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# Agricultural commodity prices, governance, and land supply in the Tropics

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## Abstract

Sustainable use of land resources is at the core of the bioeconomy, and it is of central importance for development in the coming decades. The United Nations Sustainable Development Goals reflect this aspect of development both directly and indirectly. Important global trends, such as a growing and richer world population, are consistently increasing demand for biomass products, leading to tradeoffs among related goals such as “Zero Hunger” and “Life on Land.” Regarding land supply for biomass production, there is a need for agricultural land and pressure in forest areas. Empirical evidence at regional and global levels points to land suitability, local and international markets, and governance as major drivers of land supply for the bioeconomy. However, global models lack an economically consistent description of the divergence between legal requirements for land use (de jure) and current land use trends (de facto) in tropical regions, where these tradeoffs are expected to be higher. Our analysis empirically estimates the average marginal effect of the socioeconomic, climatic, and governance drivers of land supply in the tropics. We used subnational panel data to construct a fractional response model to estimate these effects. Then, we used the econometric results to calculate heterogenous individual land supply elasticities to commodity prices at the subnational level. Our results support the idea that in forest-abundant areas, soaring prices reinforce agricultural land expansion. Further, our results support previous evidence that the type of governance (conventional or environmental) determines the likelihood of a reduction or expansion of agricultural land in the tropics but with a very small magnitude compared to other drivers.

Keywords: Land Supply, Agricultural Markets, Conservation Policy, Governance.

JEL Codes: Q15, Q13, Q28

# 1. Introduction

The use of global land resources plays an important role in achieving sustainable development pathways. In this regard, agricultural systems are a core aspect of steering land management to achieve important targets of the UN Sustainable Development Goals, such as Zero Hunger, Climate Action, and Life on Land (Obersteiner et al., 2016).

Global economic models provide some insights into the factors that affect agricultural systems, as well as factors that can simulate different economic and policy mechanisms that impact agricultural outcomes and land use allocation. These models contribute to scientific knowledge that links global challenges, such as food security, climate change mitigation, and biodiversity conservation, to agricultural practices (Golub et al., 2013; Lanz et al., 2018). This is done by characterizing different processes that influence the demand and supply of agricultural production and the use of land at different locations (Stehfest et al., 2019). One important challenge is to improve heterogeneous characterizations of agrifood systems based on parameters that reflect mechanisms that transform the system in a tele-connected world (Meyfroidt et al., 2013; Hertel et al., 2019).

One parameter that provides information on the sensitivity of agricultural land expansion is the land supply elasticity (Tabeau et al., 2017; Villoria and Liu, 2018). Different estimations of land supply elasticities have been done using different indicators that influence the rentability of land. Barr et al. (2011) used information on Brazil and the US to determine the elasticities of their agricultural sector to investigate the effect of biofuels on cropland expansion. Villoria (2019) investigated the effect of total factor productivity as a driver of cropland expansion in different regions worldwide. Through a cross-sectional analysis, Villoria and Liu (2018) used gridded information to make spatially explicit calculations of the effect of accessibility on cropland expansion in the American continent. Tabeau et al. (2017) conducted a literature review of different calculations of land supply elasticities to provide information for global economic models, assessing the European Union's economy on the world stage.

Previous empirical analyses have provided important insights into the drivers of cropland expansion. Their added value is used in the present study to update and increase the scope of land supply elasticities that are currently available. We used satellite-based land cover information to identify agricultural land in different locations. We included pasture areas in agricultural land instead of only cropland as they are an important source of land use change in agriculture-forest frontiers (Pendrill et al., 2019a). Some analyses are based on the Food and Agriculture Organization's (FAO) survey data, which enable the structuring of information for a wide range of countries for empirical analysis. However, these data can underestimate the conversion of natural land for agricultural use as they are based on self-reported information. With an explosion in the availability of satellite-based spatially explicit information for land use cover and different indicators related to drivers of land use change such as climatic variables, we retake the challenge to estimate land supply elasticities for a wide range of areas across the globe. We also used panel data structured at the subnational level to run our empirical analysis. Further, we expanded the analysis to tropical zones worldwide using a single framework. We focus on these regions as there has been land use expansion from agricultural activities in these regions (Meyfroidt et al., 2014; Harris et al., 2017; Curtis et al., 2018; Pendrill et al., 2019b).

We also tested the effect of governance on land supply. We do this because both conventional and environmental governance affect the availability and rentability of land (Hertel, 2011; Lambin et al., 2014; Wehkamp et al., 2018). Strong environmental governance leads to a virtual scarcity of land, which changes decision-making in the use of land (Angelsen, 2010). Governance can also have effects on surrounding jurisdictions. For instance, stringent conservation policies (as a reflection of stronger environmental governance) can lead to spillover effects, which can have both positive and negative land use change impacts (Meyfroidt et al., 2020). Moreover, different types of governance have different effects on land use. Regional empirical analyses have revealed that there is a relationship between governance and cropland expansion; however, the type of governance indicator determines the direction of this relationship (Ceddia et al., 2013). Therefore, we tested the effect of conventional and environmental governance indicators in our analysis. We used the effects of institutional aspects, i.e., corruption, voice and accountability (V&Acc), and rule of law (RoL), on agricultural land as proxies for conventional governance. We also included national terrestrial biome protection to represent environmental governance in our transregional study.

The elasticity of land supply is the percentage change in agricultural land after a 1% increase in its rentability for agricultural production (Villoria and Liu, 2018). We used this definition as the basis of the framework of our analysis. We then conducted a correlated random effects model suitable for fractional response variables in a panel data structure such as the share of agricultural land in the total land endowment. Our results are similar to those of previous analyses that focused on tropical zones. We found that an increment in commodity price is positively correlated with increments in the share of land allocated to agricultural use. We did not find a systematic positive correlation of conventional governance in tropical regions. We found a systematic negative relationship between stronger environmental governance and agricultural land expansion, but, on average, this effect was close to zero. Regarding individual land supply elasticities for each mesoregion, we found that an increase in agricultural commodity prices has a stronger effect in areas with a large proportion of forestland, such as the Amazon in South America, the Congo Basin in Central Africa, and forestlands in Southeast Asia (particularly Indonesia). The mean value of the elasticities calculated across different specifications for a 1% change in the agricultural commodity price index is 0.1% of land supply (with a minimum value of 0.01% and a maximum of 0.26%).

The remainder of this manuscript is as follows. In the next section, we present our theoretical framework on the relationship between land rentability and the expansion of agricultural land, as well as our empirical strategy. It is followed by our data processing section. We then present our results on the effects of agricultural markets and governance on land supply and the resulting individual land supply elasticities across the tropics. The fifth section presents the discussion, followed by the concluding section.

# 2. Theoretical framework and empirical strategy

## 2.1 Land supply response to changing economic incentives

We used the conceptual framework of land supply proposed by Villoria and Liu (2018) as the starting point of our analysis. They defined land supply as a functional relationship between land converted to cropland and rents accrued from using the land in crop production. We expanded their analysis by using agricultural land, including cropland and pastures, as our indicator of land supply. The relative size of agricultural land to total land endowment in a unit of analysis ($L_i^s$) represents land supply as a function of rents ($R_i$) factored to an individual land supply elasticity ($\varepsilon_i$).

$$L_i^s = \varepsilon_i R_i \quad (1)$$

This equation offers a simple conceptual framework that can be operationalized. This can only be fully realized if data on output and input prices are available for each observation. As it has been pointed out in previous empirical studies, these data are only available for some areas of the world, which calls for the use of alternative indicators that affect agricultural rentability for global or regional analysis such as the one in the present study (Naidoo and Iwamura, 2007; Ceddia et al., 2014; Villoria and Liu, 2018). We denote land rents as a function of socioeconomic, biophysical, and governance indicators that influence land rents accrued from agricultural activities. We then represent Equation 1 as follows:

$$L_i^s = \varepsilon_i f(B_i, S_i, G_i), \quad (2)$$

where three major components affecting the rentability of land are represented—$B_i$, denoting biophysical; $S_i$, denoting socioeconomic; and $G_i$, denoting governance. Hertel (2011) presented a conceptual framework to link different drivers of land supply that are related to the three components in Equation 2. For instance, he presented an extended discussion on the effects of trade, climate change, and demand for environmental governance on land supply. Among these indicators, we focus on the commodity price index, which is related to the socioeconomic component of land rents, to capture the effect of agricultural markets on agricultural land expansion. We must clarify that we are calculating the elasticity to commodity price instead of that of the rentability of land. We expect this elasticity to be smaller in magnitude compared with that of land rents when long-run prices for the variable inputs of production are not affected by conditions in the agricultural sector (Hertel, 2011). Equation 2 represents the target function in which its first derivatives of different indicators affecting land rent components allow the calculation of elasticity. We consider *j* indicators on a vector of socioeconomic characteristics related to component $S_i$; thus, if we derive the agricultural commodity price index ($S_{ji}$) and multiply it by relevant values of the ratio of price to the share of agricultural land, we obtain individual land supply elasticities to commodity price.

