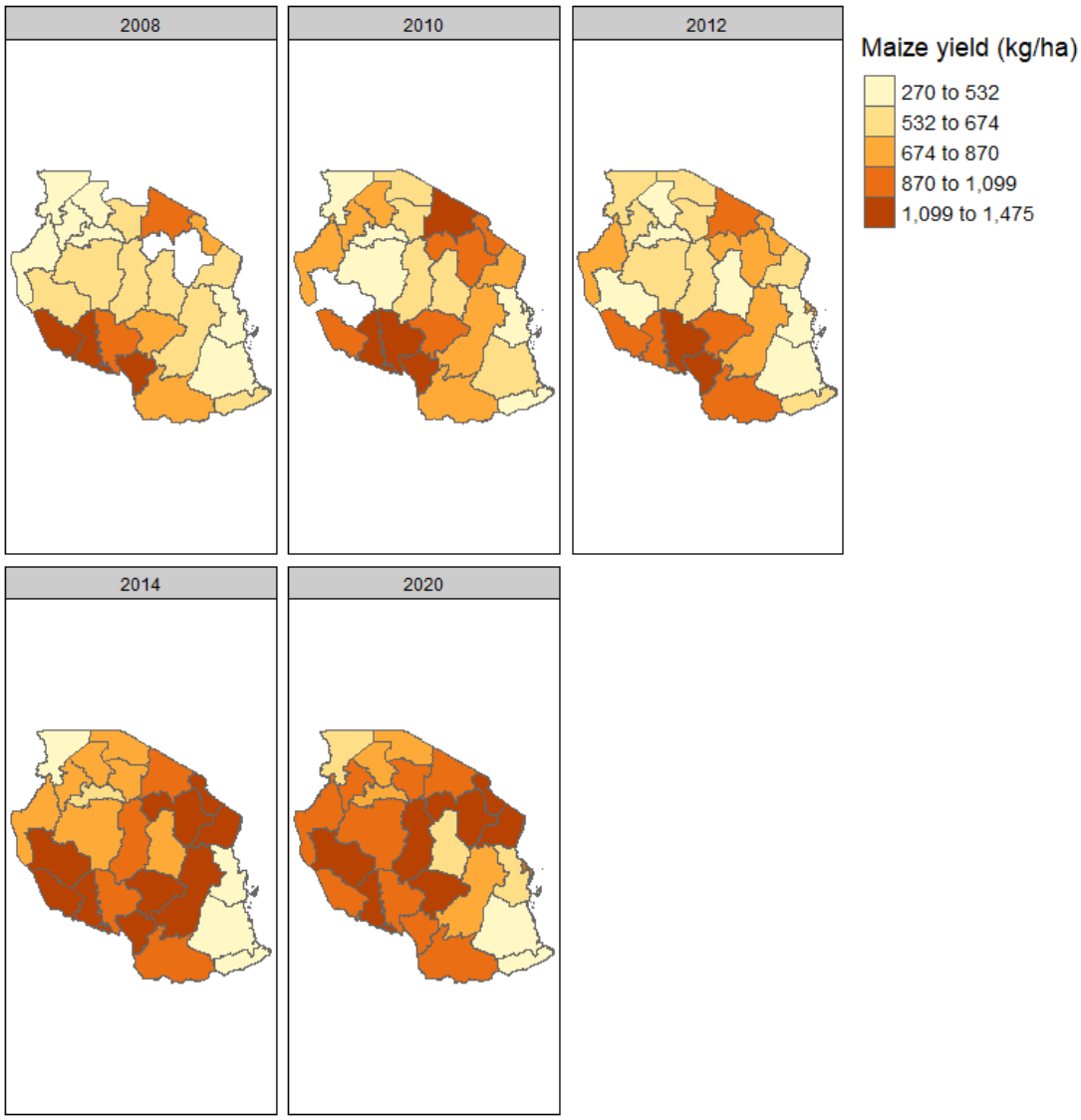

Figure A14: Maize yield