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Does smallholder maize intensification reduce deforestation? Evidence from Zambia

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ABSTRACT

Increasing food production to meet growing demand while reducing tropical deforestation is a critical sustainability challenge. This is especially true in sub-Saharan Africa, which faces serious food insecurity issues and where smallholder farming is the main driver of forest conversion. Competing theories imply opposite predictions as to whether deforestation increases or decreases with smallholder agricultural intensification, which can improve food security by increasing crop yields per area cultivated. This research provides new empirical evidence on the association between deforestation and smallholders' use of modern inputs, in particular inorganic fertilizer on maize and improved maize seeds, using Zambia as a case study. We analyze this association nationwide in a spatially disaggregated manner at the lowest administrative level using machine learning-based small area estimation, which makes use of detailed nationally representative surveys on smallholder farm households for 2011 and 2014, and census data to statistically predict modern inputs use country-wide for 2011, when average maize yields were 1.28 tons/ha. Then, we evaluate the association between improved maize seed and fertilizer inputs and subsequent deforestation, while controlling for key geospatial covariates. The results support the land-sparing hypothesis, finding that smallholder farmers' use of improved maize seed is negatively associated with deforestation on non-acidic (pH $\geq$ 5.5) soils, an effect that is enhanced by complementary inorganic fertilizer use. Fertilizer use on its own, however, is weakly associated with increased deforestation. Sustainable intensification via use of improved seeds on adequately fertile soils and improving soil health appears compatible with reducing both deforestation and food insecurity.

1. Introduction

Increasing food production to meet growing demand while reducing deforestation is one of the greatest current sustainability challenges (United Nations, 2015). Increasing food production will be required to satisfy rising food demand, which is expected to roughly double by 2050 due to population and income growth (Balmford et al., 2005; Foley et al., 2011). The situation is especially daunting in sub-Saharan Africa (SSA), whose population will increase 2.5-fold and cereal demand will triple by 2050 (van Ittersum et al., 2016).

Agricultural expansion to enable increased food production is the main driver of deforestation globally, responsible for 83% of forest cover loss across the tropics between 1980 and 2000 (Gibbs et al., 2010) and 51% from 2001 to 2015 (Curtis et al., 2018). For this latter time period, 92% of forest cover loss in Africa is attributable to expansion of smallholder farming (Curtis et al., 2018). By 2060, an additional 430 million hectares (compared to 2010) is predicted to be cleared in SSA to meet the land demand for agriculture, with accrued species extinction risks (Tilman et al., 2017). Limiting agricultural expansion into forested lands is therefore crucial for reducing deforestation and the resulting greenhouse gas emissions from this source.

Considerable research has sought to identify the best ways to reconcile the joint need to produce more food and to abate deforestation (Angelsen and Kaimowitz, 2001; Balmford et al., 2005; Byerlee et al., 2014; Green and Cornell, 2005; Matson and Vitousek, 2006; Ngoma and Angelsen, 2018; Phalan et al., 2014, 2016; Villoria et al., 2014; Waggoner and Ausubel, 2001). Agricultural intensification – that is, increasing yields per unit area of production through increased application of non-land inputs, in particular modern inputs such as improved seeds, fertilizers, irrigation, machinery, etc. – can boost food production. Many factors can influence how higher yields may affect deforestation, including market access and integration, production goals

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(utility versus profit maximization), and land rights (Angelsen, 1999, 2010). Indeed, competing theories exist about the effect of agricultural intensification on deforestation. On the one hand, the Borlaug or land-sparing hypothesis predicts that as per-hectare agricultural productivity increases, crop prices will decline, reducing farmers' demand for more cropland (Borlaug, 2007; Phalan et al., 2011; Tscharntke et al., 2012). This outcome depends on producers facing price inelastic demand for food, which is more likely true in more remote, landlocked locations and less likely true in regions well-connected to national and global markets. A competing theory, related to the Jevons Paradox, suggests that any strategy that makes agriculture more profitable, e.g., by raising income or subsidizing input costs, including through agricultural intensification, will incentivize deforestation (Alcott, 2005; Angelsen, 2010; Byerlee et al., 2014; Villoria et al., 2014). Thus, the relationship between agricultural intensification and deforestation is fundamentally an empirical question.

This research presents new empirical evidence on the relationship between deforestation and agricultural intensification, in particular for smallholder maize intensification through increased use of improved seeds and inorganic fertilizers. Smallholder farming is a cornerstone of food security in many countries, including in SSA (Samberg et al., 2016). Yet, deforestation for smallholder agriculture is accelerating in several tropical regions (Seymour and Harris, 2019), enhancing the need to resolve the empirical relationship between smallholder agricultural intensification and deforestation.

In policy terms, if agricultural intensification is associated with reduced forest cover loss, support for smallholder farmers to intensify agricultural production could be a win–win strategy for food security and forest conservation. And if specific components of agricultural intensification strategies – e.g., diffusion of improved seeds, promotion of inorganic fertilizer uptake, or both – are differentially associated with deforestation, then that might inform the design of agricultural intensification policies. If, by contrast, intensification and deforestation co-vary positively, then policies to promote increased agricultural productivity may need companion policies to protect forested ecosystems from induced expansion of the agricultural frontier. In this paper, we consider a 'passive' land-sparing approach (Phalan et al., 2016), that is, where agricultural intensification is not made conditional on or limited by forest conservation policies to constrain farmland expansion.

Previous research at the country or regional level found contrasting results. Some studies found no relationship between crop yields and cultivated area (Ewers et al., 2009; Rudel et al., 2009), while another study using a model of global agricultural land use with the same historical records but with a counterfactual, supported a land-sparing effect at regional level (Hertel et al., 2014). Other model-based simulations found that the large-scale adoption of higher-yielding cereal crop germplasm likely spared 18 to 27 million hectares of natural ecosystems, including forests, from agricultural expansion (Stevenson et al., 2013). Recent work using country-level crop yield and income data from 1960 to 2010 for 83 developing countries and the release date of higher-yielding crop varieties in these countries, showed that increasing agricultural productivity reduced the amount of land devoted to agriculture (Gollin et al., 2019). Those findings, however, came from analyses of coarse country-level statistics, ignoring subnational variation and with the possibility that confounding factors affected the relationship between agricultural intensification and deforestation. They also make no distinction between smallholder and large-scale producers. Nor do most tie outcomes to specific policies or mechanisms (e.g., inputs that lead to intensification). It therefore remains largely unclear as to what, if any, agricultural intensification strategy – fertilizer subsidies? Improved seed distribution systems? Both? – is most consistent with the joint pursuit of food security and forest conservation goals.

We study the relationship between agricultural intensification among smallholder farmers and deforestation. Smallholders, who are often labor constrained (Dillon et al., 2019), may be more likely to respond to productivity increases by reducing forest conversion, especially if households' main objective is to first produce enough food to eat and then sell any surplus, that is, utility not profit maximization (Angelsen, 1999). In the absence of soil nutrient amendments or other soil management practices to maintain soil fertility, smallholder farmers generally expand cultivation into forestland because of soil productivity declines that occur after a few years under continuous cultivation. With a long enough fallow period, soil nutrients can recover. But with expanding populations, fallow periods have shortened, rarely allowing soil fertility recovery. The increased use of modern inputs such as inorganic fertilizer and improved seeds can help increase – and sustain the increased – productivity of cultivated land. Previous studies have shown, however, that low soil fertility, including low pH and low soil organic carbon, can reduce yield response of maize to fertilizers among African smallholders (Burke et al., 2017; Marenya and Barrett, 2009, a, b). Among other mechanisms, low soil pH reduces the availability of phosphorus for plant use in soil, which affects plant growth.

We focus on Zambia as a case study, where maize is the main staple crop cultivated by about 90% of smallholder farm households and has been the object of a national subsidy program for fertilizer and improved seed inputs to support agricultural intensification. A previous study showed the positive relationship between the use of these modern inputs and maize yields for Zambia (Burke et al., 2017). Ideally, we could have used an exogenous factor, including possible variation in the input subsidy program implementation or specific program criteria to identify the causal relationship between input use and deforestation, but none could be credibly employed due to weak compliance with formal allocation rules.

Instead, we employ an innovative research method. We make use of two rounds of detailed, nationally representative panel survey data on smallholder farm households to predict modern input use at the ward level, then use national census data and small area estimation (SAE) methods to generate complete nationwide estimates for the agricultural year 2010/2011. SAE is a statistical technique that allows one to map precise parameter estimates derived from a rich random-sample survey into census data covering the entire population (Rao, 2003). This approach is widely used to generate nationwide, spatially disaggregated poverty estimates. We then use multivariate regression to relate the predicted modern input use for all wards, the lowest administrative level in Zambia, and remotely sensed forest cover loss data, while controlling for key confounding factors. The benefit of using highly spatially disaggregated data is to better account for the spatial variability of input use by smallholder farmers intensifying their production. As best as we can tell, this is the first study to use more precise household-level data on input use to generate nationwide estimates of the intensification-deforestation relationship.

Prior research on Malawi showed that the country's agricultural input subsidy program contributed to reduced deforestation, relying either on self-reported deforestation area (Chibwana et al., 2013) or district-level statistics (Abman and Carney, 2018). This study further advances knowledge on this topic with national coverage of more fine-scale spatial data and a case study that is more representative of the SSA context in terms of country size, population density, forest cover and loss.[1]

To the best of our knowledge, this is also the first study to address the association between deforestation and both inorganic fertilizer and improved maize seed use as specific, disaggregated strategies to increase agricultural productivity. Previous studies did not specify the yield-increasing intervention or focused on either inorganic fertilizers or improved seeds, but not both. Since the two are commonly used

[1] Malawi is a small country with low forest cover, covering less than 11.5% of the total land area in 2018 (https://www.globalforestwatch.org/country/MWI), unusually high historical deforestation rates, and especially high population density.

together, estimates that focus only on one or the other are vulnerable to omitted relevant variables bias.

2. Materials and methods

2.1. Study area

Zambia is a landlocked, lower-middle income country in southern Africa covering 752,000 km^2. Its economy relies on agriculture and mining, and rural poverty is widespread. Small-scale farming is the primary source of income in rural Zambia and the agricultural sector employs 72 percent of the work force (USAID, 2019). Maize is the dominant staple crop cultivated and consumed in Zambia. In 2011–2012, "smallholder farm households (defined in Zambia as households cultivating less than 20 ha of land) accounted for 99% of the farms, 94% of total cropped area, 98% of area planted in maize, 95% of maize production, 75% of total fertilizer use, and 93% of the fertilizer used on maize" (Mason et al., 2013, p. 614). The traditional mode of land acquisition and expansion is through the customary system (Sitko and Jayne, 2014). At the local level, traditional authorities (village headmen) allocate the land and give authorization for clearing forest for agriculture purposes, while nationally the Forest Act 2015 regulates forest use on customary land and state land. While in official statistics, about 94% of Zambia's land is under the customary system of land administration, it is estimated that, in practice, 51–54% of the land is under customary tenure and remains available for smallholder production (Sitko and Chamberlin, 2016). The rest of the land is under protected areas (about 36%), or other state and private lands.

The Ministry of Agriculture supports smallholder farmers with an agricultural input subsidy program that represented 32.5% of its annual budget for 2016 (Chapoto and Chisanga, 2016). The Farmer Input Support Program (FISP), previously the Fertilizer Support Program (FSP), has been in place for more than a decade. Both FSP and FISP have faced a range of implementation issues, including late delivery to farmers, diversion of inputs from intended beneficiaries, elite capture, low cost-effectiveness, deterring crop diversification and failure to crowd in private sector investments in input supply chains (Mason et al., 2013). In the 2015/2016 season, the Ministry of Agriculture launched a pilot program to shift FISP delivery to a flexible e-voucher, a pre-paid card redeemable at participating registered agro-dealers, in order to resolve some of the implementation issues. The period of analysis for this study covers years prior to the introduction of the FISP e-voucher.

The Ministry of Agriculture also provides farmers with input application rate recommendations. For one hectare of maize, it recommends 20 kg of hybrid or improved open-pollinated variety (IOPV) maize seeds, which we call here improved maize seeds, as well as four 50 kg bags of Compound D (basal) fertilizer (10:20:10 Nitrogen, Phosphorus, Potassium (NPK)) and four 50 kg bags of Urea (top dressing) fertilizer (46% N) for a total of 400 kg/ha of inorganic fertilizer, which is expected to yield about 3 tons of maize (Ministry of Agriculture and Cooperatives, 2007; World Bank, 2010). Improved maize seeds and fertilizers were provided in these relative proportions to FSP and FISP beneficiaries prior to the introduction of the e-voucher.[2]

Zambia has about 44 million hectares of forests, dominated by Miombo woodlands, covering 65.8% of the land area compared to 31.9% for agriculture lands in 2013 (The World Bank, 2017). Between 2000 and 2012, Zambia lost an estimated 1,316,300 ha of forest cover (Hansen et al., 2013), and deforestation has been increasing according to a recent national study (ILUA II, 2016). The foremost driver of deforestation in the country is agricultural expansion, followed by wood energy and mining (Republic of Zambia, 2016; Vinya et al., 2011).

In the context of climate change, Zambia is one of the fourteen pilot countries to receive financial support for Reducing Emissions from Deforestation and forest Degradation in developing countries (REDD+) by the United Nations (UN-REDD) to elaborate a national forest monitoring system, a forest reference emissions level, and a national REDD+ strategy. One of the objectives of the Zambia REDD+ strategy is to adopt "good agricultural practices that mitigate greenhouse gas emissions by 2030" (Matakala et al., 2015). Linking sustainable agricultural intensification with efforts to reduce deforestation nationally makes sense as agricultural expansion is the main driver of forest cover loss (Fisher et al., 2011). However, the empirical evidence base remains thin to guide policy on options that may help to reduce deforestation driven by agricultural expansion. One goal of this study is to bolster that evidence base.

2.2. Study design

One innovation of this research is the use of machine learning-based small area estimation (SAE) (Rao, 2003) to predict modern agricultural inputs use from detailed nationally representative survey data, in particular the intensity of household fertilizer use on maize and use of improved maize seed (each in kg/ha). Such data are not available in nationwide census data anywhere in the world. Nationally representative household survey data represent random samples of households, not of land area. Therefore, statistical analysis of the relationship between reported use of modern agricultural inputs in household survey data matched to forest cover loss data cannot provide a statistically representative estimate of the nationwide, area-based relationship between agricultural intensification and deforestation. To do so, we mapped the survey data to the census data to reflect the entirety of the country, in both human and physical geographic terms, using SAE. By expanding the data available beyond just the enumeration areas sampled in the household survey, SAE substantially increases degrees of freedom, enabling more precise estimation of the parameters of interest.

To implement the small area estimation statistical approach, we relied on the 2010 Census of Population and Housing and on two rounds of a detailed, nationally-representative agricultural households panel survey – the Rural Agricultural Livelihoods Survey (RALS) – from 2012 and 2015, covering the 2010/2011 and 2013/2014 agricultural seasons, respectively, and which provides, *inter alia*, data on inorganic fertilizer on maize and improved maize seeds application rates by smallholder farm households.

The RALS surveys provide self-reported data on input use by farming households, which is of central importance to this analysis. For improved maize seeds, we use responses to the following question, which appeared on both the 2012 and 2015 RALS, and was asked for each plot: "What main seed variety did the household use for the first planting?" Of the more than 130 maize varieties mentioned by farmers, we recoded as 'improved maize seeds' all varieties of first-generation hybrids (i.e., recycled hybrids were excluded) and IOPVs. Farmers may misreport seed varieties (and other variables), generating measurement error (e.g., Wossen et al., (2019) focusing on cassava varieties in Nigeria, and Wineman et al., (2020) focusing on maize varieties in Tanzania). Our use of ward-level aggregates should ameliorate any such classical measurement error. Any remaining classical measurement error would generate attenuation bias in our parameter estimates, thus our statistically significant results are, if anything, conservative estimates.

We obtained the 2010 Census data at the ward level, the lowest administrative unit in Zambia. We identified variables common to both the 2010 Census and the 2012/2015 RALS that could be used to predict inorganic fertilizer on maize and improved maize seeds application rates. We calculated sample-weighted averages at the ward level from the RALS data, which provides information on modern input use per

[2] FSP beneficiaries received inputs for one hectare of maize while FISP beneficiaries received inputs (in the same relative proportions) for 0.5 ha of maize.

household, as well as 58 other household and farming practice covariates that matched variables also available in the 2010 Census data. Following model comparison, we used a random forest machine learning algorithm, employing k-fold repeated cross-validation for model selection and for assessing the model's performance on training (80%) and test (20%) data based on the RALS pooled cross-sectional data. We built two separate predictive models based on the RALS data – one for each of the two modern agricultural inputs (improved maize seeds and inorganic fertilizer) and their predictors in the sampled wards. Then, applying these predictive models built on RALS survey data, we predicted the improved maize seeds and inorganic fertilizer application rates (in kg/ha) for all wards in the country by using the matching covariates from the 2010 Census data. The model evaluation comparing predicted values to the test data was done with the root-mean-square error (RMSE), R-squared (R^2) and the mean absolute error (MAE), for both inorganic fertilizer (RMSE = 16.9 kg/ha; R^2 = 0.51; MAE = 10.6 kg/ha) and improved maize seed (RMSE = 0.78 kg/ha; R^2 = 0.52; MAE = 0.47 kg/ha).

2.3. Statistical analysis

We built different multivariate regression models to look at the association between modern agricultural inputs and deforestation, using remotely-sensed forest cover loss data as the dependent variable (Hansen et al., 2013), while controlling for different geospatial covariates. These include forest cover in 2010, soil characteristics, climate variables, distance to roads and settlements, population as well as elevation, which are known variables that influence agricultural expansion into forestlands. We also looked at the association between modern agricultural inputs and deforestation by using the ratio of forest cover loss to the remaining forest cover in 2010 per ward as the dependent variable, hereafter the 'relative rate of forest cover loss'. We implemented the regressions in two main ways. First, we built models focusing on the sampled wards using the data from the two household survey rounds alone, which allowed us to control for year fixed effects (2011 and 2014) and ward fixed effects. Identification of the association between input use and forest cover loss thereby comes from differences in within-ward variation across years, effectively controlling for time invariant confounders such as location, parent soil material, spatial autocorrelation, etc. Second, we developed models for all wards by using the SAE predicted agricultural input values for the year 2011 to represent the entire country, not just a non-representative sample of the land mass. We do so because the sampling for RALS surveys is based on human populations and not on land mass. In these models, we also included the two-way interactions between fertilizer use, improved maize seed use, and mean soil pH. Eq. (1) presents the full regression model for all the wards in the country.

$$\mathrm{L}_w = \beta_0 + \beta_1 \mathrm{F}_w + \beta_2 \mathrm{F}_w^2 + \beta_3 \mathrm{I}_w + \beta_4 \mathrm{I}_w^2 + \beta_5 \mathrm{P}_w + \beta_6 P_w^2 + \beta_7 \mathrm{F}_w * \mathrm{I}_w + \beta_8 \mathrm{F}_w * \mathrm{P}_w + \beta_9 \mathrm{I}_w * \mathrm{P}_w + \beta_{10} \mathbf{X}_w + \beta_{11} \mathbf{Province} + \epsilon_w \tag{1}$$

L: forest cover loss in ward *w*.
F: inorganic fertilizer on maize application intensity (kg/ha) per ward.
I: improved maize seeds application intensity (kg/ha) per ward.
P: average soil pH per ward.
X: Other geospatial covariates at the ward level (including tree cover loss in 2010, mean soil CEC, mean soil organic carbon, mean distance to roads, and mean elevation)
Province: A vector of provincial dummy variables.

Furthermore, we split the data set based on a pH threshold (< 5.5 and ≥5.5), identified in previous studies to affect maize growth (Burke et al., 2019, 2017; George et al., 2012), to look at the change in the relationship between modern agricultural inputs and forest cover loss across soil pH values. We also statistically confirmed a pH breakpoint using segmented regression analysis. Using the RALS survey data alone, we compare average maize yields between wards with pH < 5.5 and ≥5.5 using one-way analysis of variance with permutation test to confirm that maize productivity is significantly higher on non-acidic soils.

Finally, using our preferred regression models, we predicted forest cover loss under three different scenarios of modern agricultural input application rates: 1) no input; 2) the 2010/2011 agricultural season application rates; and 3) the government recommended application rates for both fertilizer and improved seeds. For illustrative purposes, we linked these scenarios to efforts to reduce emissions from deforestation. We converted the avoided deforestation of the second and third scenarios, using the 'no input' scenario as the benchmark, into emission reductions by using a conservative average forest carbon density of 25 tons of carbon per hectare; we then converted this to carbon dioxide equivalent (CO_2e). We estimated the hypothetical value of these emission reductions by using an average price for REDD+ emission reductions traded under the voluntary carbon market (Forest Trends' Ecosystem Marketplace, 2019). Additional information on the study area, data and methods, and complementary results are provided in Appendix.

3. Results

3.1. Relationship between modern agricultural input use and forest cover loss

Fig. 1 shows the national distribution of predicted use rates of agricultural inputs, via the SAE method, and forest cover loss at the ward level (See Figure S5 for maps of percent tree cover and rates of forest cover loss). We see considerable spatial heterogeneity both in the use of modern agricultural inputs and in deforestation patterns. This underscores the value of using subnational scale data to control for variation in underlying geographic characteristics that might confound estimates of the association between modern inputs and deforestation.

Overall, we find that modern agricultural inputs, through improved maize seeds and the interaction between improved maize seeds and inorganic fertilizer, is negatively and statistically significantly associated with deforestation on neutral soils. These results also hold when the relative rate of forest cover loss (i.e., the ratio of forest cover loss to the remaining forest cover in 2010 per ward) is the dependent variable instead of the area of forest cover loss. Our results show heterogeneous relationships between the two types of modern inputs (inorganic fertilizer and improved seeds) and forest cover loss, as well as spatial heterogeneity linked to soil characteristics. We present the forest cover loss area as our primary outcome variable of interest because we are more interested in the spatial extent of deforestation than in the proportional change in tree cover relative to ex-ante forest cover. The spatial extent of deforestation also gives a better sense of the extent of greenhouse gas emissions. The models using relative rates of forest cover loss also explain less variance than those for the area of forest cover loss, but the results are qualitatively very similar.

Using just the nationally representative household survey data aggregated to the ward level, the regression model, with ward and year fixed effects, identified a strong and statistically significant negative association between improved maize seed application rates (kg/ha) and forest cover loss (ha) for the targeted years (2011 and 2014), plus a weak and insignificant positive association with fertilizer use (Table 1, model 1). The interaction between improved maize seeds and fertilizer also shows a significant negative association with forest cover loss. These patterns are robust to the inclusion of geospatial covariates, with the 2010 tree cover and soil pH having a strong and significant association with forest cover loss, positive for tree cover and negative for pH (Table 1, model 2). These results are qualitatively similar to those from models with the relative rate of forest cover loss as the dependent

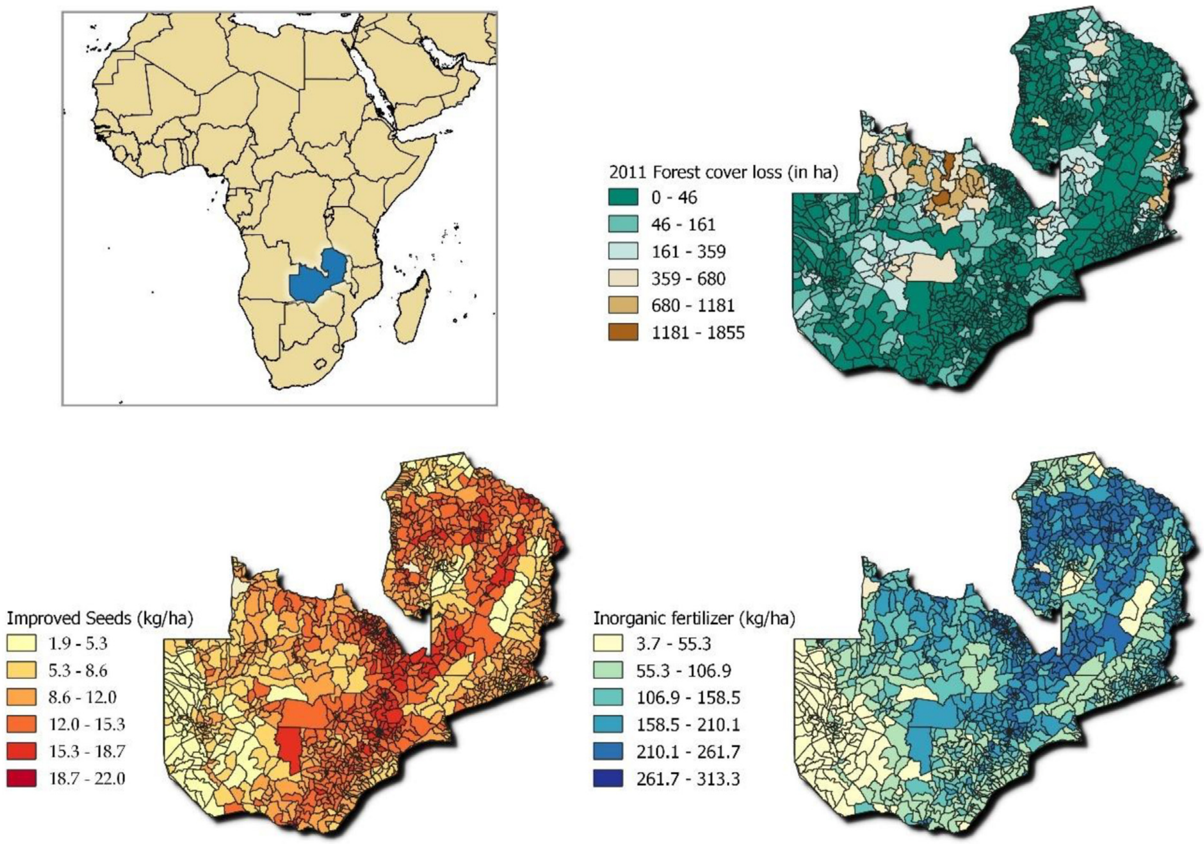

Fig. 1. Predicted application rates for improved maize seeds (lower left panel) and fertilizer on maize (in kg/ha) (lower right panel) for agricultural year 2010/2011 obtained via small area estimation procedure, as well as forest cover loss in hectares for year 2011 (top right panel).

variable, where improved maize seeds and the interaction between inorganic fertilizers and improved maize seeds have a significant negative association with the relative rate of forest cover loss (Appendix, Table S3). The relationship between inorganic fertilizer and the relative rate of forest cover loss is positive but not significant. For the surveyed wards, we were also able to include three wealth-related variables, of which farm size showed a positive and significant association with forest cover loss (Table 1, model 3). The core parameter estimates of interest remain unchanged by the inclusion or omission of these wealth-related variables.

The household survey data are representative of Zambia's smallholder farm household population but not of its land area. So, we use

Table 1
Forest cover loss (in log of hectares per ward) regressed on modern agricultural inputs application rates at the ward administrative level using data from the 2012 (n = 420 wards) and 2015 (n = 433) RALS survey, for agricultural seasons 2010/2011 and 2013/2014, respectively. In Model 1, we control for year and ward fixed effects and in Model 2 for year and province fixed effects as well as key geospatial covariates. Model 3 is similar to model 2 but adds three wealth-related variables (adult equivalents, asset value and farm size).

	Model 1		**Model 2**		**Model 3**	
Predictors	*Estimates*	*Std. Error*	*Estimates*	*Std. Error*	*Estimates*	*Std. Error*
Maize improved seeds (kg/ha)	−0.280 *	0.126	−0.162 *	0.074	−0.187 *	0.075
Fertilizer on maize (kg/ha)	0.011	0.036	0.013	0.018	0.013	0.018
Mean soil pH			−1.468 ***	0.318	−1.515 ***	0.318
Tree cover in 2010 (ha)			0.737 ***	0.052	0.713 ***	0.053
Mean soil carbon density (tons/ha)			−0.012 **	0.004	−0.011 **	0.004
Mean elevation (1,000 m)			1.121 **	0.348	0.878 *	0.357
Mean distance to roads (m)			−0.097	0.086	−0.099	0.087
Adult equivalent					−0.038	0.074
Asset value (ZMW)					0.086	0.057
Farm size (ha)					0.293 *	0.119
Improved seeds × fertilizer	−0.038 **	0.013	−0.024 ***	0.007	−0.024 ***	0.007
Fertilizer × soil pH			0.002	0.041	0.003	0.041
Improved seeds × soil pH			0.202	0.193	0.223	0.194
Ward fixed effect	Yes		No		No	
Province fixed effect	No		Yes		Yes	
Year fixed effect	Yes		Yes		Yes	
Observations	853		853		853	
R^2 / adjusted R^2	0.762 / 0.512		0.548/ 0.537		0.552/ 0.540	

* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$.

Table 2
Regression model using nation-wide ward-level (n = 1420) predicted fertilizer and improved maize seed application rates for the 2010/2011 agricultural season, with 2011 forest cover loss data as dependent variable (SE: standard error; AME: Average marginal effect).

Dependent variable = forest cover loss (ha/ward)				
Predictors	*Estimates*	*Std. Error*	*AME*	*Std. Error*
Maize improved seeds (kg/ha)	−0.920 ***	0.198	−0.909 ***	0.197
Fertilizer on maize (kg/ha)	0.105 *	0.043	0.107 *	0.043
Mean soil pH	−0.652 **	0.219	−0.694 **	0.216
Tree cover in 2010 (ha)	0.539 ***	0.033	0.539 ***	0.033
Mean soil carbon density (tons/ha)	−0.014 ***	0.002	−0.014 ***	0.002
Mean distance to roads (m)	−0.252 ***	0.045	−0.252 ***	0.045
Mean elevation (1,000 m)	1.148 ***	0.299	1.148 ***	0.299
Improved seeds × fertilizer	−0.029	0.018		
Fertilizer × soil pH	0.173	0.091		
Improved seeds × soil pH	−0.489	0.474		
Province fixed effect		Yes		
Observations		1420		
R^2 / adjusted R^2		0.553/0.547		

* p < 0.05 ** p < 0.01 *** p < 0.001.

Table 3
Regression model using nation-wide ward-level (n = 1420) predicted fertilizer and improved maize seed application rates for the 2010/2011 agricultural season, with 2011 the relative rates of forest cover loss, that is the ratio of forest cover loss to the remaining forest cover in 2010 per ward, as dependent variable (AME: Average marginal effect).

Dependent variable = rates of forest cover loss (ha/ha)				
Predictors	*Estimates*	*Std. Error*	*AME*	*Std. Error*
Maize improved seeds (kg/ha)	−0.050 **	0.016	−0.050 **	0.016
Fertilizer on maize (kg/ha)	0.004	0.004	0.004	0.004
Mean soil pH	−0.043 *	0.018	−0.045 *	0.018
Tree cover in 2010 (ha)	0.008 **	0.003	0.008 **	0.003
Mean soil carbon density (tons/ha)	−0.001 ***	0.000	−0.001 ***	0.000
Mean distance to roads (m)	0.005	0.004	0.005	0.004
Mean elevation (1,000 m)	0.090 ***	0.025	0.090 ***	0.025
Improved seeds × fertilizer	−0.006 ***	0.001		
Fertilizer × soil pH	0.022 **	0.007		
Improved seeds × soil pH	−0.125 **	0.039		
Province fixed effect		Yes		
Observations		1420		
R^2 / adjusted R^2		0.322/0.313		

* p < 0.05 ** p < 0.01 *** p < 0.001.

SAE to project the household-level analysis to the entire country for the 2010/2011 agricultural season. Not only does the SAE method expand coverage to be representative of the whole country, it also triples the degrees of freedom available, thereby generating more precise estimates.

With SAE predicted input use for all wards, we consistently obtain a very strong and negative association between improved maize seeds use (in kg/ha) and forest cover loss (Table 2). The relationship between inorganic fertilizer use (in kg/ha) and forest cover loss is more complex. By itself, fertilizer use has a positive and significant association with forest cover loss (Table 2). The interaction between improved maize seeds and inorganic fertilizer on forest cover loss is negative but not statistically significant (Fig. 2A). The interaction between improved maize seeds and pH (Fig. 2B) is negatively associated with forest cover loss, while the interaction between inorganic fertilizer and pH (Fig. 2C) is weakly positive, but these interactions are not statistically significant either.

Similarly, for the relative rate of forest cover loss, improved maize seeds show a negative association with the relative rate of loss (Table 3). The interaction between improved seeds and fertilizer use is also negatively associated with the relative rates of forest cover loss. However, there are differences worth noting. The positive association between fertilizer use and the relative rate of forest cover loss is not significant. Both interactions of input use and soil pH are significant, with a negative association for improved seeds and soil pH on the rate of forest cover loss and a positive one for fertilizer and soil pH on this rate.

A range of biophysical factors are directly associated with forest cover loss. Soil pH shows a strong and significant negative association with forest cover loss (Table 1, model 2 and Table 2). Mean soil carbon density is also mildly and significantly negatively associated with forest cover loss. Unsurprisingly, tree cover in 2010 is one of the best

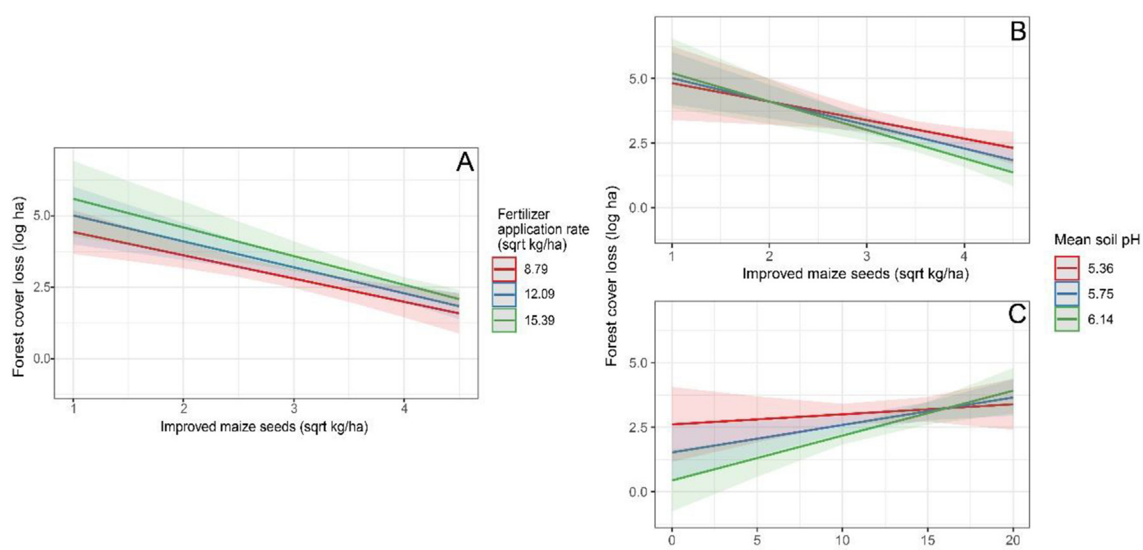

Fig. 2. Interactions between A) improved maize seeds (in kg/ha; square root transformed) and inorganic fertilizer on maize (in kg/ha; square root transformed), B) improved maize seeds and soil pH, as well as C) inorganic fertilizer in maize and soil pH, as related to predicted forest cover loss (in ha; log-transformed). The interaction of increasing application rates for both improved seeds and fertilizer is associated with reduced forest cover loss. Increasing use of improved maize seeds at different pH levels is associated with reduced forest cover loss. Increasing use of inorganic fertilizer on maize is weakly associated with increased forest cover loss, at various pH levels. All of these interactions are statistically insignificant (Table 2). Variables are log-transformed or square root-transformed.

predictors of forest cover loss, for the simple reason that deforestation can only happen where forests still stand. The negative association of the distance to roads and forest cover loss is consistent with long-standing literature that finds higher deforestation in more accessible locations (Barber et al., 2014; Cropper et al., 2001; Ferretti-Gallon and Busch, 2014; Laurance et al., 2014). Elevation is positively associated with forest cover loss, but the effect is small, with a large section of Zambia located on plateaus. The area of protected land, including National Parks, Game Management Areas and Forest Reserves, is not significantly associated with forest cover loss.

3.2. Mediating effect of soil pH

Modern agricultural inputs are developed for fertile soil conditions. So, one might reasonably hypothesize that the effects will vary with soil conditions. Maize growth is optimal under neutral and nearly neutral pH soils (pH 5.5–7.0) (FAO, 2017). Indeed, when we use the model shown in Table 2 but separately estimate the regressions based on a pH threshold important for maize growth identified in previous studies (Burke et al., 2019, 2017; George et al., 2012), we find striking contrasts in the estimated association between modern agricultural inputs and forest cover loss (Table 4). Using segmented regression to find an optimal structural breakpoint in pH, we also validated the use of this threshold empirically, and found that the relationship between input use and forest cover loss differs in an important way at the soil pH threshold (results presented in the Appendix). On acidic soils, pH $<$ 5.5, we found no significant relationship between forest cover loss and fertilizer, improved maize seeds, pH, or the interactions between any pair of these variables. This is not a matter of weaker fit on poorer soils. At low pH, the explained variation is appreciably higher (adjusted $R^2 = 0.70$) than in the model of wards with pH $\geq$ 5.5 (adjusted $R^2 = 0.44$). For wards with mean pH values $\geq$ 5.5, however, the results are more similar to those found in Table 2. Forest cover loss is significantly and negatively associated with improved maize seed use and soil pH, while it shows a smaller positive association with fertilizer use. The interaction between improved maize seed and fertilizer use on forest cover loss, however, is negative and significant, as we found with the household survey data (Table 1). Interestingly, the threshold separating the country into high pH and low pH soils shows clear spatial patterns (Fig. 3), with low pH areas overlapping the higher tree cover areas (Appendix, Figure S5).

For the relative rate of forest cover loss, we also find qualitatively similar results (Appendix, Tables S4). The main difference observed is a significant negative association of the interaction between improved maize seeds and inorganic fertilizers under low pH ($<$ 5.5) conditions with the relative rate of forest cover loss.

We also split the 2012 (n = 420) and 2015 (n = 433) RALS survey data according to the pH threshold mentioned above in order to look at the relationship between pH and maize yields. Using one-way ANOVA with permutation test, we found a significant difference in maize yield (in tons/ha) between the wards with pH $<$ 5.5 and pH $\geq$ 5.5 ($F_{\alpha=0.05, \upsilon=853} = 28.5$, $p = 0.001$), with an average yield of 0.71 ton/ha and 1.04 ton/ha for low and high pH wards, respectively. These results underscore the importance of soil fertility both for crop productivity and for tapping the productivity-boosting power of modern inputs to reduce forest cover loss through agricultural intensification.

3.3. Predictive scenarios of modern input use on forest cover loss

Using the regression models presented in Table 4, we compared three application rate (AR) scenarios: 1) no modern inputs (seed or fertilizer) applied (No Input Scenario); 2) 2010/2011 agricultural season predicted ward-level application rates (Actual AR Scenario), where mean (and median) application rates were 12 and 157 kg/ha for improved maize seed and inorganic fertilizer, respectively (Table S1); and 3) the government recommended application rates for both fertilizer (400 kg/ha total) and improved seeds (20 kg/ha) (Recommended AR Scenario). We show the predicted distribution of forest cover loss per ward (in ha) under these different scenarios, given ward-specific values for the other covariates (Fig. 4). Since we project the regression estimates beyond the support of the survey data in the No Input Scenario, these are coarse estimates meant only to illustrate broad patterns, not to generate precise quantitative estimates. The highest predicted deforestation, by far, happens under the No Input Scenario. Under this scenario, deforestation is almost two times higher than under the Actual AR scenario. Universal adoption of the government's recommended improved seed and fertilizer application rates would hypothetically result in an additional 54% reduction in deforestation compared to the Actual AR scenario. We estimate a difference of 74,751 ha in forest cover loss annually between the No Input Scenario and the Recommended AR scenario, a ~80% reduction. These results illustrate the considerable cumulative effect of the ward-specific reductions in deforestation potentially attainable because of expanded uptake of improved maize seed; even if the exact magnitude of those gains should be interpreted with caution, the ordering among them is striking and clear. We estimate that the reduction in deforestation, using the No Input Scenario as a benchmark, generated roughly 4.73 megatons (Mt) and 6.72 Mt of CO_2e emissions reductions in 2011 for the Actual and Recommended AR scenarios, respectively. If we monetize these emission reductions using an average price of US$3.01 per ton of CO_2e for REDD

Table 4
Regression models separating wards based on soil pH threshold (< 5.5 and ≥5.5) (SE: standard error; AME: Average marginal effect). The dependent variable is the log of forest cover loss (ha/ward).

	pH < 5.5 model				pH ≥ 5.5 model			
Predictors	*Estimates*	*Std. Error*	*AME*	*Std. Error*	*Estimates*	*Std. Error*	*AME*	*Std. Error*
Maize improved seeds (kg/ha)	1.376	1.334	0.106	0.365	−1.607 ***	0.280	−1.399 ***	0.235
Fertilizer on maize (kg/ha)	−0.210	0.313	−0.089	0.084	0.126 *	0.059	0.147 **	0.049
Mean soil pH	−0.043	1.033	0.038	0.861	−1.084 ***	0.284	−1.253 ***	0.262
Tree cover in 2010 (ha)	0.573 ***	0.059	0.573 ***	0.059	0.431 ***	0.044	0.431 ***	0.044
Mean soil carbon density (tons/ha)	−0.018 *	0.008	−0.018 *	0.008	−0.010 ***	0.003	−0.010 ***	0.003
Mean distance to roads (m)	−0.240 **	0.079	−0.240 **	0.079	−0.169 **	0.056	−0.169 **	0.056
Mean elevation (1,000 m)	2.229 **	0.713	2.229 **	0.713	1.238 ***	0.352	1.238 ***	0.352
Mean annual precipitation (1,000 mm)	−0.109	0.728	−0.109	0.728	−2.093 ***	0.579	−2.093 ***	0.579
Fertilizer × Improved Seed	−0.013	0.046			−0.056 **	0.021		
Fertilizer × soil pH	−0.321	0.822			0.063	0.136		
Improved Seed × soil pH	3.304	3.420			0.717	0.704		
Province fixed effect	Yes				Yes			
Observations	496				924			
R^2 / adjusted R^2	0.711/0.701				0.456/ 0.444			

* p < 0.05 ** p < 0.01 *** p < 0.001.

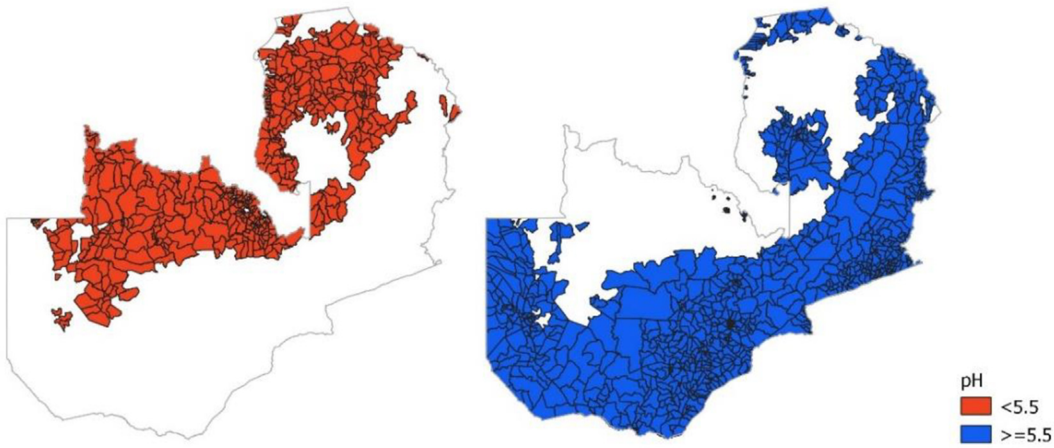

Fig. 3. Map showing the separation of the wards based on a pH threshold used in analysis presented in Table 4, for wards with mean pH < 5.5 (red color) and wards with mean pH ≥ 5.5 (blue color). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

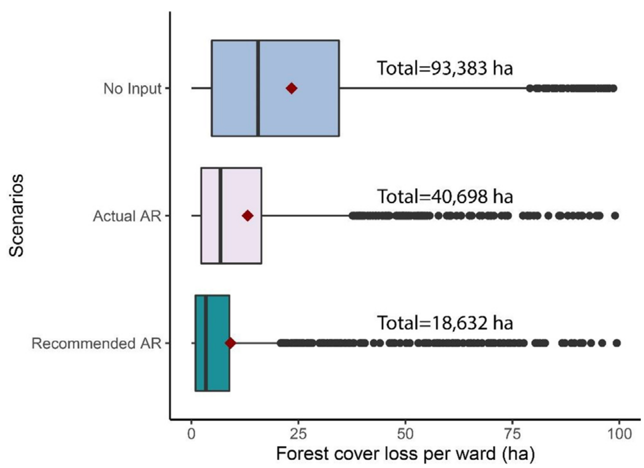

Fig. 4. Predicted forest cover loss in hectares (ha) per ward for different application rate (AR) scenarios for fertilizer on maize and improved maize seeds, estimated from the models presented in Table 4. Maximum predicted forest loss occurs when no improved seed or fertilizer are applied. The lowest predicted forest loss occurs under the scenario using the government recommended (20 kg/ha) application rate for improved maize seeds and inorganic fertilizer on maize (400 kg/ha). The central line of the interquartile range box represents the median ward-level forest cover loss, while the mean is shown by the red diamond. The total forest cover loss for all wards per scenario and included to the figure are as follows: the actual application rate for the agricultural season 2010/2011 (Actual AR) equals 40,698 ha; the No Input scenario equals 93,383 ha; and Recommended application rate for fertilizer and improved seeds equals 18,632 ha. The upper tail of the distribution has been truncated for display. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

+ emission reductions traded under the voluntary carbon market, we estimate value creation of US$14,245,862 to US$20,212,690 for the Actual and Recommended AR scenarios, respectively.

4. Discussion

4.1. A win–win strategy?

To design policies that enable both increased food security and reduced deforestation in the tropics, solid evidence is needed on the relationship between efforts to increase food production and subsequent forest cover loss. This research need is especially critical in SSA, which faces enormous food insecurity challenges associated with looming population and income growth, and where deforestation is especially strongly associated with agricultural expansion by smallholder farmers (Curtis et al., 2018). With a new empirical approach that makes use of detailed nationally representative agricultural household surveys and census data, integrated with remotely sensed forest cover loss data, we provide what is, to the best of our knowledge, the first study of the association between modern agricultural inputs use by smallholder farmers and deforestation using spatially disaggregated, country-wide data, allowing for a better match between detailed information about farmers' practices, forest cover loss, and other important geospatial biophysical covariates.

Focusing on Zambia and on maize, the country's most important staple crop, we show that increased use of improved maize seeds is significantly and robustly associated with a sharp decline in deforestation. The use of hybrid maize seeds, which were included in the Zambian input subsidy package, have been shown in meta-analysis to provide significantly higher maize yield response, compared to improved open-pollinated or local varieties (Vanlauwe et al., 2011). The agronomic efficiency of N for IOPV was higher than local varieties but not significantly different. The negative association of improved maize seeds with forest cover loss can increase in magnitude when they are combined with inorganic fertilizers under neutral pH soils. This makes sense as hybrid maize varieties have been bred to take advantage of inorganic fertilizer blends and thus respond better to inorganic fertilizer application under neutral soils.

Our results thereby reinforce simulation-based and statistical findings based on aggregate country-level observations that agricultural intensification based on the use of improved crop germplasm is associated with reduced deforestation (Gollin et al., 2019; Stevenson et al., 2013). These results broadly support the land-sparing or Borlaug hypothesis and suggest that smallholder agricultural intensification can help reduce deforestation, at least in low-income, landlocked settings like Zambia that are not well integrated into global markets. A previous evaluation of the input subsidy program showed that increasing maize production had only a minimal negative effect on maize retail prices (Ricker-Gilbert et al., 2013). These results suggest that crop price reductions might not drive the reduced deforestation observed. Rather, this likely arises from income effects that reduce smallholder farming households' forest clearing effort. Further studies should address the underlying mechanisms that generate the outcome observed.

With the shift in the delivery of Zambia's input subsidy program to an e-voucher delivery scheme, which gives farmers flexibility to decide how they use the subsidy, early indications suggest that many beneficiaries redeemed the e-voucher for fertilizers only and not fertilizers and hybrid maize seeds, or other inputs (Mason et al., 2020). If this trend is confirmed, this new delivery scheme may inadvertently increase deforestation because farmers are choosing less of the inputs that we found to be associated with reduced deforestation. Continuing education efforts will be key to inform beneficiaries' decisions, including about the importance of hybrid maize seeds and the complementary use of fertilizer and of pH management.

4.2. The role of soil fertility

Adequately fertile soil conditions appear critical to obtain win–win outcomes for agricultural productivity and forest conservation. Two key constraints for soil fertility are soil acidity and low reserves of intrinsic nutrients typically contained in soil organic matter[3]. Soil conditions are important because of their significant association with deforestation and because they mediate the agricultural productivity gains to modern inputs use, and thus the relationship between modern agricultural inputs and deforestation. The strong and significantly negative relationships of soil pH and soil carbon density with forest cover loss indicate that better soils are associated with lower deforestation by smallholder farmers. These two soil characteristics have also been associated with higher maize yields, including in Zambia (Burke et al., 2019).

Under the first constraint of acidic soils (pH $<$ 5.5), we found no significant relationship between input use and deforestation, as well as significantly lower average maize yield compared to nearly neutral soil pH conditions (pH $\geq$ 5.5). Acidic soils can affect plant growth and crop productivity, and they often do not respond well to inorganic fertilizers (Vanlauwe et al., 2011). More than half of the soils in Africa are characterized by old, highly weathered, acidic soils with high levels of iron and aluminum (Al) oxides (Jones et al., 2013). Acidic soils affect the uptake of phosphorus by plants. The optimum pH when phosphorus (P) is in its most plant available form is between 5.5 and 7. At lower pH, P tends to bind to iron or aluminum in the soil and becomes unavailable to support plant growth. Soil acidity can lead to land degradation, which can push farmers to open new land for agriculture. These soils require careful management when they are cultivated (Jones et al., 2013), including pH management with lime, agroforestry or other strategies that control soil acidity (Burke et al., 2017). In Zambia, less than 1% of farmers use lime for soil pH management (IAPRI, 2016), which has been explained by the high transportation costs for this input and the lack of awareness by farmers of pH management benefits (Burke et al., 2017). The zones with the lowest soil pH also have higher precipitation and higher remaining forest cover. In these high rainfall zones of Zambia, lime application, by reducing soil acidity, was shown to reduce soluble Al and improve maize yields (McKenzie et al., 1988). Maize yields can be further improved with the joint application of lime and manure (Lungu et al., 1993). Farmers from these zones, which also have lower average maize yield (0.71 ton/ha), should be especially targeted for training and support in boosting soil pH and broader soil health management.

When the first soil chemical constraint is lifted (pH $\geq$ 5.5), we observed a significant negative relationship between improved maize seeds and forest cover loss (see Table 4, pH threshold $\geq$ 5.5) as well as significantly higher maize yield compared to areas under acidic soils. The use of inorganic fertilizer, by contrast, is found to have no significant association (Table 1) or a weakly positive association (Tables 2 and 4) with forest cover loss. The average maize yields of 1.04 ton/ha, even on these nearly neutral soils, remains low compared to the government predicted yield of 3 tons/ha (under recommended fertilizer and improved seed application rates) and is well below the global average. The average fertilizer and improved maize seed application rates of 193.9 kg/ha and 13.3 kg/ha, respectively, by smallholder farmers during the 2013/2014 agricultural season (Table S1) fall considerably below the recommended application rates (400 and 20 kg/ha, respectively), which could partially explain the gap between actual and government predicted maize yields.

The absence or weak positive relationship between fertilizer and deforestation we identified under nearly neutral soils is intriguing. We believe it is linked to the second key constraint to soil fertility, limited soil organic matter. Under poor and less responsive soil conditions, chemical fertilizers requires the addition of organic inputs and organic resource management to be effective (Vanlauwe et al., 2011, 2014). The use of chemical fertilizers, especially those containing ammonium and sulfur, also tends to decrease soil pH over time, which can negatively feedback on yield response.

Fertilizer use might be positively associated with forest cover loss for at least two reasons. First, if farmers do use fertilizer and find it unprofitable, the resulting added financial pressure they face might induce forest clearing. Second, farmers often respond to declining soil fertility by applying fertilizers, clearing more land, or both. At the ward level, this would manifest in positive correlations between fertilizer use and forest cover loss. This would be consistent with other evidence from SSA, including for Zambia, showing that low soil organic matter can limit the marginal maize yield gains of fertilizers and the profitability of fertilizer use by smallholder farmers constrained by low soil fertility (Burke et al., 2019; Marenya and Barrett, 2009a, b).

The differential association of improved seed and fertilizer with deforestation is consistent with prior research in Zambia that found much higher marginal maize productivity effects from improved maize seed than from inorganic fertilizers (Burke et al., 2017). Combined with the fact that fertilizer costs at least ten times more than improved seeds at the recommended application rate, and that farmers incur significant costs even with the government fertilizer subsidy, for most Zambian smallholders, the government recommended application rate for fertilizers is not profitable (Xu et al., 2009). We cannot, however, pin down exactly the underlying mechanisms that lead to one input – improved maize seeds – being associated with far better forest outcomes than the other – inorganic fertilizers.

4.3. Implications for sustainable intensification

Smallholder agricultural intensification based on improved crop germplasm and good soil management practices appears to be a win–win strategy for food security and protecting forest and woodland ecosystems in places like Zambia. This is good news. Our results suggest that deforestation would be more than twice as high without the use of modern inputs for maize. Improved seeds appear, by far, to be the most impactful part of the modern agricultural input subsidy package in terms of reducing deforestation. The diffusion of improved seeds is therefore the component of agricultural intensification strategies that is most compatible with preserving forests based on our results. Given the importance of variable soil conditions to our results, it might be worthwhile to consider linking improved seed subsidies with soil fertility management practices, rather than just providing inputs unconditionally (Morgan et al., 2019). This information is relevant to Zambia's Intended Nationally Determined Contribution under the Paris Agreement, which aims to reduce emissions by 25–47% by 2030 relative to the base year 2010 (Government of the Republic of Zambia, 2015), because deforestation for agriculture is one of the main sources of emissions.

We also find that there is room for improvements. Much greater investments are needed in crop and soil science as well as extension services for smallholder farmers to propel sustainable intensification that helps conserve forests (Jayne et al., 2019). Now, the most important negative impact on ecosystem services is through the continued expansion of agriculture on forestlands which needs to be addressed, but in the long run, the judicious use of some agricultural inputs, especially inorganic fertilizers, will also be important (Rasmussen et al., 2018). To make smallholder production more profitable and

[3] Soil organic matter is directly proportional to soil organic carbon, the indicator used in this study.

sustainable, as well as to spare forestland from conversion to agriculture, recommendations for agricultural input application rates could be better adapted to diverse intra-national agro-ecological systems and better targeted to farmers' needs and conditions. These results from Zambia illustrate that sustainable intensification requires place-based knowledge and location-specific recommendations to achieve reductions in both deforestation and food insecurity.

Over a longer period, the linkages between input use and deforestation may be influenced by other factors, in particular that higher incomes due to higher crop productivity may translate into investments in activities that may impact forests. Other strategies, including land use zoning, enforcement of forest protection laws, and other incentives for forests protection may be important, complementary tools to promote sustainable intensification. These strategies can help to avoid possible rebound effects by linking yield increases with forest conservation (Phalan et al., 2016).

In conclusion, this study supports the land-sparing hypothesis by showing empirically that agricultural intensification by smallholder farmers has been strongly associated with reduced deforestation in Zambia, and that this reduction comes mainly from the use of improved maize seeds on non-acidic soils, which is also consistent with the findings of coarser global-scale models (Stevenson et al., 2013). Increased fertilizer use on its own shows a slight positive association, in some models significant, with deforestation. The interaction between improved maize seeds and fertilizer is also associated with less forest clearing under sufficiently neutral (pH $\geq$ 5.5) soils. Soil pH and soil organic carbon are both directly and negatively associated with forest cover loss. Based on our estimates, actual application rates of these modern agricultural inputs are associated with roughly a halving of deforestation relative to the predicted deforestation level under a scenario without modern input use, while further improvements could be attained if all Zambian smallholder farmers followed the government's recommended application rates for improved maize seeds. Sustainable intensification via the use of improved seeds on adequately fertile soils seems to be a pathway to achieve reduction in both deforestation and food insecurity.

CRediT authorship contribution statement

Johanne Pelletier: Conceptualization, Formal analysis, Methodology, Visualization, Writing - original draft, Writing - review & editing. **Hambulo Ngoma:** Conceptualization, Investigation, Methodology, Writing - review & editing. **Nicole M. Mason:** Conceptualization, Investigation, Methodology, Writing - review & editing. **Christopher B. Barrett:** Conceptualization, Methodology, Investigation, Supervision, Validation, Writing - review & editing.

Declaration of Competing Interest

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

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.gloenvcha.2020.102127.

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