$$\varepsilon_{ji} = \frac{\partial \hat{L}_i^s}{\partial s_{ji}} \times \frac{s_{ji}}{\hat{L}_i^s} = f'(B_i, S_i, G_i) * \frac{s_{ji}}{\hat{L}_i^s} \quad (3)$$

Equation (3) is a standard calculation for elasticities in economic analyses. We assume that $\varepsilon_{ji}$ is proportional to $\varepsilon_i$ to allow spatial heterogeneity of land supply elasticities that are not affected by scale (Villoria and Liu, 2018). The first element on the right side of Equation 3, $f'(\cdot)$, is the first derivative of the functional form of land supply to the commodity price. The second element on the right side of Equation 3, $\hat{L}$, represents fitted values of land supply in an empirical estimation. An important challenge is to determine a functional form of $f$ that allows an empirically viable alternative to calculating individual land supply elasticities. We present our chosen alternative and the methodological steps of our analysis in the next section.

## 2.1 Fractional response model apply to land supply

We are interested in the effect of indicators related to land rentability on the expected agricultural land shares in a mesoregion (see the “Data processing” section for an explanation of our unit of analysis). Thus, we focus on calculating the sensitivity of agricultural land shares to changes in indicators that affect land rentability, i.e., individual land supply elasticities.

A linear function is one of the approaches that can be used to empirically estimate the effect of observed covariates on the outcome of interest. The use of standard linear models to test the effect of covariates on a fractional response variable, as in our present analysis, is seen as inappropriate in empirical approaches (Papke and Wooldridge, 1996; Loudermilk, 2007; Papke and Wooldridge, 2008; Ramalho et al., 2011). First, a linear functional form on the conditional mean of the response variable does not account for important nonlinearities inherent in a truncated and continuous variable (Papke and Wooldridge, 2008; Bluhm et al., 2018). Further, it is a common practice to use linear functional forms on logarithmic transformations of the response and covariates to determine elasticities. However, this poses difficulties for corner values of the outcome variable (Papke and Wooldridge, 2008). Third, linear models describe a misleading behavior of the outcome variable as there is no restriction on the range of values obtained from the structural function that relates the outcome with the observable covariates and unobservable heterogeneity (Ramalho and Ramalho, 2017). In addition, a linear model needs a specification that can disentangle the individual effects from the global (average) effect on the sample to determine individual elasticities. One possibility is to include an interaction between the relevant covariate (i.e., our focus indicator of land rentability) and the individual fixed effects in the model. However, in our analysis, this would increase the likelihood of overfitting the model as the ratio of the number of observations to the number of predictors becomes smaller (McNeish, 2015). For these reasons, we decide to use the nonlinear model for a fractional outcome proposed by Papke and Wooldridge (2008) (P&W hereafter). P&W’s model proposed that an outcome variable is continuous but bounded to the range of 0 to 1. It is suitable for panel data structures and explicitly models time-constant unobserved heterogeneity. Furthermore, it is easy to empirically implement in conventional statistical programs.[1]

### 2.1.1. Econometric specification

P&W's model starts with modeling the expectation of a fractional response variable $y_{it}$ conditional on a set of *K* explanatory observed variables $\mathbf{x}_{it}$ and an unobserved individual effect $c_i$ for *N* individuals in *T* time steps, in which $i = 1, \dots, N$ and $t = 1, \dots, T$. Following P&W, the conditional expectation takes the following form:

$$E(y_{it}|\mathbf{x}_{it}, c_i) = \Phi(\mathbf{x}_{it}\boldsymbol{\beta} + c_i), \text{for } i = 1, \dots, N; t = 1, \dots, T, \tag{4}$$

where $\Phi(\cdot)$ represents the standard normal cumulative distribution function, and $\boldsymbol{\beta}$ is a vector of *K* coefficients to be estimated. In this study, the set of covariates includes variables related to socioeconomic, biophysical, and governance (details are in the "Data processing" section). The term $c_i$ represents the time-invariant individual unobserved heterogeneity.

Some useful properties of the normal function that help to derive partial effects and elasticities are that it is strictly monotonic, continuously differentiable, and nonadditively separable (Ramalho and Ramalho, 2017). In particular, the monotonic property allows the elements of $\boldsymbol{\beta}$ to give the direction of the partial effects of each covariate on the outcome variable (Papke and Wooldridge, 2008).

P&W included two additional assumptions to identify $\boldsymbol{\beta}$ and the partial effects of relevant covariates. First, conditional on the unobserved heterogeneity, $\mathbf{x}_{it}$ in $t = 1, \dots, T$ is strictly exogenous. This implies that $E(y_{it}|\mathbf{x}_i, c_i) = E(y_{it}|\mathbf{x}_{it}, c_i)$ for $t = 1, \dots, T$, where $\mathbf{x}_i$ comprises the set of covariates in all periods. Second, the distribution of the unobserved heterogeneity $c_i$ is assumed to behave as a normal distribution conditional on the set of covariates such that

$$c_i|(\mathbf{x}_{i1}, \mathbf{x}_{i1}, \dots, \mathbf{x}_{iT}) = \mathrm{Normal}(\alpha + \bar{\mathbf{x}}_i\boldsymbol{\delta}, \sigma_u^2) \tag{5}$$

where $\bar{\mathbf{x}}_i \equiv T^{-1}\sum_{t=1}^{T}\mathbf{x}_{it}$ represents the time averages of the time-varying covariates in the model. We also assume that $u_i \equiv \ c_i - \alpha - \bar{\mathbf{x}}_i\boldsymbol{\delta}$. These assumptions imply that $u_i$ conditional on$(\mathbf{x}_{i1}, \mathbf{x}_{i1}, \dots, \mathbf{x}_{iT})$ is also a normal distribution with a mean of 0 and a conditional variance, where $\sigma_u^2 = \mathrm{Var}(c_i|\mathbf{x}_i)$. P&W's model is known as a correlated random effects approach as it allows correlation between unobserved effects and covariates using the Chamberlain–Mundlak strategy (Mundlak, 1978; Chamberlain, 1980; Bluhm et al., 2018).

Combining the previous assumptions and integrating them into Equation (4), P&W demonstrated that both scaled elements of $\boldsymbol{\beta}$ and partial effects are identified as long as the

[1] More complex models such as an exponential fractional model could have been used to relate our covariates to agricultural shares, but they require complex transformations of the estimations to determine the elasticities for each individual observation in the data (see Ramalho and Ramalho (2017) for an example of these type of models). Moreover, they are hard to compare with other specifications.

covariates have some time variability, and perfect linear relationships do not exist among them. This yields a model such that

$$E(y_{it}|\mathbf{x}_{it}, u_i) = \Phi(\alpha + \mathbf{x}_{it}\boldsymbol{\beta} + \bar{\mathbf{x}}_i\boldsymbol{\delta} + u_i) \tag{6}$$

$$E(y_{it}|\mathbf{x}_i) = E[\Phi(\alpha + \mathbf{x}_{it}\boldsymbol{\beta} + \bar{\mathbf{x}}_i\boldsymbol{\delta} + u_i)|\mathbf{x}_i] = \Phi\big([\alpha + \mathbf{x}_{it}\boldsymbol{\beta} + \bar{\mathbf{x}}_i\boldsymbol{\delta}]/[\mathbf{1} + \sigma_u^2]^{\mathbf{1/2}}\big) \tag{7}$$

$$E(y_{it}|\mathbf{x}_i) \equiv \Phi(\alpha_u + \mathbf{x}_{it}\boldsymbol{\beta}_u + \bar{\mathbf{x}}_i\boldsymbol{\delta}_u) \tag{8}$$

In Equation (8), the parameters to be estimated has a subscript *u*, which refers to their transformation with a common scaling factor ($[\mathbf{1} + \sigma_u^2]^{\mathbf{1/2}}$).

One major advantage of the P&W approach is that it avoids the need to use fixed effects on the empirical specification, which can cause an incidental parameters problem when *N* is large and *T* is small, as in our case (Neyman and Scott, 1948; Lancaster, 2000).[2] Moreover, when the assumptions described above hold, this approach offers an option to calculate individual elasticities without explicitly modeling individual fixed effects.

### 2.1.2. Individual elasticities

From our set of *K* covariates, we are primarily interested in the effect of an agricultural commodity price on land supply (see the "Data processing" section). The aim is to calculate individual elasticities of land supply to agricultural prices. The first step is to determine the marginal effects from the empirical econometric model for each unit of observation. We used an approach similar to the average partial effects proposed for discrete response models (Wooldridge, 2007). However, instead of averaging at the cross section, we found the average for each $i$ in $T$ years. We multipled the marginal effect with the ratio of the average value of the covariate of interest, that is, agricultural commodity price, and the average fitted value of the share of agricultural land per individual observation, $\bar{x}_{ki}/\bar{\hat{y}}_i$. The calculation of each data point takes the following form:

$$\frac{\partial E(y_{it}|\mathbf{x}_i)}{\partial x_{kit}} = \beta_{ku} \times \phi(\alpha_u + \mathbf{x}_{it}\boldsymbol{\beta}_u + \bar{\mathbf{x}}_i\boldsymbol{\delta}_u) \tag{9}$$

from which a time-averaged individual land supply elasticity is computed as follows:

$$\varepsilon_i = \frac{\partial E(y_i|\mathbf{x}_i)}{\partial x_{ki}} \times \frac{\bar{x}_{ki}}{\bar{\hat{y}}_i} = \beta_{ku} \times \frac{\sum_{t=1}^{T}\phi(\alpha_u + \mathbf{x}_{it}\boldsymbol{\beta}_u + \bar{\mathbf{x}}_i\boldsymbol{\delta}_u)}{T} \times \frac{\bar{x}_{ki}}{\bar{\hat{y}}_i} \tag{10}$$

where $\beta_{ku}$ is the estimated scaled coefficient related to variable $k$, e.g., commodity price; $\phi(\cdot)$ is the probability density function; and $\hat{y}$ is the fitted value of the response variable. The symbol "‾" reflects average values for the research period.

[2] P&W explained that when the number of observations tends to infinity, the fixed-effects' estimators are inconsistent. This inconsistency also affects the common slope coefficients (Papke and Wooldridge, 2008).

## 3. Data processing

We conducted a subnational analysis using a mesoregion as the unit of observation. We refer to these mesoregions as agroecological zones (AEZ)-country units. These regions are obtained by intersecting spatial information on the Global AEZ (GAEZ) (Fischer et al., 2002) and national administrative boundaries for the whole world from the Database of Global Administrative Areas.[3] We identified 876 AEZ-country regions, from which we selected tropical areas.[4] Finally, 267 mesoregions were identified, as depicted in Fig. 1.[5] The fundamental reason for using this level of analysis is that mesoregions are the units used in several applications of global computable general equilibrium (CGEs) models such as those in the GTAP family (Golub and Hertel, 2012; Golub et al., 2013; Stevenson et al., 2013; Plevin et al., 2014).[6] Moreover, the main objective of this analysis is to provide relevant information that would help to calibrate land use change processes in CGE models.

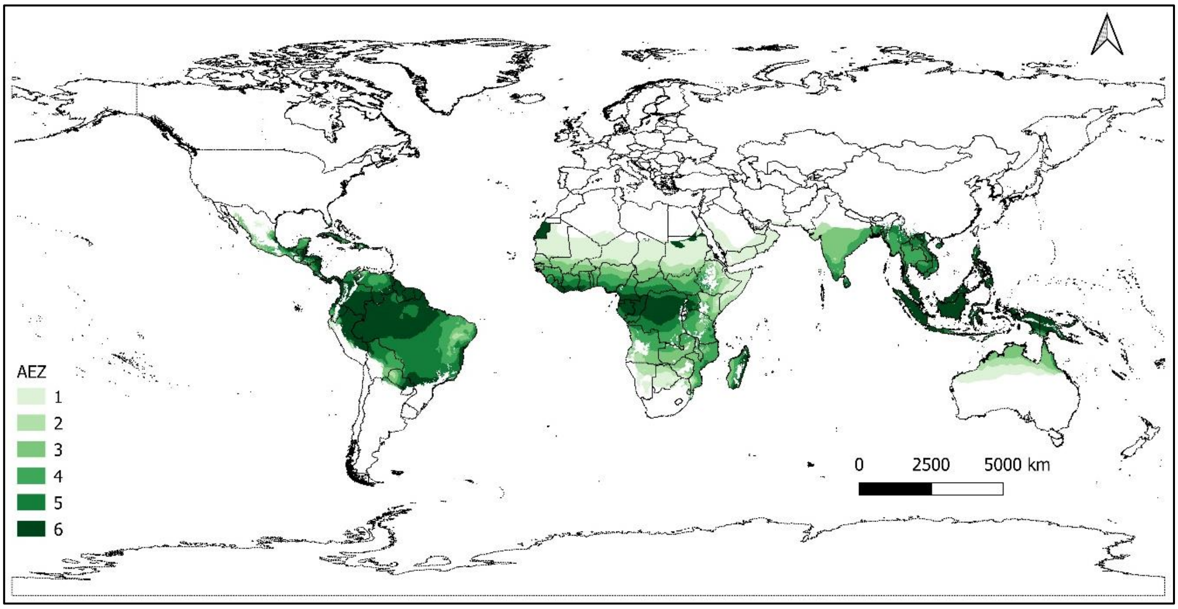



Figure 1: Tropical AEZ-country regions

*Note*: Shades of green reflect the different tropical zones considered for data collection. We do not include those with a desert climate in the final econometric estimation, i.e., AEZ 1.

We measured *agricultural land*, which is the outcome variable in the empirical analysis, as the share of the total land in an AEZ-country unit. It is common to use only cropland as a response variable to analyze drivers of land supply and calculate its elasticities (Barr et al., 2011; Ceddia et al., 2014; Villoria and Liu, 2018). As rapid agricultural expansion is happening in tropical

[3] https://gadm.org/index.html

[4] Plevin et al. (2014) offered an overview of types of global AEZ. In the Results section, we elaborate further on our decision to focus on these AEZ. In Appendix A2, we present a map with all 876 AEZ-country observations.

[5] We chose these AEZ-country observations as they have also been subject of deforestation in the current century (visit https://globalforestwatch.org/ for a spatially explicit assessment on deforestation).

[6] The calculation of elasticities offers information to calibrate land use change in a general equilibrium framework.

zones, we decided to add pasture areas to natural forest areas, as previous studies relate it to agricultural land expansion (Pendrill et al., 2019a; Fischer et al., 2021; Winkler et al., 2021). We used publicly available land cover information at ~300 m pixel resolution from the European Space Agency's Climate Change Initiative for 2004–2015.[7] The land cover information presents 22 land cover categories consistent at the global level (see Appendix A1), from which we identify all pixels with categories related to cropland, pasture, forest, and other uses (residual category). We matched these pixels with their corresponding AEZ-country region so that we can add them up to obtain the number of $km^2$ of agricultural land per mesoregion. Next, we used geometry tools from a geographic information system (GIS) to calculate the total area of each region. Finally, we calculated the ratio of agricultural land to the total area, resulting in our measure of agricultural land share per region.

We used a set of covariates that affect the socioeconomic, biophysical, and governance components of land rents. Among the set of socioeconomic variables, we mainly focus on the agricultural *commodity price index*. The index considers all commodities classified as primary crops, cattle, and milk products by FAO. It is important to note that our commodity price indicator includes agricultural commodities (except wood fiber) that are related to deforestation in tropical regions (Goldman et al., 2020). All commodities considered are presented in Appendix A3. To construct the index, we used national-level information on farm-gate prices provided by FAOSTAT. We used a methodology similar to FAO's Laspeyres index with the average value of 2004 to 2006 as the base year. Further, we used weights to account for the value share of each commodity and downscaled our price index at the mesoregional level. The weights used to capture differences at the subnational level reflect the average ratio of cropland and pasture to agricultural land in each AEZ country. Finally, we deflated the index using an agriculture value-added deflator proposed by FAOSTAT. In the empirical model, we used the average value of the previous three years of each cross section to represent rationale price expectations (Magrini et al., 2016). A more detailed description of our calculations is presented in Appendix A5.

We included additional indicators that affect the socioeconomic component of land rents. *Population density* (Pop) in each mesoregion is included to capture its potential role in the profitability and use of land resources. We employed the spatial estimation of the total population available on the WorldPop project.[8] This is a global rasterized layer at 100 m resolution in which each pixel offers a measure of the population count. We summed up the pixel information at the mesoregional level and divided it by the total area. In the empirical application, we included its quadratic transformation. We also tested different indicators of *fertilizer* use, namely the average national use of nitrogen, phosphorus (*P2O5*), and potassium

[7] These years are also covered in the GTAP v10A database for 2004, 2007, 2011, and 2014 (Aguiar *et al.*, (2019)). The land use cover database is publicly available at http://www.esa-landcover-cci.org/

[8] WorldPop is a research programme based in the School of Geography and Environment Sciences at the University of Southhampton in the UK (https://www.worldpop.org), which generates gridded high-resolution data on population distributions.

per hectare obtained from FAOSTAT. Due to the high correlation among these indicators, we reported the results from the P205 indicator. The ratio of the agricultural sector's value-added *exports and imports* (X/M) is included to control for trade effects on agricultural land use. The data on this variable are obtained also from FAOSTAT, measured at the national level, and like our commodity price index variable, we used the previous three years' average in the analysis for each cross-sectional point. Unlike the commodity price, we could not downscale the fertilizer use and the trade indicators due to a lack of disaggregated sectoral information, so they are included at the national level.

We considered two indicators that affect the biophysical component of land rentability—*growing season length* (GSL) and *rain above 20 mm* (R20 mm) measured in days per year. These are climate extreme indices disaggregated at $0.25° \times 0.25°$ pixel resolution obtained from Mistry (2019). We aggregated these indicators at the mesoregion level by calculating the yearly average of pixels in a unit of observation.

Conventional and environmental governance indicators are also part of the covariates that account for the governance component. As conventional indicators, we tested the World Bank's national perception indicators on corruption, RoL, and V&Acc. *V&Acc* denotes the degree to which citizens can participate in their government's decisions, freedom of expression, freedom of association, and free media*; control of corruption* reflects the extent to which public officials use their power for private gain and when a state is overcome by elites and private interests; *RoL* indicates the ability to enforce contracts and the security of property rights (Kaufmann et al., 2011). As a proxy for environmental governance, we employ a *terrestrial biome protection index* (TBN), which is part of the environmental performance index prepared by the YALE Center for Environmental Law and Policy.[9] The TBN reflects the size of protected area per biome type within national boundaries weighted by the prevalence of each biome in a country. This indicator evaluates a country's achievement in reaching Aichi Target 11, i.e., 17% protection for all biomes within its borders (Wendling et al., 2020).[10]

[9] This index uses information on 32 performance indicators across 11 categories related to environmental health and ecosystem's vitality. Air quality, sanitation and drinking water, heavy metals, and waste management are categories that represent environmental health. Biodiversity and habitat, ecosystem services, fisheries, water resources, climate change, pollution emissions, and agriculture are related to the ecosystems' vitality (https://epi.yale.edu/).

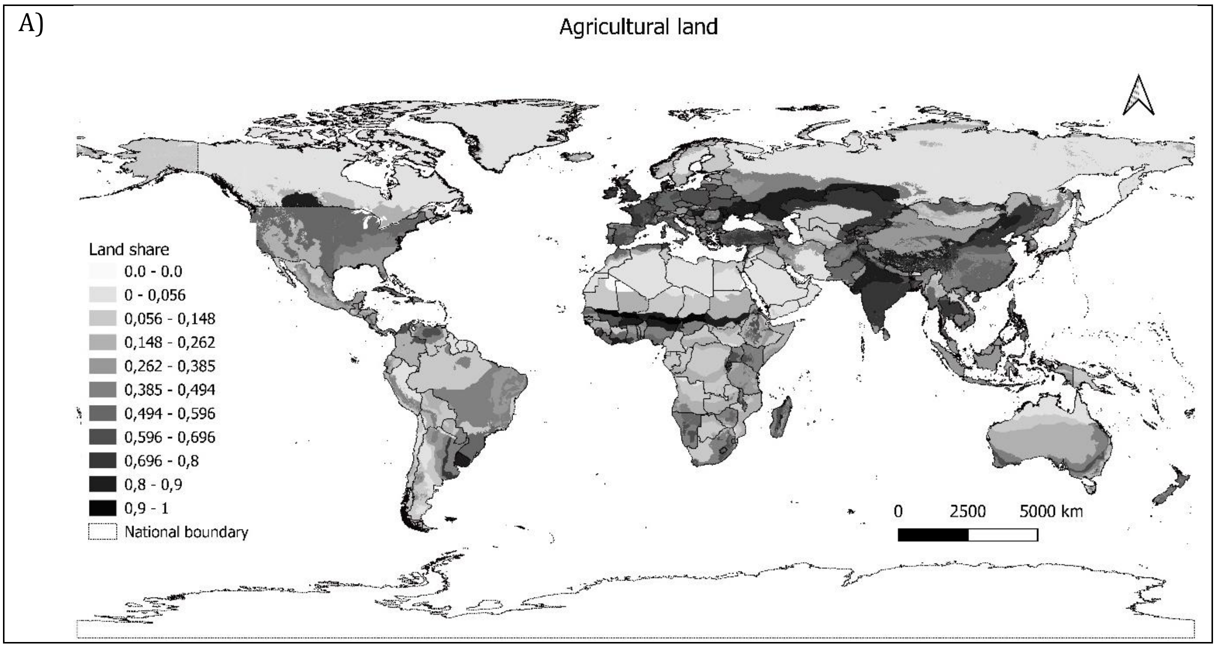
[10] The Aichi Targets were established by the UN Convention of Biological Diversity in 2011. They provided the international community a framework to address the challenge of biodiversity loss.

# 4. Results

## 4.1 Land supply and forests

Figure 2.A depicts the share of agricultural land (our indicator of land supply) to the total land endowment in each mesoregion in 2015. In temperate AEZs, i.e., zones 7–12 (see Appendix A2), we observed a high concentration of regions with an agricultural land share above 0.5. Areas in Central and Eastern Europe, the West of North America, and Asia primarily hold higher shares of their land for agricultural use. Such a pattern hints at the relatively small room to expand land supply for agriculture in these areas. In the tropical zones (AEZs 1–6), there are areas whose share ranges from 50% to 100%, such as India or the south of the Sahel region. However, this spatial pattern seems sparse and with less extension as compared with temperate zones. Figure 2.B depicts forest shares per AEZ-country region. Here the pattern from the agricultural share is reversed. We find that besides regions with a high land endowment (e.g., those in Russia or Canada), the share of forest cover is relatively smaller compared with agricultural land shares in temperate zones (darker gray hues depict a higher share). Larger forest land shares are observed and concentrated in the tropical zones, e.g., the Amazon, Congolian, and Indonesia's rainforests. As previous analyses have pointed out, these maps hint that tropical areas of the world with abundant forest areas can increase the use of land as a means to increase agricultural production if incentives to do so are in place, i.e., higher rentability of agricultural land.

As our definition of land supply implies a change in land use and forest is in competition with agricultural production for land, the remainder of this section focuses on subnational regions in the tropical zones.



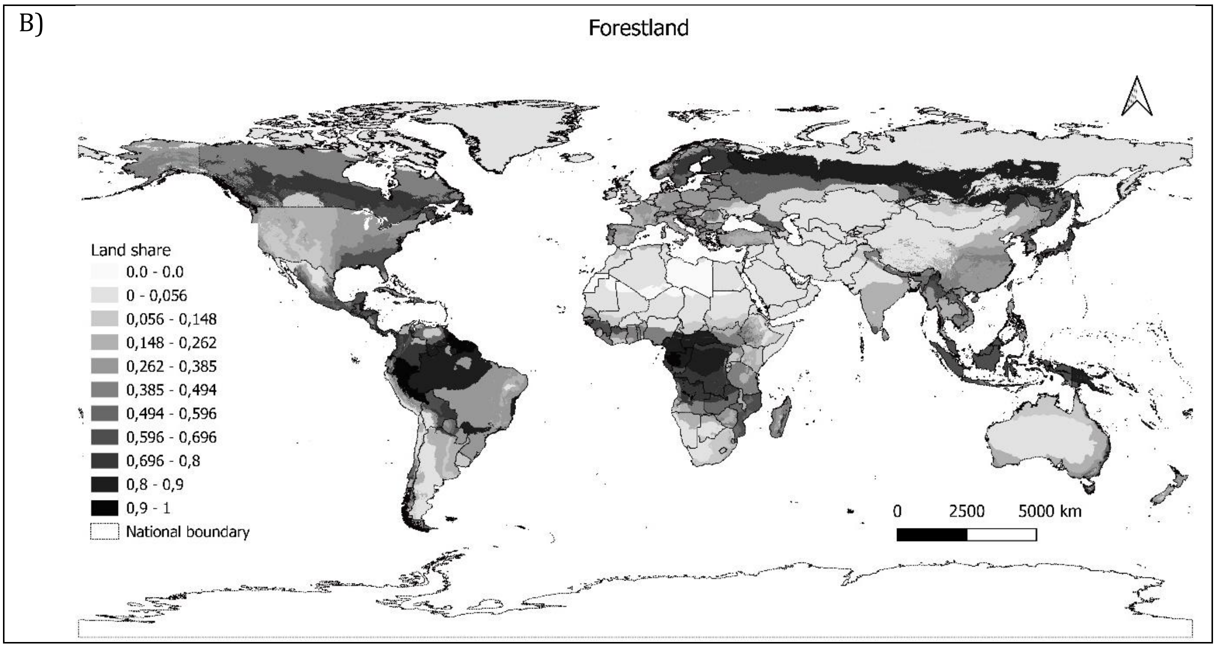



Figure 2: Land shares

*Note*: A) and B) represent shares of land use endowment within each AEZ-country observation in 2015.

The upper and lower rows of Figure 3 depict the size of land allocated to agricultural use and forest in the tropics from 2004 to 2015, respectively. We observed that the movement in the levels of these two land use indicators is divided into two different periods. First, from 2005 to 2009, agricultural land and forest increased simultaneously, suggesting less competition between these land uses. Agricultural land increased by 0.11%, while forest areas in the tropics recovered 0.04% of the territory in the same period. This development may be related to some of the effects of conservation policies on reducing forest loss in Brazil in the mid-2000s (Arima et al., 2014; Nepstad et al., 2014; Gibbs et al., 2015). However, the effects of conservation policies were fading away in the second decade of the 21st Century due to a continuous weakening in environmental governance in the South American country since 2012 (Silva Junior et al., 2021). Second, from 2009 to 2015, the annual allocation of these two land uses moved in opposite directions, reinforcing the idea of competition in our sample (Curtis et al., 2018; Goldman et al., 2020). For instance, from 2009 to 2012, agricultural land expanded by 0.25%, while forests lost 0.28% of their territory. Finally, the total change from 2004 to 2015 was 0.33% and -0.24% for agricultural land and forests, respectively.

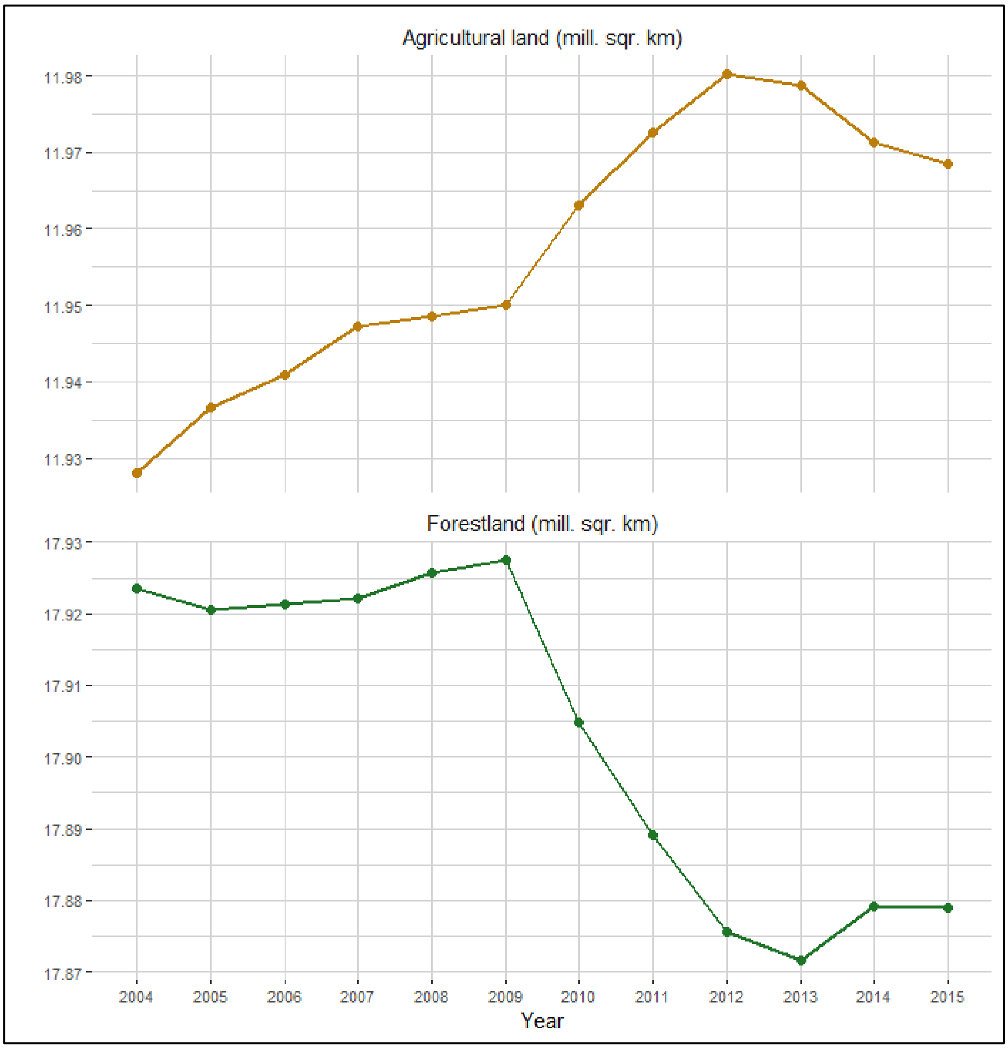



Figure 3: Agricultural land and forest in the tropics

*Note*: Each line depicts the total size of land in each use within the tropical AEZs analyzed in the study.

## 4.2 Drivers of land supply

In this section, we present our results of the fractional response model explained in Section 2.2. We estimated nine models for the three governance and fertilizer use indicators. We only reported the results of one of the fertilizer indicators (P205) because the main results did not change across specifications. Therefore, the specifications reported are similar, except for the variable representing conventional governance. The rest of the results are available upon request. We did not include all the governance indicators in one estimation as they are highly correlated among themselves (see A6). The econometric results of the fractional response models are presented in A7. The scaled coefficients presented in the table only give information on the quality of the relationship between each covariate and our dependent variable—agricultural land share (Wooldridge, 2007; Papke and Wooldridge, 2008). Therefore, we perform a normal transformation of the linear relationships to obtain the average marginal effects for tropical AEZ. The results are reported in Figure 4. In the figure, the different points represent the average marginal value estimated, and the length of the lines denotes confidence intervals at the 95% level. Models (1) to (3) denote a different specification, depending on the conventional governance indicator used, that is, V&Acc (red), corruption (green), and RoL (blue).

We observed that the commodity price index is positively related to land supply, with an average marginal effect ranging from 0.021% to 0.024% across the different specifications. We used this result to calculate individual elasticities for each AEZ-country unit, which are presented in the next section. Regarding the other socioeconomic indicators, we found that the effect of population density is positively correlated with land supply and negatively correlated in its quadratic form. This suggests that although increases in population density pushed for land expansion, as the population continued to increase, it reached an inflection point. The value-added ratio of agricultural exports to imports reveals a negative relation with land supply, although it is not statistically significant across the different specifications. Based on the available information, we could not find systematic evidence that when products are more costly in a country compared with international markets, the demand for land supply reduces. Moreover, we did not find a systematic relationship between the fertilizer indicator and land supply. This can be due to the low disaggregation in the fertilizer information that we used, which can blur its effect on land supply. Similarly, our bundle of indicators to account for the biophysical component of land rents indicate a small magnitude of scaled coefficients, where only the effect of the growing season period is statistically significant across specifications. The aggregation of these variables might lose some of the richness that spatial variation at the pixel level might capture. Improvements in conventional governance across all specifications and indicators have a positive relationship with increments in land supply, but we did not find statistically significant results. The coefficients related to terrestrial biome protection suggest a negative relationship with land supply, but, on average, the marginal effect is close to zero. This variable seems also highly significant across different specifications.

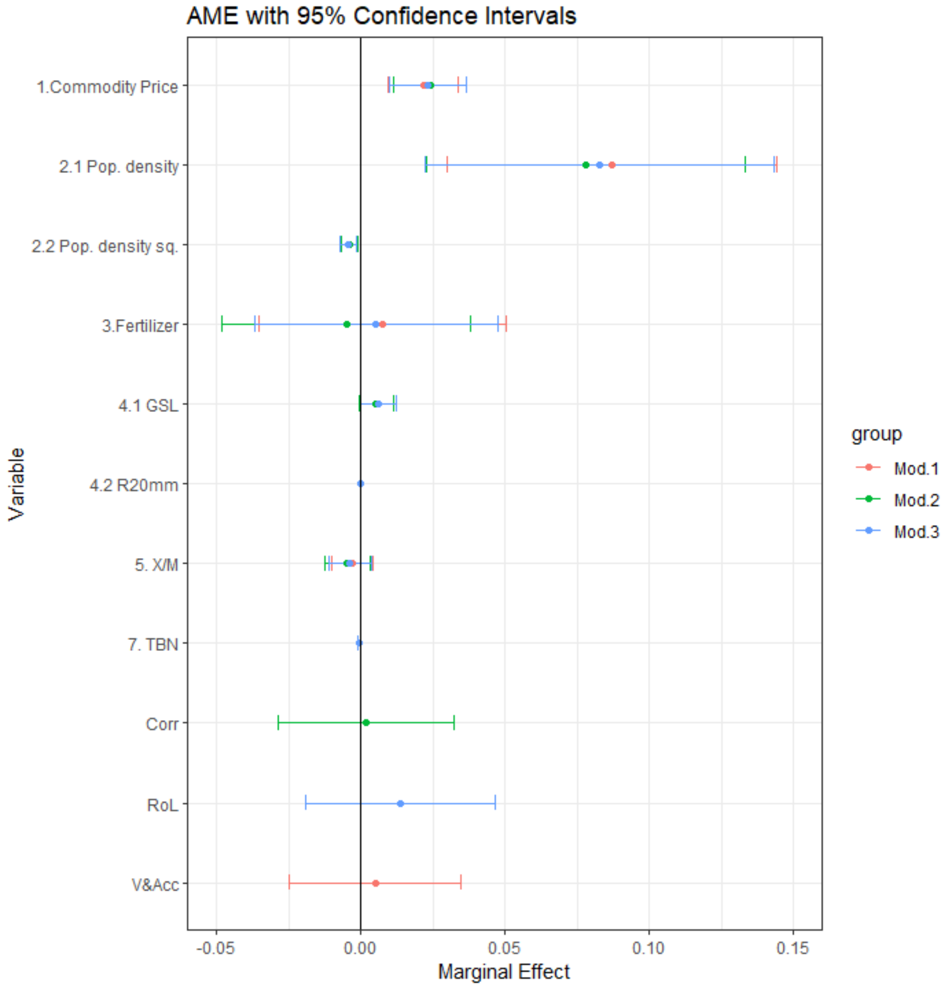



Figure 4: Average marginal effects

*Note*: The figure depicts the average marginal effects for each of our covariates tested as drivers of land supply. Models (1) to (3) represent the different specifications using different conventional governance indicators, which are V&Acc (red), corruption (green), and RoL (blue).

### 4.3 Individual land supply elasticities

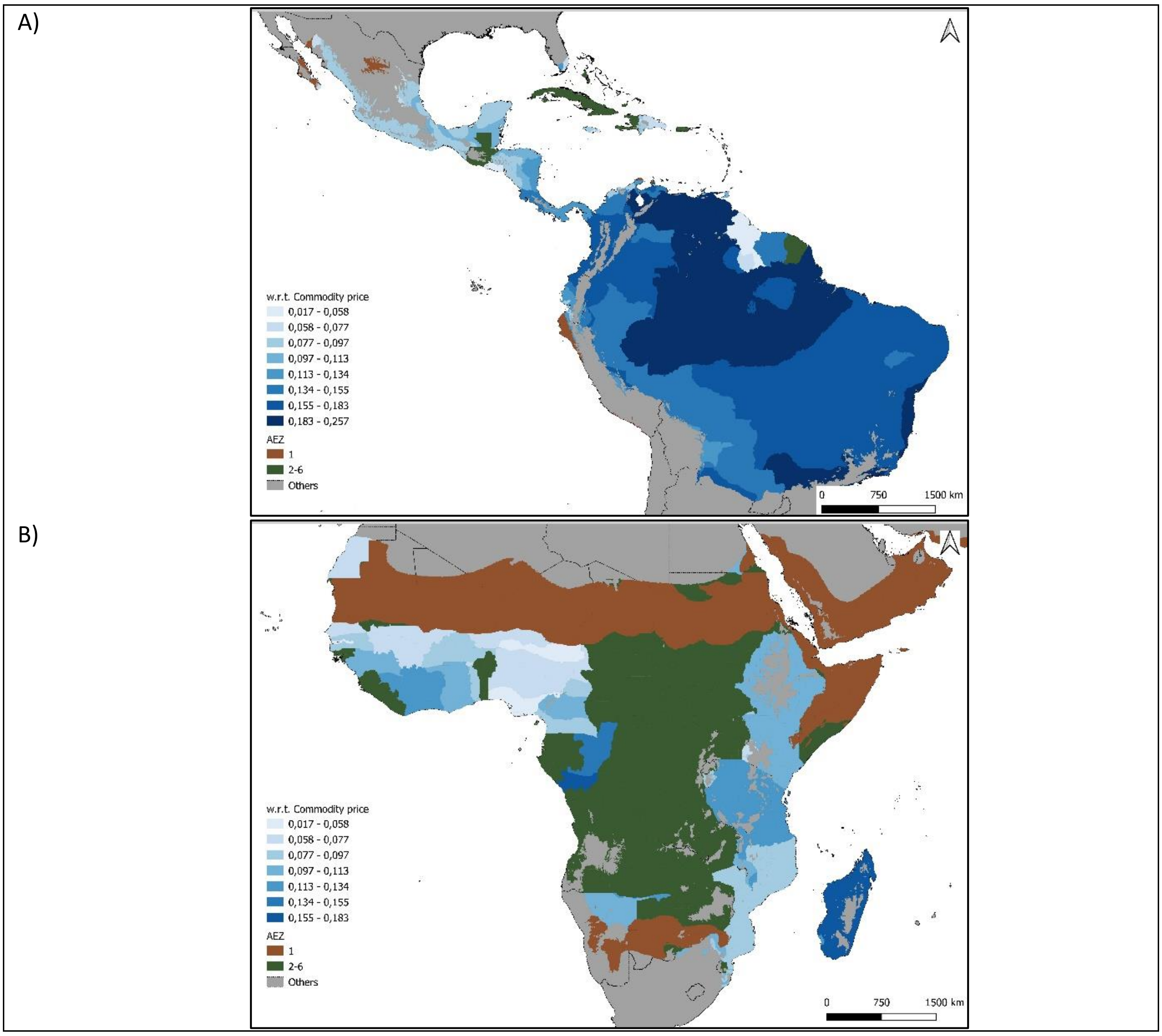
We used the results in column (2) in Table A7.1 in the Appendix to calculate individual land supply elasticities, as explained in our empirical strategy. We presented the results of this analysis in a spatial format in Figure 5,[11] and the range of individual elasticities is from 0.017 to 0.257. It is important to clarify that the land supply elasticities depicted are measures (i.e., specific to each unit of observation) of the sensitivity of agricultural land expansion to agricultural prices. They measure the percentage change in land supply expansion when there is a 1% change in prices. Therefore, we expect a different size of agricultural area (in absolute terms) to expand depending on the AEZ-country observation. For instance, the AEZ-5 in Brazil and Madagascar has a similar elasticity of approximately 0.17 for some of our specifications. This represents an expansion (compare to 2015 levels) of nearly 60 km$^2$ in Madagascar

[11] A table with the individual elasticities calculated for all specifications are presented in A8.

compared with approximately 2,190 $km^2$ in Brazil per percentage increments in average yearly prices.

We found higher mean (0.12) and maximum (0.25) values in the AEZ 6, which comprises rainforests such as the Amazon rainforest, the Congolian rainforest, and those in Indonesia. Our estimations suggest a higher likelihood of agricultural land expansion in areas with vast forest endowments. This is not surprising as these areas also host business-oriented agricultural production linked to deforestation risks.

In contrast, lower values were found in highly populated areas with relatively little land available to expand agriculture, such as some mesoregions in China, Bangladesh, India, or Nigeria (with no more than 0.05 elasticity magnitudes). Small values were also found in areas with a less developed agricultural sector, such as Guyana, Jamaica, and the Dominican Republic.



C)

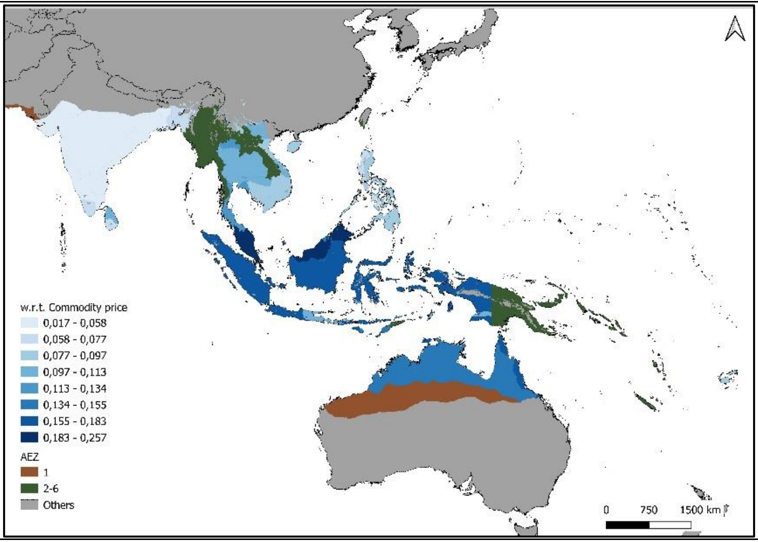



Figure 5. Individual land supply elasticities in the tropics

*Note:* The elasticities depicted in A), B), and C) are calculated using the coefficients estimated in column (2) of Table A7.1. The shades of blue represent individual land supply elasticities to changes in the agricultural commodity price index during the research period. Green areas are tropical mesoregions for which we did not have information to test our model implementation. Brown areas are mesoregions in desert areas not considered in our estimation. Greater sensitivity (i.e., higher elasticities in darker hues) is located in areas where the extensive margin of agricultural production can be activated due to relatively abundant land resources, e.g., Brazil and Indonesia. The tabular format of the elasticities is presented in A8.

In Africa, land use change from forest to agriculture happens more prominently due to small-scale shifting cultivation (Curtis et al. 2019). Unfortunately, we do not have access to information on all the covariates tested in the model to calculate individual elasticities for important forested countries located in the Congo Basin, such as the Democratic Republic of the Congo, Angola, and Zambia (depicted with green fill in Figure 5). However, we measured elasticities for other countries within this basin, such as the Republic of Congo (0.157 and 0.141 in AEZ 5 and 6, respectively) and Tanzania (from 0.117 to 0.134 across AEZs 3 to 6) in Central Africa. The country with the highest individual elasticities in Africa is Madagascar (from 0.125 to 0.171), which has been subject to high levels of deforestation in the past two decades.

The calculated individual elasticities suggest different flexibility of agricultural systems across the tropics. We found smaller elasticity values across Africa in comparison with South America or Southeast Asia. The maximum value found in Africa is 0.17% and up to 0.21% in Southeast Asia. As agribusiness requires more capital, it can only be more flexible to changes in factors of production if there are more investments in fertilizer use or land use conversion. In Africa, agricultural systems are mostly characterized by small-scale production, while those in South America or Southeast Asia are large-scale export-oriented systems. Our results reveal this pattern across the mesoregions analyzed.

## 5. Discussion

Our empirical analysis to investigate drivers of land supply and calculate individual land supply elasticities across the tropics led to two major sets of results. One set of results suggests that agricultural commodity prices have a positive relationship with land supply expansion; however, this effect is not homogenous across the tropics. We found that areas with large forest shares have a higher likelihood to allocate more agricultural land for production when prices soar. This result is particularly strong in areas where agribusiness targeting the international market is prominent, such as Brazil and Indonesia. In areas where shifting cultivation is common, the distribution in the sensitivity of land supply to changes in agricultural prices varies such as Central Africa. In densely populated areas with large shares of agricultural land, we found small to almost null magnitudes of land supply elasticities, which emphasizes the little flexibility of these agricultural systems to expand agricultural land.

Comparing our individual elasticities with previous analyses, we found similar or smaller magnitudes of land supply elasticities. For instance, Barr et al. (2011) calculated land supply elasticities for Brazil and found that they range from 0.66 to 0.89. When they included pasture, they obtained values ranging from 0.20 to 0.24 for Brazil, similar to our values ranging from 0.14 to 0.20. Villoria and Liu (2018) found lower magnitudes of land supply elasticities for their analysis of the Americas than the ones we calculated in our study. Compared with the land supply elasticities reported in Appendix B in the study by Tabeau et al. (2017), we found some strong similarities for some elasticities reported at the national level, such as those in Brazil (0.120) and Mexico (0.103), but there were high discrepancies with some of them, such as those in Indonesia (0.602) or Viet Nam (0.917). Some of the deviations in the results of various analyses are due to differences in the research period, indicators used, and scope of analysis. These studies used data from the 1990s and early 2000s to draw their estimations, while we used information from 2004 to 2015 in our calculations. We also used agricultural land instead of only cropland as the outcome variable. Moreover, we used a commodity price index while others approximated the effect of land rents through cost-to-market accessibility or derived land rentability. A major strength of our analysis is that it uses a unified framework applied to a panel data structure to estimate elasticities in global tropical zones.

The second set of results pertains to the role of governance in changes in land supply. Our econometric estimations reveal a systematic negative relationship between stronger environmental governance and agricultural land expansion. We also observed that conventional indicators of governance are positively related to land supply. RoL seems to have a stronger effect on land supply increments among these conventional indicators. However, the systematic effect of conventional governance on land supply is not conclusive based on the statistical significance of the parameters calculated. These results are similar to those found by Ceddia et al. (2014) for tropical South America. They also used agricultural land as a measurement of land supply in their analysis. Our results indicate that not all the effects are endemic to South America but go beyond other areas of the tropics, especially the effect of environmental governance, which is a proxy for terrestrial biome protection.

Our results should be interpreted with care because of the following reasons. First, we calculated land supply elasticities of commodity prices instead of land rents. Commodity prices are just a single factor. Various variables of production have different levels of scarcity due to factors such as accessibility to markets, competition of chemicals for other industries and purposes, and higher competition in agricultural systems for factors of production. There are different levels of factor scarcity around the globe just like how there is production specialization for different agricultural commodities and land suitability characteristics in different locations. Therefore, future analysis should include subnational information that can capture variation in different variable factors of production.

We also included governance indicators at the national level, which might underestimate or overestimate the effect of governance in subnational observations. Excluding the magnitude of the effect, our results suggest that environmental governance has a virtual land scarcity effect that reduces land conversion for agriculture in the tropics. This result is similar to subnational studies investigating the effect of environmental governance on agricultural deforestation at the subnational level in regions in South America and Indonesia.

Future studies on the drivers of land supply and respective elasticities can benefit from new sources of information combined with a framework similar to the one implemented in this analysis. Using satellite-based information to detect land use change processes and estimate additional socioeconomic factors (e.g., accessibility to markets) can improve currently available models. This information can also allow a higher disaggregation of the unit of analysis to capture heterogeneous effects. A Bayesian framework can be used to extend the estimations made in this analysis as it can be compared to a fractional response model, which is similar to the one we implemented (Kessler and Munkin, 2015).

# 6. Conclusion

In this study, we calculated land supply elasticities and investigated potential drivers of land supply in tropical AEZ. This study calculates land supply elasticities for tropical areas, treating markets and governance as important drivers of agricultural land expansion. The relevance of tropical areas is that they are regions that are prone to engage in the extensive margin of agricultural production, and they possess large forest shares. This study focuses on the effect of commodity prices and stronger governance on the expansion of agricultural land allocation. Consistent with previous analyses, we found that areas with larger forest shares and higher commodity prices are more prone to engage in agricultural land expansion. Our results also suggest that stronger environmental governance halts the use of the extensive margin of production. The positive effect of improvements in conventional governance on land supply is inconclusive in our analysis.

Our results provide estimations of land supply elasticities for a wide range of the world using a single framework. The use of secondary open data sources in our study would facilitate its implementation for similar applications and improvements. New data sources are released each year, which can be easily incorporated into our framework. A major improvement for future research is to increase the spatial resolution of the estimations to capture localized heterogeneous effects of different drivers of land supply using a panel data structure to account for unobserved heterogeneity. An additional direction for future research is to expand the scope of analysis to include temperate regions and information on the forestry sector, which was not included in this analysis to construct our commodity price index.

The challenge to better characterize heterogeneous agricultural systems in the tropics and other AEZ is latent in global studies that investigate the impact of different shocks in the global economic system. Land supply is a crucial aspect to calibrate these global models. A good understanding of the sensitivity of land supply to different socioeconomic, biophysical, and governance indicators is key for shaping agricultural and conservation policies and is an important avenue for research. Such efforts will help society in the quest to find solutions for an agricultural system that provides essential commodities to society, allows livelihoods to thrive, and, while doing so, preserves natural ecosystems.

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# Appendix

## A1. Land cover aggregation

| Aggregated Classes | Code in Raster | Pixel Categories |
|---|---|---|
| No Data | 0 | No Data |
| Agriculture | 10 | Rainfed cropland |
| | 11 | Rainfed cropland |
| | 12 | Rainfed cropland |
| | 20 | Irrigated cropland |
| | 30 | Mosaic cropland/vegetation |
| | 40 | Mosaic cropland/vegetation |
| | 110 | Mosaic herbaceous/tree and shrub |
| | 130 | Grassland |
| Forest | 50 | Tree cover, broadleaved, evergreen |
| | 60 | Tree cover, broadleaved, deciduous |
| | 61 | Tree cover, broadleaved, deciduous |
| | 62 | Tree cover, broadleaved, deciduous |
| | 70 | Tree cover, needleleaved, evergreen |
| | 71 | Tree cover, needleleaved, evergreen |
| | 72 | Tree cover, needleleaved, evergreen |
| | 80 | Tree cover, needleleaved, deciduous |
| | 81 | Tree cover, needleleaved, deciduous |
| | 82 | Tree cover, needleleaved, deciduous |
| | 90 | Tree cover, mixed leaf type |
| | 100 | Mosaic tree and shrub / herbaceous cover |
| | 160 | Tree cover, flooded, fresh or brakish water |
| | 170 | Tree cover, flooded, saline water |
| Other Land Uses | 140 | Lichens and mosses |
| | 150 | Sparse vegetation |
| | 151 | Sparse vegetation |
| | 152 | Sparse vegetation |
| | 153 | Sparse vegetation |
| | 200 | Bare areas |
| | 120 | Shrubland |
| | 121 | Shrubland |
| | 122 | Shrubland |
| | 220 | Snow |
| | 190 | Urban |
| | 210 | Water |
| | 180 | Shrub or herbaceous cover, flooded, fresh-saline or brakish water |

*Note*: These are the codes from the ESA-CCI-LC from which we obtained the dependent variable. The sum of all pixels in the land cover data within an AEZ country classified as agriculture in the table constitute the total land devoted to agriculture. We divided this information with the total area of the region (calculated using GIS tools) to obtain our agricultural land use share per unit of each year observation.

## A2. Global AEZ-country regions

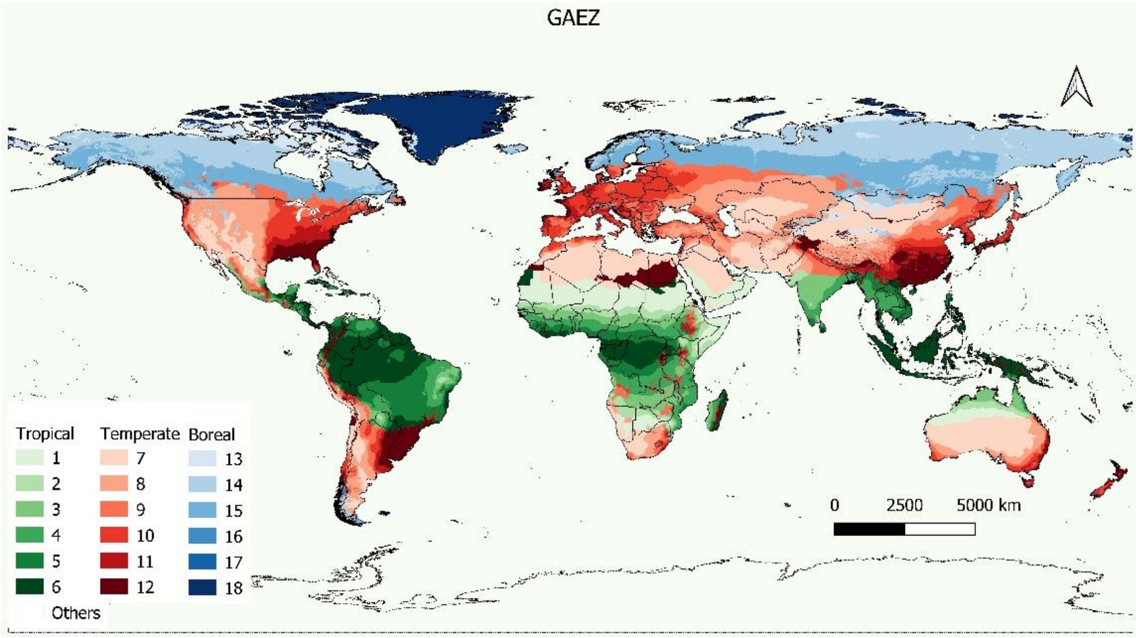


**Figure A.2.1 Global AEZ-country observations**

*Note*: The map depicts the intersection of GAEZ and the national boundaries of the world. Adapted from Fischer et al. (2002) and Plevin et al. (2014).

## A3. Agricultural commodities considered

| FAO id | Commodity |
|---|---|
| 800 | Agave fibers nes |
| 221 | Almonds, with shell |
| 711 | Anise, badian, fennel, coriander |
| 515 | Apples |
| 526 | Apricots |
| 226 | Areca nuts |
| 366 | Artichokes |
| 367 | Asparagus |
| 572 | Avocados |
| 203 | Bambara beans |
| 486 | Bananas |
| 44 | Barley |
| 782 | Bastfibres, other |
| 176 | Beans, dry |
| 414 | Beans, green |
| 558 | Berries nes |
| 552 | Blueberries |
| 216 | Brazil nuts, with shell |
| 181 | Broad beans, horse beans, dry |
| 89 | Buckwheat |
| 358 | Cabbages and other brassicas |
| 101 | Canary seed |
| 461 | Carobs |
| 426 | Carrots and turnips |
| 217 | Cashew nuts, with shell |
| 591 | Cashewapple |
| 125 | Cassava |
| 265 | Castor oil seed |
| 393 | Cauliflowers and broccoli |
| 531 | Cherries |
| 530 | Cherries, sour |
| 220 | Chestnut |
| 191 | Chick peas |
| 459 | Chicory roots |
| 689 | Chillies and peppers, dry |
| 401 | Chillies and peppers, green |
| 698 | Cloves |
| 661 | Cocoa, beans |
| 249 | Coconuts |

| FAO id | Commodity |
|---|---|
| 656 | Coffee, green |
| 195 | Cow peas, dry |
| 554 | Cranberries |
| 397 | Cucumbers and gherkins |
| 550 | Currants |
| 577 | Dates |
| 399 | Eggplants (aubergines) |
| 821 | Fiber crops nes |
| 569 | Figs |
| 773 | Flax fiber and tow |
| 94 | Fonio |
| 512 | Fruit, citrus nes |
| 619 | Fruit, fresh nes |
| 541 | