ORIGINAL PAPER

Evolution of Fertiliser Use and its Impact on Maize Productivity in Kenya: Evidence from Multiple Surveys

Pradyot Ranjan Jena^{1,2} \cdot Hugo De Groote² \cdot Bibhu Prasad Nayak³ \cdot Annina Hittmeyer²

Received: 6 May 2019 /Accepted: 7 September 2020 / Published online: 16 September 2020 \odot International Society for Plant Pathology and Springer Nature B.V. 2020

Abstract

During the 1990s, the Kenyan agricultural sector became increasingly liberalised. For many years, both government- and nongovernment organisations have advised farmers on fertiliser doses, and therefore, an increase in fertiliser adoption resulting in higher yields has been expected. We analyse the evolution of fertiliser use and its impact on maize productivity and household incomes in Kenya, using four household surveys conducted between 1992 and 2013. Each survey represented all six maizeproducing zones of Kenya. The results show that the percentage of fertiliser users among maize farmers has increased slightly over the years (from 62% in 1992 to 65% in 2013), and the quantity of fertiliser applied per ha has increased (from 82 kg/ha in 1992 to 100 kg/ha in 2013) but remains far below recommended levels. Therefore, maize yields have remained stagnant, or even decreased slightly (from 1360 kg/ha in 1992 to 1116 kg/ha in 2013). We also observe that the following factors affect fertiliser use and maize yields: education of the household head; area under maize cultivation; agroecological zone; uneven access to extension services; and food insecurity. We also find that fertiliser use has a positive impact on both maize yields and household income. We conclude that the liberalisation of fertiliser markets in Kenya did not have the desired effect of increasing fertiliser use and consequently maize yields, except in the high potential maize-growing areas. Possible explanations include both market factors, e.g. high prices, and non-market factors, e.g. access to information. We make two policy recommendations based on these findings – firstly, the targeted outreach of extension services should be considered, to increase fertiliser use and yields in less-productive regions, and secondly, policies should be considered that incorporate provisions for weather shocks.

Keywords fertiliser \cdot adoption \cdot maize \cdot impact

1 Introduction

The use of fertiliser has always been an important issue in sub-Saharan Africa (SSA) (Tully et al. [2016;](#page-15-0) Ariga and Jayne [2009\)](#page-13-0), engaging both researchers (Vanlauwe et al. [2017](#page-15-0)) and policy makers (Berazneva et al. [2018\)](#page-13-0) in designing the best agricultural policies for increasing farm productivity, while balancing the needs of other stakeholders. The population in SSA is rising fast; a substantial increase in food production is required to keep up with the population growth (Godfray et al. [2010](#page-14-0); Gregory and George [2011](#page-14-0); Tilman et al. [2002\)](#page-15-0) and malnutrition is increasing (FAO [2009](#page-14-0); FAO [2014](#page-14-0)). To increase food production, the availability and use of agricultural technologies such as improved varieties and fertiliser remain a central focus of agricultural policy in these countries (Jena and Odendo [2014](#page-14-0)). The promotion of fertiliser especially has become a resounding theme across SSA in the past decades (Ariga and Jayne [2011;](#page-13-0) Takeshima and Lee [2012\)](#page-15-0), particularly following the first African Fertiliser Summit in Abuja, Nigeria in 2006. However, the question of whether or not farmers' fertiliser adoption patterns are determined by the profitability of fertiliser application has not been paid serious attention. Farmers in general weigh the opportunity cost of investing in fertiliser against the returns that they are likely to obtain (Duflo et al. [2007](#page-14-0)). Any uncertainty in returns from cultivation will reduce their tendency to apply fertiliser.

Few credible studies have used an experimental set-up to examine the issue of fertiliser uptake. Duflo et al. [\(2008\)](#page-14-0) explored the factors leading to the low adoption of fertiliser in

 \boxtimes Pradyot Ranjan Jena pradyotjena@nitk.edu.in

School of Management, National Institute of Technology Karnataka, Surathkal 575025, India

International Maize and Wheat Improvement Center (CIMMYT), Nairobi, Kenya

³ School of Livelihood, Tata Institute of Social Sciences, Hyderabad, India

Kenya, including lack of information on the availability of inputs at reasonable prices, and farmers' difficulties in saving sufficient money for their purchase. They suggested simple interventions that could substantially increase fertiliser use without affecting the cost, such as offering farmers the option to buy fertiliser at the full market price but with free delivery immediately after the harvest; this would have an effect comparable to a reduction in price. Further, Duflo et al. [\(2008\)](#page-14-0) showed that small, time-limited reductions in the cost of fertiliser at harvest time induced substantial increases in fertiliser use, and that these increases were comparable to those induced by much larger price reductions given later in the season. A study in western Kenya by Waithaka et al. [\(2007\)](#page-15-0) found that the use of chemical fertiliser and manure influenced each other reciprocally, and were positively influenced by household factors such as the education of the household head.

Sheahan et al. [\(2013\)](#page-15-0) showed that farmers in Kenya, over time, and in the most productive areas, consistently and steadily moved towards risk-adjusted, economically optimal rates of fertiliser use. According to Matsumoto and Yamano [\(2009\)](#page-14-0), relatively lower prices for nitrogen-based fertiliser in Kenya played a decisive role in its high uptake for fertilising maize, as compared to Uganda where nitrogen fertiliser prices were much higher.

Ariga and Jayne ([2011\)](#page-13-0) showed that between 1997 and 2007 there was a 34% increase in smallholders' application of fertiliser per ha in maize cultivation systems, which was led by public investments in support of input-market development, and by fertiliser-subsidy policies in Kenya. Other studies observed that government fertiliser subsidies and government intervention in fertiliser distribution had crowded out private investment in the sector (Makau et al. [2016\)](#page-14-0).

Faced with an increasing population and the associated demand for food, as well as the rising cost of fertilisers in Kenya, the Kenya Agricultural Research Institute (KARI) started the Fertiliser Use Recommendation Project (FURP) in 1985. Fertiliser trials were conducted at 70 different sites, all of which were representative of different soil types and agroecological zones. The goal of FURP was to design zone- and crop-specific fertiliser-recommendation packages, which were expected to contribute in turn to higher degrees of self-sufficiency in supplying food throughout Kenya (Kenya Agricultural Research Institute [1995](#page-14-0)). FURP led to fertiliser recommendations for crops such as maize, beans and sorghum in 24 districts (Kibunja et al. [2017\)](#page-14-0). Using data from FURP, Schnier et al. [\(1996](#page-14-0)) analysed the variance in crop yields, including maize, in order to estimate the significance of treatment effects. Step-wise multiple regressions using data for individual seasons and the pooled data, i.e. the average over all the seasons, revealed two major risks that farmers faced when optimizing fertiliser use against their net income per ha: firstly, the crop response to fertiliser may be lower than

anticipated due to crop diseases, pests or unfavourable seasonal conditions, and secondly, the price of the crop may be lower than anticipated. The first risk can be mitigated by increasing farmers' knowledge about crop pests and diseases, and increasing their farm management skills, the second by guaranteeing crop prices at harvest time. Schnier et al. [\(1996\)](#page-14-0) did not find any significant correlations between rainfall data, maize yields and fertiliser responses. The total amount of rainfall was not correlated with the response either to the application of nitrogen fertiliser or to maize yields. They also pointed out that rainfall variability constituted a serious constraint when it came to fertiliser recommendations for raindependent agricultural systems, since soil moisture is an important determinant of yield. Consequently, they suggested that under certain conditions, such as adversely high risks in terms of rainfall variability, prohibitive input prices, or very low prices for produce, it was advisable not to apply any fertiliser. Following Schnier et al. [\(1996\)](#page-14-0), Smaling et al. ([1992](#page-15-0)) also used FURP data, and recommended agroecological-specific fertiliser. They also pointed out that farm heterogeneity, in particular soil type, slope and altitude, must be taken into account when recommending fertiliser rates, as the applicability and overall profitability of these depend on farm labour and capital resources.

A more recent example of a fertiliser-recommendation project is the Optimizing Fertiliser Recommendations in Africa (OFRA) 2013–2017 project, during which 37 trials were conducted for various crops in four regions of Kenya ([http://](http://africasoilhealth.cabi.org/aboutshc/ashc/ofra/) [africasoilhealth.cabi.org/about-ashc/ashc/ofra/\)](http://africasoilhealth.cabi.org/aboutshc/ashc/ofra/). The aim of OFRA was to deliver decision-making tools to farmers that would enable them to choose the appropriate fertiliser type and rate of application for various crops in different agroecological zones, knowledge of which famers often lack. OFRA found crop responses to fertiliser application to be non-linear, i.e. fertiliser application has a positive effect on crops until a plateau is reached. Like Schnier et al. [\(1996](#page-14-0)), Kibunja et al. [\(2017\)](#page-14-0) also recommended that fertiliser application rates should be based on input and output prices, and depend on access to information about these. The interaction of fertiliser use with other aspects of integrated pest-, disease-, and soilfertility management practices should also be considered.

Research into the efficient use of fertiliser on maize is important to help establish food security in Kenya, where maize is the most common cereal (FAOSTAT [2020b](#page-14-0)) and the primary staple food, with an average consumption of 76 kg/year, accounting for 30% of calorie intake and 28% of protein intake (FAOSTAT [2020a](#page-14-0)). Maize production cannot keep up with the growing population, and poor soil fertility is one of the major constraints (Vanlauwe and Giller [2006\)](#page-15-0). Therefore, in order to provide food security in Kenya, especially for the rural poor, the issue of soil fertility in relation to maize production needs to be addressed, and the use of fertiliser plays a major role in this.

Kenya has undergone agricultural liberalisation since the mid-1990s, and policies have been introduced that allow private actors into the seed- and fertiliser-sector markets (Wangia et al. [2004](#page-15-0)). However, after several years of agricultural liberalisation, the question still remains as to whether the increased participation of the private sector has increased agricultural productivity and brought growth. This study therefore analyses the changes in fertiliser use in the maize sector in Kenya, from the centrally controlled markets in the early 1990s, over the liberalisation period, and afterwards, and the impact of these changes on maize productivity and economic profitability.

Against this backdrop, our study has three objectives: firstly, we analyse the changes in fertiliser use in maize cultivation from before until after the opening up of the agricultural sector to the private sector through the liberalisation of input and output markets. We make use of repeated cross-sectional data collected in Kenya at four points in time – in 1992, 2002, 2010 and 2013. The data for 1992 account for the pre-liberalisation period, in which the national government controlled the prices of maize, inputs and fertiliser. The data for 2002 show the scenario immediately after liberalisation, when private participation was allowed, whereas the latter two periods can be considered as ones in which liberalisation of the fertiliser market was well-established. The second objective is to identify the determinants of fertiliser adoption and rate of application. Although the number of farmers using fertiliser has increased over the years, the rate of application remains well below the recommended amount. The third objective is to measure the impact of the changes in fertiliser use on farm productivity and income. The impact of fertiliser on maize yield is limited when fertiliser is used alone; fertiliser is more effective when used in combination with other technologies such as organic manure, improved maize varieties, integrated pest control, and good agronomic practices (Kibunja et al. [2017](#page-14-0)). Therefore, in this paper, we attempt to measure the impact of fertiliser use on maize yields in Kenya, controlling for the use of hybrid seed and other factors.

2 Material and Methods

2.1 Sampling Design

The data were collected during rural household surveys conducted in Kenya over the last twenty years: in 1992 (Hassan et al. [1998](#page-14-0)); in 2002 (De Groote et al. [2005\)](#page-14-0); in 2010 (De Groote et al. [2016](#page-14-0)); and in 2013 (Wainaina et al. [2016](#page-15-0)). The first three surveys were cross-sectional, and representative of all the major maize-growing areas of the country, where the large majority of rural households live. All the surveys used a stratified two-stage design, with agroecological zones as strata, sub-locations (the lowest administrative units in Kenya) as

primary sampling units, and households as secondary sampling units. During the most recent (2013) survey, the households visited in the third survey were revisited, with a replacement of 20% of the households, randomly selected. Since data were based on repeated cross-sectional surveys and were collected over a long period of time, the same households were not followed over time except in the last survey. The data from the four surveys were previously used to analyse trends in

mechanisation in Kenya (De Groote et al. [2018\)](#page-14-0). The first survey was conducted in 1992 by the International Maize and Wheat Improvement Centre (CIMMYT) and the Kenya Agricultural Research Institute (KARI) in the major maize agroecological zones of Kenya (Hassan [1998](#page-14-0)). This survey covered 79 enumeration clusters, randomly selected from the sampling frame of the Central Bureau of Statistics, comprising 1397 farmers (Hassan et al. [1998\)](#page-14-0). The second survey, conducted in 2002, covered 185 sub-locations, ran-domly selected from the 1999 census report (CBS [2001](#page-13-0)), and 1657 farmers (De Groote et al. [2005\)](#page-14-0). The third survey, in 2010, covered 120 sub-locations, with 1341 farmers (De Groote et al. [2016](#page-14-0)). The fourth survey (2013) revisited the 2010 sub-locations and the same households except for a replacement of 20% of randomly selected households (Wainaina et al. [2016](#page-15-0)).

We follow Hassan's [\(1998\)](#page-14-0) categorisation of six maizegrowing agroecological zones in Kenya. From east to west, these include the coastal lowland tropics, followed by the dry mid-altitude- and dry transitional zones around Machakos. While these zones include 50% of the maize-growing area, they only produce 30% of Kenyan maize, as they are characterised by relatively low yields of around 1 t/ha (0.2 to 1.2 t/ha). Further inland, the highland tropics are located in central and western Kenya, bordered by the moist transitional zones on the east and west. These zones include 30% of the maize-growing area but produce about 50% of Kenya's maize, with comparatively good yields of over 2.5 t/ha (0.6 to 3.3 t/ha). Finally, the moist mid-altitude zone by Lake Victoria has moderate yields of 1.5 t/ha (0.4 to 2 t/ha). While Kenya in general has two maize-growing seasons, the seasons differ in importance between zones. In the highlands, for example, 99% of maize production takes place in the long rainy season (March–July). In the moist transitional zone, on the other hand, 49% of the maize is produced in the short rainy season (October–February).

In this study, the data from the four surveys were used to describe trends in fertiliser use and maize yields. We used the panel data of 2010 and 2013 to make a rigorous examination of the determinants of fertiliser adoption and rate of application. The same panel data set was used to estimate the impact of fertiliser use on maize productivity and household income. As these two surveys were conducted in the same households, we were able to examine the changes that occurred from one period to the other (Table [1](#page-3-0)).

2.2 Analysis

2.2.1 Fertiliser Adoption and Application Rate

Econometric adoption models often use a binary variable as the dependent variable (Maddala [1983](#page-14-0)); in our study, this is the variable showing whether the household has used fertiliser or not. The standard models used for panel data analysis are fixed effects and random effects models (Wooldridge [2002\)](#page-15-0). Compared to the random effects model, the fixed effects model is less restrictive in assumptions; it does not make the parametric assumption of the distribution of unobserved heterogeneity, and permits correlation between individual specific effects and explanatory variables. This allows the fixed effects model to control for time-invariant unmeasured characteristics of individuals. Since it is based on the time-demeaned data and uses the variation over time within each cross-sectional observation, explanatory variables that are constant over time are removed by the time-demeaning and cannot be estimated with the fixed effects model (Wooldridge [2002](#page-15-0)) The random effects model, on the other hand, assumes that the error term is normally distributed, and that the explanatory variables are uncorrelated with the unobserved heterogeneity, which is a strong assumption. These models use between-household variations to allow for the estimation of time-variant covariates, but they do not control for time-invariant individual differences (Greene [2012](#page-14-0)).

To estimate the fertiliser adoption model, random effects logit (RE logit), RE probit and Chamberlain's correlated random effects (CCRE) probit models were used. In addition, to estimate the determinants of the fertiliser application rate, we used a hybrid random effects model that combines the features of both fixed and random effects (Allison [2005](#page-13-0)). The basic equation of the hybrid random effects model is given as:

$$
Y_{it} = \alpha_i + Z_i \gamma + X_{it} \beta_1 + D_{it} \beta_2 + u_{it}
$$
 (1)

Table 1 Sample size for the different surveys in the six agroecological zones (AEZ) in Kenya

AEZ	Year of survey			
	1992	2002	2010	2013
Coastal lowland tropics	99	300	90	89
Dry mid-altitude	177	200	216	216
Dry transitional	78	93	202	203
Moist transitional	412	521	353	355
Highland tropics	448	288	240	238
Moist mid- altitude	183	250	240	239
Total	1397	1652	1341	1340

Where,

Y_{it} is the dependent variable for each individual at each time point.

i indicates the individual,

t denotes the time period,

ɑ is the intercept,

Z is a vector of time-invariant characteristics,

X is a vector of time-varying characteristics,

 u_{it} is an error term.

Given the panel nature of our data, Eq. 1 can be written in a panel version as (Allison [2005](#page-13-0)):

$$
Y_{it} = \alpha_i + Z_i \gamma + X_{it} \beta_1 + D_{it} \beta_2 + (\tau_i + \varepsilon_{it})
$$
 (2)

Where, τ_i is the unobserved heterogeneity term assumed to be individual-specific and time-invariant and ε_{it} is the random error term. The hybrid approach decomposes the time-varying independent variables into between-household variation and within-household variation. The between-household variation is simply the mean of the variable for each individual across time points and is given by:

$$
\overline{X} = \frac{1}{T} \sum_{i=1}^{T} X_{it}
$$
\n(3)

The within-household variation is the difference between each individual's group mean and his or her variable value at each time point:

$$
\Delta X_{it} = X_{it} - \overline{X}_i \tag{4}
$$

Now, the decomposed components are added as predictors in Eq. 1. The hybrid model can be specified as follows:

$$
Y_{it} = \alpha_i + Z_i \gamma + \overline{X}_i \beta_{b_1 i} + \Delta X_{it} \beta_{w_1 i} + \overline{D}_i \beta_{b_2 i} + \Delta D_{it} \beta_{w_2 i} + u_{it}
$$
 (5)

A hybrid approach has two advantages over traditional fixed- and random-effects estimations: firstly, it provides two interpretations of time-variant explanatory variables – coefficient estimates for the between-household effects and the within-household effects; secondly, it allows the timeinvariant variables to be included in the model in addition to providing within-household coefficients identical to the estimates obtained from the fixed effects model.

2.2.2 Impact of Fertiliser Use on Yield and Income

A major criticism of the observational survey data is that they suffer from self-selection bias arising due to unobservable variables. We used a two-stage endogenous switching regression (ESR) model (Lokshin and Sajaia [2004](#page-14-0)) to deal with unobservable bias. The ESR model has been used extensively to study impact evaluations of agricultural technologies (Jaleta et al. [2016;](#page-14-0) Jena [2019;](#page-14-0) Jena et al. [2017;](#page-14-0) Kassie et al. [2015](#page-14-0); Kleemann et al. [2014;](#page-14-0) Teklewold et al. [2013](#page-15-0)) .

The ESR specifies two regimes – the first regime corresponding to the households that adopt the technology under study, and the second regime comprising the households that do not adopt the technology – and uses a two-stage estimation process. In the first stage, the selection equation is estimated as:

$$
A_i^* = Z_i \cdot + v_i \qquad \text{where } A_i = \begin{cases} 1 & \text{if } Z_i \cdot + v_i > 0 \\ 0 & \text{otherwise} \end{cases} \tag{6}
$$

A farmer adopts fertiliser if the expected utility from adoption is higher than the corresponding utility from non-adoption. Let A^* capture the benefit from adopting fertiliser by the ith farmer and be a latent variable. Z_i is a vector of explanatory variables explaining the selection into the two regimes, α is the parameter vector, and v_i is the error terms.

The second stage estimates the outcome equation. Based on the first stage selection equation, farmers select themselves to join one of the two regimes. The outcome equations for the two regimes, i.e. for fertiliser adopters and fertiliser nonadopters, corrected for endogenous adoption are given as:

Regime 1 :
$$
Y_{1i} = X_{1i}\beta_1 + \sigma_{1u1i}\hat{\lambda}_{1i} + u_{1i}
$$
 if A_i
= 1 (Adoption) (7a)

Regime 2 : $Y_{2i} = X_{2i}\beta_2 + \sigma_{2u2i}\hat{\lambda}_{2i} + u_{2i}$ if A_i

$$
= 0 \text{ (Non-Adoption)} \tag{7b}
$$

where, Y_{1i} and Y_{2i} , $i = 1, ..., N$, denote the dependent variables in each of the two regimes; X_{1i} and X_{2i} are the explanatory variables relevant to each regime, β_1 and β_2 are the parameters to be estimated, and u_{1i} , u_{2i} are the corresponding error terms; λ_{1i} and λ_{2i} are the inverse Mill's ratios (IMR) computed from the first stage selection equation, and are included in Eqs. (7a) and (7b) to correct for selection bias.

The second-stage outcome regressions compute four estimates: (a) the real scenario outcome from adoption of fertiliser; (b) the real scenario outcome from non-adoption; (c) the counterfactual outcome scenario from adoption (i.e. the outcome had the adopting households decided not to adopt) and (d) the counterfactual outcome scenario for nonadoption (i.e. had the non-adopting households decided to adopt). Situations (a) and (b) are observed from the survey data and hence are real scenarios, whereas (c) and (d) are hypothetical situations (counterfactual scenarios) that would be expected to occur if the treated had been untreated, and if the untreated had been treated. The average treatment effect on the treated (ATT) is computed as (a) - (c) and the average treatment effect on the untreated (ATU) is computed as (b) - (d).

3 Results

3.1 Trends of Fertiliser Use and Application Rates in the Pre- and Post-liberalisation Period

Figure [1](#page-5-0) shows the proportion of households that used fertiliser over the four survey years. In 1992, the year of the first survey, 62% of farmers used fertiliser. However, the results show significant inter-regional variations; agroecological zones with good rainfall showed the highest adoption rates, in particular the moist transitional zone with 80%, and the highland tropics with 57%. Agroecological zones with medium productivity clearly showed lower adoption rates, in particular the moist mid-altitude zone with 50%, and the dry transitional zone with 40%. The marginal areas showed low to zero adoption rates: the dry mid-altitude zone had a 12% adoption rate, and in the lowland tropics, farmers had not applied any fertiliser at all.

Ten years later, in 2002, the average percentage of fertiliser users had increased only slightly, to 65%. The zones with good rainfall – the high tropics and the moist transitional zone – again showed the highest percentage of fertiliser users, at 89% and 83% respectively. In the medium-potential areas, the rate of fertiliser adoption was 53% in the dry transitional zone and 33% in the moist mid-altitude zone, while in the marginal maize areas, the rate was 13% in the lowland tropics and 9% in the dry mid-altitude zone.

The next survey, eight years later in 2010, showed a fertiliser adoption rate of 58%, substantially lower than the adoption figures in 1992 and 2002. In 2010, the highland tropics and the moist transitional zones again saw the highest levels of fertiliser adoption, with rates of 77% and 76% respectively; the dry transitional zone and the moist mid-altitude zone (medium-potential zones) followed with rates of 58% and 30% respectively; and lastly, the marginal zones of the lowland tropics and the dry mid-altitude zone had adoption rates of 26% and 16% respectively. Finally, the 2013 survey, which was a follow-up survey to the 2010 survey, showed an average fertiliser adoption rate of 65%, a significant increase over 2010, yet not significantly higher than the 1992 and 2002 rates. In the high-potential areas, the high tropics at 87% now registered a significant improvement in fertiliser adoption, followed by the moist transitional zone at 82%. In the medium-potential areas, adoption rates were 64% for the dry transitional zone and 48% for the moist mid-altitude zone, while in the low-potential areas, the rates were 24% for the low tropics and 21% for the dry mid-altitude zone.

The rates of fertiliser application, expressed in kg per hectare, are presented in Fig. [2](#page-5-0). The total averages per year were calculated using AEZ population and area weights to ensure representativeness at a national level, following De Groote et al. ([2020\)](#page-14-0). The seasonally weighted average figures for the four survey years show that the rates of fertiliser Fig. 1 Trend in fertiliser adoption rates in Kenya from 1992 to 2013 (in % of farmers adopting). Source: Own calculation. Standard deviations are in parentheses. The total yearly average was calculated using AEZ population and area weights to ensure representativeness at a national level following De Groote et al. ([2020](#page-14-0))

application fluctuated. In the first survey in 1992, the application rate was 82 kg per ha; this had increased slightly to 89 kg per ha in 2002. The rate declined substantially, however, to 68 kg per ha in 2010, before eventually rising again to 100 kg per ha in 2013. The high standard deviations for the average figures indicate a high variability in fertiliser application rates between farmers, with a standard deviation higher than the mean in all the years. Such high dispersion suggests heterogeneity in fertiliser application rates in Kenya, which could be influenced by many factors such as availability of fertiliser in the locality, access to credit, level of education, and farmers' willingness to relate fertiliser use to yield and profitability.

Among the six agroecological zones, the variability is also significant over the four survey years. In 1992, the highest application rate was recorded in the high-potential areas: the highland tropics in particular with 109 kg/ha, and the moist mid-altitude zones with 76 kg/ha, followed by the dry transitional areas with 48 kg/ha, the moist transitional zone with 47 kg/ha and the dry mid-altitude zone with 19 kg/ha. A significant increase in application rates can be observed in the lowland tropics, the moist transitional zone and the highland tropics between 1992 and 2002. In that period, there was only a marginal increase in application rates in the dry mid-altitude zone. During the same period, the dry transitional and moist mid-altitude zones experienced a significant decline in application rates.

In 2010, the weighted average fertiliser application rate dropped significantly compared to 2002. Among the AEZs, the highest level was again recorded in the highland tropics (113 kg/ha), followed by the moist transitional zone with 102 kg/ha. Application rates in the other zones were substantially less: 38 kg/ha in the dry transitional zone, 27 kg/ha in the moist mid-altitudes, 26 kg/ha in the lowland tropics and 6 kg/ ha in the dry mid-altitudes. The fertiliser application rates had increased again by 2013, when the highland tropics and moist transitional zones had regained the 2002 levels. The lowland tropics and dry mid-altitude zone also showed higher application rates than in previous years.

We observe that there is no clear sign of an increasing or decreasing trend in fertiliser adoption and application rates, as is shown by the fluctuations from year to year; this may be partly due to erratic weather conditions. However, there is a clear indication that fertiliser adoption and application rates were stagnant during the period from 1992 to 2013.

Fig. 2 Fertiliser application rate in Kenya between 1992 and 2013 (kg/ha)

3.2 Trends in Maize Yields in Kenya from 1992 to 2013

Next, we analyse the trends in maize yields in Kenya over the same four survey years (Fig. 3). Our results indicate that the average maize yield in the country did not increase between 1992 and 2013 – a major concern for a country that relies heavily on maize for its food security. The weighted average maize yield was 1360 kg/ha in 1992 but then declined to 1220 kg/ha in 2002; it reached its lowest level in 2010 at 1058 kg/ha before recovering marginally to 1116 kg per ha in 2013. Note, however, that the standard errors are between 63 kg/ha (2002) and 125 kg/ha (1992), so the small differences between the survey years are not significant.

To support this finding, we also analysed the FAOSTAT data on maize yields in Kenya from 1961 to 2017 (FAO [2019\)](#page-14-0), presented as a solid line in Fig. [4](#page-7-0), with the average yields from the different surveys indicated as dots (error bars indicate standard errors). The FAO time-series graph shows large year-to-year fluctuations in maize yields, but two trends clearly emerge: firstly, in the period from 1961 to 1990, there was a significant increase in yield (Y = $-50,893***+27***$ x year; $R^2 = 0.78$). Secondly, in the period since 1990, maize yields have stagnated, with no statistically significant change over time.

Comparing the two data sets presented some difficulty, as the data were collected using different methodologies. The survey data were collected using standard sampling methodology leading to unbiased estimates with an indicator of precision, the standard error. The FAOSTAT data, on the other hand, were not derived from farm surveys, but from estimates by extension and other officers at the local level, basically from expert opinions, which were subsequently aggregated into national figures. As this method is not based on sampling, it does not produce a measure of statistical precision, but it is commonly used because of its low cost. Despite the different methodologies, both estimates show the same trends, although FAOSTAT consistently produces a higher yield estimate, of 476 kg/ha (between 293 and 576 kg/ha) on average.

The survey results also show high regional differences, as expected, and these remain high over the 30 years of the study period. The highland tropics recorded the highest maize yields in 1992 with 1921 kg per ha, followed by the moist transitional zone with 1722 kg per ha; these are the two zones most suitable for maize production. The other four zones registered significantly lower yields. Nevertheless, yields had increased in the moist mid-altitude zone (812 kg/ha), the dry transitional zone (657 kg/ha) and the dry mid-altitude zone (457 kg/ha). Yields in the lowland tropics remained low and stagnant, between 426 and 547 kg/ha, but with no significant difference over the years. However, the large standard deviations indicate that there is high variation across the farming population in each agroecological zone. This heterogeneity across the country requires rigorous quantitative analysis to identify the specific factors leading to it. Such modelling is presented in the next section.

3.3 Fertiliser Adoption and Application by Various Socio-economic Groups

The previous two sections presented fertiliser adoption and application rates across the agroecological zones over the four survey periods. This section classifies adoption and application rates across various socio-economic strata such as gender, prevalence of food insecurity and the seasonally weighted area under maize, using the data pooled over the last two survey years, i.e. 2010 and 2013, that are panel surveys. With regard to gender, fertiliser adoption by male-headed households (57%) was on average 6% higher than adoption by female-

Fig. 4 Comparing trends in household survey data (four years) with FAO statistics for Kenya, 1961–2018 (error bars are standard errors)

headed households (51%) (Table 2). Similarly, the fertiliser application rate was 76 kg/ha for male-headed households, but 57 kg/ha – 33% lower – for female-headed households. The higher rates of fertiliser adoption and application in maleheaded households reinforce the often-argued issue of lack of access to inputs, extension services and credit by femaleheaded households in comparison to their male counterparts.

Secondly, we examine socio-economic groups with respect to their usual food security status, and analyse their fertiliser use according to this criterion. Four categories of foodsecurity prevalence were identified based on the responses to a series of questions (Coates et al. [2007\)](#page-13-0): highly food-insecure, moderately food-insecure, mildly food-insecure, and food secure. Food-secure households had the highest rate of fertiliser adoption (70%), while the highly food-insecure

group had the lowest (44%). The other groups, mildly foodinsecure and moderately food-insecure, had rates of 60% and 53% respectively. Similarly, rates of fertiliser application declined with decreasing food security: from 102 kg/h by the highly food-secure group to 48/ha by the highly food-insecure group.

Finally, the third variable that we used to compute fertiliser adoption and application was the seasonally weighted area under maize, again classifying households into four groups: 0 to 1 ha; 1.1 to 5 ha; 5.1 to 10 ha; and above 10 ha per household. Among the first three groups, the highest adoption rate, 58%, was found among households with the smallest maize area (0–1 ha); for households with 1.1–5 ha of maize, the adoption rate was 48%, and for households with 5.1– 10 ha, it was 55%. The households with the largest maize area

Source: Own calculation, standard deviation in parenthesis. N for all the categories is 1970

(> 10 ha) all used fertiliser, although this group comprised very few households. Similarly, application rates also formed a U-curve in the maize area function: they were higher for the very small areas, at 75 kg $(< 1$ ha) than in the middle range at 59 kg/ha (1.1–5 ha), and then increased again to 179 (5–10 ha) and 173 kg/ha (> 10 ha).

3.4 Determinants of Fertiliser Use

In this section we model the determinants of fertiliser use. The average marginal effects from the random effects (RE) logit model, RE probit model, and Chamberlain's correlated random effects (CCRE) probit model are presented in Table [3.](#page-9-0) Both the RE logit and the RE probit models failed the Mundlak test, implying that the results were not consistent, and therefore we turned to the CCRE probit model. However, there was consistency among the results from the CCRE and RE models, except for those for education (formal years of schooling of the household head) and total area under maize. Both the RE logit and RE probit models showed a positive effect of education of the household head on fertiliser adoption. The marginal effect was 0.013 (statistically significant at 1% level of significance). The probability of fertiliser adoption increased by 1.3% for each extra year of education of the household head. As shown in the CCRE probit model, the seasonally weighted area under maize also had a positive effect on fertiliser use. An increase in the average area allocated to maize by 1 ha increased fertiliser adoption by 3%.

The agroecological zones were also included in the model, and compared to the lowland tropics (the base category), farmers in the dry transitional zone, moist transitional zone and highland tropics were more likely to adopt fertiliser. Weather variables were also included, but only annual precipitation had a positive but small effect on fertiliser adoption $(p < 10\%)$.

Among the institutional variables, distance to the nearest agricultural extension office, used as a proxy for access to extension, was found to have a negative effect on the probability of fertiliser adoption. The final variable affecting fertiliser adoption was the household food insecurity access scale $(HFIAS)$ ¹. The marginal effect of this was in the range of −0.004 to −0.006, meaning that if the index value increased by a unit, i.e. if a household became more food insecure, then the probability of the household using fertiliser decreased by 0.4 to 0.6%. This is in line with the descriptive results in Table [5,](#page-10-0) which show that highly food-insecure households tend to use less fertiliser.

3.5 Determinants of Fertiliser Application Rate

In this section, we identify the factors that affect the fertiliser application rate, using both the random effects model and Allison's hybrid model. The random effects model again failed the Mundlak test, hence we focus more on the hybrid model results. The results show that the year dummy is statistically significant and positive, meaning that the application rate in 2013 has increased compared to the application rate in 2010. This finding is corroborated by the statistics in Table [3,](#page-9-0) which show that the fertiliser application rate has increased in 2013 compared to that in 2010.

Among the five agroecological zones, the moist transitional zone showed high levels of fertiliser application compared to the base category of the lowland tropics, while the estimated coefficient for the highland tropics was not statistically significant. Furthermore, households who faced greater food insecurity tended to use less fertiliser, as a higher value of the food-insecurity access scale is associated with a reduction in fertiliser application. In addition to the variables discussed, the random effects model has other variables that are statistically significant compared to Allison's hybrid model, in particular the education of the household head. The results also show an association between education of the household head and fertiliser application rates: each additional year of education is associated with an increase of 3 kg/ha (Table [4](#page-10-0)).

4 Impact of Fertiliser Use on Maize Productivity and Household Income

Finally, we analyse the effect of fertiliser use on maize productivity and total household income, by using the endogenous switching regression model to calculate the average treatment effect on the treated (ATT) and the average treatment effect on the untreated (ATU) (Table [5\)](#page-10-0). The ATT for maize productivity is 458 kg/ha and significant at 1%, suggesting that households that use fertiliser gain 458 kg/ha compared to the counterfactual scenario in which they do not use fertiliser. The ATU is 87 kg/ha and also statistically significant (at 1%), meaning that households that do not use fertiliser would have gained 87 kg/ha had they chosen to fertilise their maize.

Next, we analyse the impact of fertiliser use on the log of total household income (bottom panel of Table [5](#page-10-0)). The ATT is positive (0.06) and statistically significant for log household income, indicating that households that used fertiliser earned more than they would have earned had they not used fertilizer. The ATU for log household income, on the other hand, is not

¹ The HFIAS variable (household food insecurity access scale) used in the regression is a quantitative indicator of food insecurity constructed from the responses to nine occurrence questions that represent a generally increasing level of severity of food insecurity (access) (from "In the past four weeks, did you worry that your household would not have enough food?" to "In the past four weeks, did you or any household member go a whole day and night without eating anything because there was not enough food?"), and nine "frequency-of-occurrence" questions that are asked as a follow-up to each occurrence question to determine how often the condition occurred (Coates et al. [2007\)](#page-13-0).

Table 3 Determinants of fertiliser use

Note: Cluster robust standard errors in parenthesis, *** significant at 1%, ** significant at 5%, * significant at 10% Means for time-varying variables not displayed for CCRE

statistically significant, indicating that households that did not use fertiliser would not have obtained a higher total income had they used fertiliser. Because household income also includes income from other sources (although income from maize constitutes the major proportion of household income), it is not surprising that the counterfactual scenario is statistically inconclusive. The ATT, which is a measure of a real scenario, is more important and that has come out as positive. These findings indicate that fertiliser use has a positive impact on both farm productivity and household income, and therefore on household welfare, at least on the adopters.

ATT = Average Treatment effect on Treated (Fertiliser used);

ATU = Average Treatment effect on Untreated (Fertiliser not used);

- (a) = adopters with adoption;
- (b) = non-adopters with no-adoption;
- (c) = adopters with no adoption;
- (d) = non-adopters with adoption;

Table [6](#page-11-0) presents the endogenous switching regression coefficients, indicating the factors that affect maize yields, for both fertiliser adopters and non-adopters. Education has a negative impact on maize yields for non-adopters, with a decline of 28 kg/ha for each year of education. This may be because non-adopters have a lower threshold level of education, such that an increase in education does not induce any difference in fertiliser application and thus maize yield. Household size (in adult equivalents), on the other hand, has a positive impact on yield for both adopters and non-adopters. The use of hybrid maize also positively affects yield for both groups, with an increase of 291 kg/ha for adopters and 174 kg/ha for nonadopters, indicating the synergistic effect of combining both technologies. Maize area per household, in contrast, has a negative and significant coefficient for non-adopters, indicating that a larger maize area leads to a reduction in yield for this group. Among institutional variables, access to extension services has a positive and significant impact, increasing maize yields by 240 kg/ha for fertiliser adopters and 184 kg/ha for non-adopters, indicating a synergy between extension and fertiliser use.

Among weather variables, an increase in minimum temperature has a positive effect: for every 1° C, maize yield increases by 78 kg/ha for adopters and 61 kg/ha for nonadopters. However, an increase in maximum temperature decreases yields for non-adopters. Furthermore, annual rainfall has a positive effect on yields for adopters, whereas an increase in relative humidity decreases yields for that group.

Table 4 Determinants of fertiliser application rate

Note: Standard errors in parenthesis, *** significant at 1%, ** significant at 5%, * significant at 10%

The ESR results for the log of total household income show significant positive effects of age of the household head and number of adult equivalents on household income for both fertiliser adopters and non-adopters, while the year dummy is found to have a positive effect for non-adopters only. While maize area positively affects household income for adopters, farming experience of the household head has a negative effect. Access to extension services is found to have a positive and statistically significant effect on income for both adopters and non-adopters. Among the AEZ dummies, farmers in the dry transitional, moist transitional, highland tropics and moist mid-altitude zones had less income compared to farmers in the lowland tropics for both adopters and non-adopters. While an increase in minimum temperature increases the average household income for both groups, an increase in maximum temperature reduces it (Table [7\)](#page-12-0).

5 Discussion and Concluding Remarks

This paper studies the evolution of fertiliser use in the Kenyan maize sector after the agricultural liberalisation policies put in place in the mid-1990s, and the impact of fertiliser use on maize productivity, controlling for other key variables. The

Note: Standard errors in parenthesis; *** significant at 1%, ** significant at 5%, * significant at 10%

Table 6 Endogenous switching regression on maize productivity

Note: Robust standard errors in parenthesis, *** significant at 1%, ** significant at 5%, * significant at 10%

present study is unique as it exploits a rich data set collected through four surveys undertaken at different times. The study sets three objectives to contribute to the existing literature: firstly, to analyse the trends in fertiliser adoption and maize yields in Kenya from 1992 to 2013; secondly, to examine the determinants of the adoption and application rates of fertiliser, and, finally, to measure the impact of fertiliser use on maize productivity and household income.

The results from the trend analysis show that fertiliser adoption and application rates have been quite volatile over the two decades. When comparing the four time periods, it is apparent that the average uptake of fertiliser adoption in the country has not significantly increased over time.

However, these average figures should not hide the wide heterogeneity observed among the AEZs. The two highpotential zones: the highland tropics and the moist transitional zones, have shown high rates of both fertiliser adoption (in % of farmers) and fertiliser application rates (in kg/ha). The other AEZs, in particular the marginal areas of the lowland tropics, moist mid-altitude and dry transitional zones, still lag far behind.

Our results are in line with the generally low levels of fertiliser use in sub-Saharan Africa, which are very low compared to Asian and Latin American standards (IFDC [2007\)](#page-14-0). These results, however, contrast with those of other studies, particularly those based on the Tegemeo panel data that show an increase in fertiliser use and maize yields from 1997 to 2007 (Sheahan et al. [2013](#page-15-0); Olwande et al. [2009;](#page-14-0) Ariga and Jayne [2011\)](#page-13-0). The FAO yield data for this particular period also show an increase in maize yields (Fig. [4](#page-7-0)). However, our analysis, based on both our survey and the FAOSTAT data, indicates that this increase over a short period is not part of a larger trend.

The stagnating fertiliser application rates are a matter for grave concern, and it is therefore important to explore possible explanations. Two competing hypotheses try to explain the low rate of fertiliser application in Kenya. Market-based hypotheses suggest that farmers are responding to the high fertiliser prices that are the result of high transportation and marketing costs in Africa (Bumb and Gregory [2006;](#page-13-0) Jayne et al. [2001\)](#page-14-0), and the resultant low availability of fertilisers and their accessibility to smallholder farmers (Ariga and Jayne [2011\)](#page-13-0). Non-market-based hypotheses emphasise

Table 7 Endogenous switching regression on log total household income

Note: Robust standard errors in parenthesis, *** significant at 1%, ** significant at 5%, * significant at 10%

farmers' lack of knowledge about inorganic fertilisers and high yielding varieties, as well as their financial constraints (Morris et al. [2007](#page-14-0)).

Our findings cast doubt on the success of the agricultural liberalisation policies. Although private companies are now allowed to operate in the input markets, there is still heavy indirect government control through import policies and domestic distribution policies. Such indirect control inhibits the growth of private participation in providing inputs to farmers. Previous studies have shown that the lack of availability of fertiliser in the market, and limited access to finance are important bottlenecks for farmers (Jena and Odendo [2014](#page-14-0)).

Nevertheless, our results show that fertilisers have a positive and significant impact on both maize productivity and net total household income of adopters. Moreover, our results show a clear synergistic effect of the use of fertiliser and the cultivation of improved maize varieties: the combined use of these has a clear positive effect on yield.

The stagnation of yields of maize, Kenya's major food staple, is worrying. It is also surprising, given the government's efforts in supporting the maize sector. Not only were the control of input provision relaxed and output markets liberalised, paving the way for private investment, but there has also been increased research into agricultural technologies, an enormous growth in financial institutions, and an amazing expansion of mobile phone technology. In view of all these developments, the stagnation of maize yields in Kenya has puzzled policy makers and researchers alike.

One probable explanation is that agricultural extension services may not have reached the socially and geographically disadvantaged farmers who live in remote areas away from the location of extension offices. Our findings consistently show that lack of access to extension is a major reason for low adoption rates. Our discussions during focus group discussions (FGDs) and with key extension officers revealed that it is mostly progressive farmers, i.e. those who are socially wellconnected and exposed to modern communication methods, who attend extension meetings regularly and take advantage of available technology. A substantial number of farmers who lacked proper communication facilities and a critical level of education could not grasp the benefit of switching to using prescribed levels of fertiliser and other necessary inputs. This in turn prevented them from operating at the forefront of agricultural technological development.

Another possible reason for stagnating maize yields in Kenya is a general decline in soil fertility, with the result that the potential benefits of applying fertiliser cannot be fully harnessed. Our study clearly shows that, although large numbers of farmers in Kenya are now using fertiliser, they cannot apply it consistently in the prescribed doses, and the average application has not been increasing. In SSA, one of the main causes of soil nutrient depletion and the resultant low yields is the intensification of land use without the adequate replenishment of lost nutrients (Henao and Baanante [1999\)](#page-14-0); this was confirmed by a recent study in six other SSA countries, which indicated that fallow areas have disappeared, and that the use of organic and chemical fertilisers is too low to maintain soil fertility (Binswanger-Mkhize and Savastano 2017).

To increase maize production and yields and to improve food security, the problem of soil fertility should be urgently addressed. Our results indicate that the use of fertiliser is an important practice that increases maize yields for households that have adopted its use.

Five important lessons can be drawn for policy formulation. First, because fertiliser recommendation initiatives create awareness and provide information and training, a targeted outreach towards socially and geographically disadvantaged farmers is required. Micro-plans can be developed, especially at smaller administrative levels. This is particularly important given the decentralization in the new constitution, which devolves agricultural extension to the county level. Second, price policies matter: a change in the input/output price ratio can drive changes in fertiliser use. However, while subsidies increase the use of chemical fertiliser, they also lead to a displacement of commercial fertilisers (Sheahan et al. [2013](#page-15-0); Mather and Jayne [2018\)](#page-14-0). It is therefore important to look at the whole price situation, and to stabilize input as well as output prices. Third, erratic weather conditions and the emergence of diseases and pests such as maize lethal necrosis and fall armyworm negate much of the benefit from investment in inputs, which discourages farmers from consistently adopting the best agricultural practices. Policies need to be considered that incorporate provision for such uncertainties. Shock-prone locations should be identified and preparedness incorporated in the micro-plans. Fourth, more research is clearly required to understand the behavioral bottlenecks that exist among lowadopting farmers, in order to understand their apprehension regarding technology adoption. Finally, while fertiliser is clearly important, it is only one factor in maintaining soil fertility and increasing yield. Our research also indicates that other factors, in particular the cultivation of improved maize varieties, have a synergetic effect with the use of fertiliser. Many other factors also play a role in optimizing the use of fertiliser, although the survey data used did not include information for incorporating these in the analysis. Nevertheless, other studies and analyses have shown that organic matter, soil testing, fertiliser mixtures adjusted to specific soils and

crops, integrated pest management, and good agronomic practices can help optimize fertiliser use (Sheahan et al. [2013;](#page-15-0) Vanlauwe and Giller [2006\)](#page-15-0). A holistic approach is therefore needed to better understand the economics of integrated soilfertility management, in order to guide research and extension in this field that has clear implications for maize production and food security in Kenya.

Acknowledgements The authors thank two anonymous reviewers and the editor of this journal for very useful comments and suggestions, and Elizabeth Way good for copy-editing the manuscript.

Funding Data collection for this research was financially supported by the Kenya Maize Data Base (KMDB) project (the 1992 survey); the Insect Resistant Maize for Africa (IRMA) project (2002 survey); the Aflacontrol project (2010 survey); and the CGIAR Research Program (CRP) on Climate Change, Agriculture, and Food Security (CCAFS) (2013 survey). Staff time for the analysis was provided by the Bill and Melinda Gates Foundation through the Improved Maize for African Soils (IMAS) project and the CGIAR Research Program on Maize Agrifood Systems (CRP-MAIZE).

Data Availability The dataset is available as a separate Stata file.

Compliance with ethical standards

Conflicts of interest/Competing interests The authors hereby declare that they have no conflict of interest.

Code Availability Not applicable.

References

- Allison, P. D. (2005). Fixed Effects Regression Methods for Longitudinal Data Using SAS. Cary, NC: The SAS Institute.
- Ariga, J., & Jayne, T, S. (2009). Private Sector Responses to Public Investments and Policy Reforms The Case of Fertiliser and Maize Market Development in Kenya. IFPRI discussion papers (Vol. 00921).
- Ariga, J., & Jayne, T. S. (2011). Fertiliser in Kenya: Factors Driving the Increase in Usage by Smallholder Farmers. In P. Chuhan-Pole & M. Angwafo (Eds.), Yes Africa Can: Success Stories from a Dynamic Continent (pp. 269–288). Washington, DC: World Bank.
- Berazneva, J., McBride, L., Sheahan, M., & Güereña, D. (2018). Empirical assessment of subjective and objective soil fertility metrics in east Africa: Implications for researchers and policy makers. World Development, 105, 367–382.
- Binswanger-Mkhize, H. P., & Savastano, S. (2017). Agricultural intensification: the status in six African countries. Food Policy, 67, 26–40.
- Bumb, B. L., & Gregory, D. I. (2006). Factors affecting supply for fertiliser in Sub-Saharan Africa Agriculture and Rural Development Discussion Paper (Vol. 24, pp. 1-81). Washington, DC: World Bank.
- CBS (2001). 1999 Population and Housing Census. Volume 1. Population Distribution by Administrative Areas and Urban Nairobi, Kenya: Central Bureau of Statistics (CBS), Ministry of Planning and National Development.
- Coates, J., Swindale, A., & Bilinsky, P. (2007). Household Food Insecurity Access Scale (HFIAS) for Measurement of Food Access: Indicator Guide. Food and Nutrition Technical Assistance III Project (FANTA), 3, 1–34.
- De Groote, H., Owuor, G., Doss, C., Ouma, J., Muhammad, L., & Danda, K. (2005). The Maize Green Revolution in Kenya Revisited. Electronic Journal of Agricultural and Development Economics (eJADE), 2(1), 32–49.
- De Groote, H., Narrod, C., Kimenju, S., Bett, C., Scott, R., & Tiongco, M. (2016). Measuring rural consumers' willingness to pay for quality labels using experimental auctions: the case of aflatoxin free maize in Kenya. Agricultural Economics, 47(1), 33–45. [https://doi.org/10.](https://doi.org/10.1111/agec.12207/) [1111/agec.12207/.](https://doi.org/10.1111/agec.12207/)
- De Groote, H., Marangu, C., & Gitonga, Z. M. (2018). Trends in Agricultural Mechanization in Kenya's Maize Production Areas from 1992-2012. Agricultural Mechanization in Asia, Africa and Latin America, 49(4), 20.
- De Groote, H., Kimenju, S, C., Munyua, B., Palmas, S., Kassie, M., & Bruce, A. (2020). Spread and impact of fall armyworm (Spodoptera frugiperda J.E. Smith) in maize production areas of Kenya. Agriculture, Ecosystems & Environment, 292, doi:[https://doi.org/](https://doi.org/10.1016/j.agee.2019.106804) [10.1016/j.agee.2019.106804.](https://doi.org/10.1016/j.agee.2019.106804)
- Duflo, E., Kremer, M., & Robinson, J. (2007). Why are Farmers Not Using Fertiliser: Fertiliser in Western Kenya, Preliminary Results from Field Experiments. Mimeo. Boston: MIT.
- Duflo, E., Kremer, M., & Robinson, J. (2008). How High Are Rates of Return to Fertiliser? Evidence from Field Experiments in Kenya. American Economic Review, 98(2), 482–488. [https://doi.org/10.](https://doi.org/10.1257/aer.98.2.482) [1257/aer.98.2.482](https://doi.org/10.1257/aer.98.2.482).
- FAO (2009). The state of food insecurity in the world 2009. Food and Agriculture Organization, United Nations, International Fund for Agricultural Development, and World Food Programme, Rome
- FAO (2014). The state of food insecurity in the world 2014. Food and Agriculture Organization, United Nations, International Fund for Agricultural Development, and World Food Programme, Rome
- FAO (2019). FAOSTAT Crops. In Food and Agricultutal Organisation of the United Nations (Ed.). Rome
- FAOSTAT (2020a). FAOSTAT Food Supply Crops Primary Equivalent, [http://www.fao.org/faostat/en/#data/CC,](http://www.fao.org/faostat/en/#data/CC) accessed on June 9, 2020.
- FAOSTAT (2020b). FAOSTAT Production Data Base. URL: [http://](http://faostat.fao.org/site/339/default.aspx) [faostat.fao.org/site/339/default.aspx,](http://faostat.fao.org/site/339/default.aspx) accessed on June 9, 2020.
- Godfray, H. C. J., Beddington, J. R., Crute, I. R., Haddad, L., Lawrence, D., Muir, J. F., Pretty, J., Robinson, S., Thomas, S. M., & Toulmin, C. (2010). Food security: the challenge of feeding 9 billion people. Science, 327(5967), 812–818.
- Greene, W, H. (2012). Econometric Analysis, 7th Edition (6th Edition ed.). Boston, MA: Prentice Hall.
- Gregory, P. J., & George, T. S. (2011). Feeding nine billion: the challenge to sustainable crop production. Journal of Experimental Botany, 62(15), 5233–5239. [https://doi.org/10.1093/jxb/err232.](https://doi.org/10.1093/jxb/err232)
- Hassan, R. (1998). Maize Technology Development and Transfer: A GIS Application for Research in Planning in Kenya. Oxon, UK Mexico Nairobi, Kenya: Centre for Agricultural Bioscience International (CABI) International Maize and Wheat Improvement Center (CIMMYT) KARI.
- Hassan, R, M., Lynam, J., & Okoth, P. (1998). Maize Technology Development and Transfer. A GIS Application for Research Planning in Kenya. Oxon: CAB International.
- Henao, J., & Baanante, C. A. (1999). Nutrient depletion in the agricultural soils of Africa. In 2020 Brief 62. Washinton DC: International Food Policy Research Institute (IFPRI).
- IFDC (2007). Africa Fertiliser Summit proceedings: June 9–13, 2006, Abuja, Nigeria. Alabama, USA International Fertiliser Development Center (IFDC).
- Jaleta, M., Kassie, M., Tesfaye, K., Teklewold, T., Jena, P. R., Marenya, P., & Erenstein, O. (2016). Resource saving and productivity enhancing impacts of crop management innovation packages in Ethiopia. Agricultural Economics, 47(5), 513–522. [https://doi.org/](https://doi.org/10.1111/agec.12251) [10.1111/agec.12251.](https://doi.org/10.1111/agec.12251)
- Jayne, T, S., Yamano, T., Nyoro, J, K., & Awour, T. (2001). Do Farmers Really Benefit from High Food Prices? Balancing Rural Interests in Kenya's Maize Pricing and Marketing Policy. Working Papers 202678 (pp. 1-6): Egerton University, Tegemeo Institute of Agricultural Policy and Development.
- Jena, P. R. (2019). Can minimum tillage enhance productivity? Evidence from smallholder farmers in Kenya. Journal of Cleaner Production, 218, 465–475. <https://doi.org/10.1016/j.jclepro.2019.01.278>.
- Jena, P, R., & Odendo, M. (2014). Assessment of the maize situation, outlook and investment opportunities in Eastern and Southern Africa (Regional Synthesis -Regional Assessment Eastern and Southern Africa). Nairobi: International Maize and Wheat Improvement Center.
- Jena, P. R., Stellmacher, T., & Grote, U. (2017). Can coffee certification schemes increase incomes of smallholder farmers? Evidence from Jinotega, Nicaragua. Environment, Development and Sustainability, 19(1), 45–66. [https://doi.org/10.1007/s10668-015-9732-0.](https://doi.org/10.1007/s10668-015-9732-0)
- Kassie, M., Teklewold, H., Marenya, P., Jaleta, M., & Erenstein, O. (2015). Production Risks and Food Security under Alternative Technology Choices in Malawi: Application of a Multinomial Endogenous Switching Regression. Journal of Agricultural Economics, 66(3), 640–659. [https://doi.org/10.1111/1477-9552.](https://doi.org/10.1111/1477-9552.12099) [12099.](https://doi.org/10.1111/1477-9552.12099)
- Kenya Agricultural Research Institute (1995). Fertiliser Use Recommendations Volume 15 Kericho District Fertiliser Use Recommendation Project (FURP) (pp. 1–20): Kenya Agricultural Research Institute (KARI).
- Kibunja, C. N., Ndungu-Magiroi, K. W., Wamae, D. K., Mwangi, T. J., Nafuma, L., Koech, M. N., et al. (2017). Optimizing Fertiliser Use within the Context of Integrated Soil Fertility Management in Kenya. In C. S. Wortmann & K. Sones (Eds.), Fertiliser use optimization in sub-Saharan Africa (pp. 82-99). Wallingford, UK: CABI.
- Kleemann, L., Abdulai, A., & Buss, M. (2014). Certification and Access to Export Markets: Adoption and Return on Investment of Organic-Certified Pineapple Farming in Ghana. World Development, 64, 79– 92. <https://doi.org/10.1016/j.worlddev.2014.05.005>.
- Lokshin, M., & Sajaia, Z. (2004). Maximum likelihood estimation of endogenous switching regression models. The Stata Journal, 4(3), 282–289.
- Maddala, G. S. (1983). Limited-dependent and qualitative variables in econometrics. New York: Cambridge University Press.
- Makau, J. M., Irungu, P., Nyikal, R. A., & Kirimi, L. W. (2016). An assessment of the effect of a national fertiliser subsidy programme on farmer participation in private fertiliser markets in the North Rift region of Kenya. African Journal of Agricultural and Resource Economics, 11(4), 292–304. [https://doi.org/10.22004/ag.econ.](https://doi.org/10.22004/ag.econ.252459) [252459.](https://doi.org/10.22004/ag.econ.252459)
- Mather, D. L., & Jayne, T. S. (2018). Fertiliser subsidies and the role of targeting in crowding out: evidence from Kenya. Food Security, 10(2), 397–417.
- Matsumoto, T., & Yamano, T. (2009). Soil Fertility, Fertiliser, and the Maize Green Revolution in East Africa. [Journal Article]. Policy Research Working Paper. World Bank, Washington, DC.(5158), 1-34, doi[:https://doi.org/10.1596/1813-9450-5158.](https://doi.org/10.1596/1813-9450-5158)
- Morris, M., Kelly, V. A., Kopicki, R. J., & Byerlee, D. R. (2007). Fertiliser use in African agriculture: Lessons learned and good practice guidelines (Directions in development). Washington, DC: World Bank.
- Olwande, J., Sikei, G., & Mathenge, M. (2009). Agricultural technology adoption: A panel analysis of smallholder farmers' fertiliser use in Kenya. . CEGA Working Paper Series No. AfD0908.
- Schnier, H. F., Recke, H., Muchena, F. N., & Muriuki, A. W. (1996). Towards a practical approach to fertiliser recommendations for food crop production in smallholder farms in Kenya. Nutrient Cycling in

 \mathcal{D} Springer

Dr. Pradyot Ranjan Jena currently works at National Institute of Technology Karnataka, Surathkal. Dr. Jena's core research area of expertise are impact evaluation, environmental impact valuation and climate change. He has worked across continents and have experience about rural livelihoods in many developing coun-

tries

Agroecosystems, 47(3), 213–226. [https://doi.org/10.1007/](https://doi.org/10.1007/BF01986276) [BF01986276](https://doi.org/10.1007/BF01986276).

- Sheahan, M., Black, R., & Jayne, T. S. (2013). Are Kenyan farmers under-utilizing fertiliser? Implications for input intensification strategies and research. Food Policy, 41, 39–52. [https://doi.org/10.1016/](https://doi.org/10.1016/j.foodpol.2013.04.008) [j.foodpol.2013.04.008.](https://doi.org/10.1016/j.foodpol.2013.04.008)
- Smaling, E. M. A., Nandwa, S. M., Prestele, H., Roetter, R., & Muchena, F. N. (1992). Yield response of maize to fertilisers and manure under different agroecological conditions in Kenya. Agriculture, Ecosystems & Environment, $41(3-4)$, $241-252$. [https://doi.org/10.](https://doi.org/10.1016/0167-8809(92)90113-P) [1016/0167-8809\(92\)90113-P.](https://doi.org/10.1016/0167-8809(92)90113-P)
- Takeshima, H., & Lee, H, L. (2012). Agricultural Inputs Subsidy and Their Developmental Impact: Conventional Wisdom. MozSSP Policy Note 1. Washington, D.C.: IFPRI Policy Note 1, October 2012. Washington DC, IFPRI. Tsulostettu 25.11 ….
- Teklewold, H., Kassie, M., Shiferaw, B., & Köhlin, G. (2013). Cropping system diversification, conservation tillage and modern seed adoption in Ethiopia: Impacts on household income, agrochemical use and demand for labor. Ecological Economics, 93, 85–93. [https://doi.](https://doi.org/10.1016/j.ecolecon.2013.05.002) [org/10.1016/j.ecolecon.2013.05.002.](https://doi.org/10.1016/j.ecolecon.2013.05.002)
- Tilman, D., Cassman, K. G., Matson, P. A., Naylor, R., & Polasky, S. (2002). Agricultural sustainability and intensive production practices. Nature, 418(6898), 671–677.
- Tully, K. L., Hickman, J., McKenna, M., Neill, C., & Palm, C. A. (2016). Effects of fertiliser on inorganic soil N in East Africa maize systems: vertical distributions and temporal dynamics. Ecological Applications, 26(6), 1907–1919. <https://doi.org/10.1890/15-1518.1>.
- Vanlauwe, B., & Giller, K. E. (2006). Popular myths around soil fertility management in sub-Saharan Africa. Agriculture, Ecosystems & Environment, 116(1–2), 34–46.
- Vanlauwe, B., AbdelGadir, A., Adewopo, J., Adjei-Nsiah, S., Ampadu-Boakye, T., Asare, R., et al. (2017). Looking back and moving forward: 50 years of soil and soil fertility management research in sub-Saharan Africa. International Journal of Agricultural Sustainability, 15(6), 613–631.
- Wainaina, P., Tongruksawattana, S., & Qaim, M. (2016). Tradeoffs and complementarities in the adoption of improved seeds, fertiliser, and natural resource management technologies in Kenya. Agricultural Economics, 47(3), 351–362. <https://doi.org/10.1111/agec.12235>.
- Waithaka, M. M., Thornton, P. K., Shepherd, K. D., & Ndiwa, N. N. (2007). Factors affecting the use of fertilisers and manure by smallholders: the case of Vihiga, western Kenya. Nutrient Cycling in Agroecosystems, 78(3), 211–224. [https://doi.org/10.1007/s10705-](https://doi.org/10.1007/s10705-006-9087-x) [006-9087-x](https://doi.org/10.1007/s10705-006-9087-x).
- Wangia, C., Wangia, S., & De Groote, H. (2004). Review of maize marketing in Kenya: Implementation and impact of liberalisation, 1989-1999. In D. K. Friesen & A. F. E. Palmer (Eds.), Integrated Approaches to Higher Maize Productivity in the New Millennium. Proceedings of the 7th Eastern and Southern Africa Regional Maize Conference Nairobi, Kenya, February 2002 (pp. 10–20). Mexico, D. F: CIMMYT.
- Wooldridge, J. M. (2002). Econometric Analysis of Cross Section and Panel Data. Cambridge, MA: MIT Press.

products, policy analysis, and impact analysis of new technologies for welfare and health. Previous, he was coordinator of the biological control project at the International Institute for Tropical Agriculture (IITA), in Benin, conducting economic analysis and participatory evaluation of biological control of pests such as water hyacinth, locusts and mango mealybug. He also worked in Farming Systems Research with the Royal Tropical Institute (KIT), developing and evaluating new technologies, and evaluated group-based credit and loan associations with the International Food Policy Research Institute (IFPRI), both in Mali. Before this research, he worked as an agriculturalist in rural development for Non-Governmental Organizations in Togo and Thailand.

Bibhu P. Nayak is an Associate Professor at School of Livelihoods and Development, Tata Institute of Social Science (TISS), Hyderabad Campus. He is an economist by training and has been working on environmental and resource governance issues. He teaches courses like Ecological Economics, Theories of Economic Development and other courses linking institutions, environment and development. Prior to TISS, he worked for The Energy and Resources Institute

(TERI), New Delhi and Institute for Social and Economic Change (ISEC), Bengaluru in India.

Annina Hittmeyer completed a BSc degree in economics at Heidelberg University after which she pursued an MSc degree in development economics at the University of Göttingen and the Javeriana University. Currently, she is a visiting researcher at the International Maize in Wheat Improvement Centre in Nairobi, Kenya. There she focuses on panel data methods, including pseudo-panels, to model fertilizer use and adoption trends. She has worked within a range of disci-

plines, including the monitoring of water, carbon and nutrient budgets of forest ecosystems at the Leibniz Centre for Agricultural Landscape Research and the intra-household allocation of micro-health insurance in Burkina Faso at Heidelberg University.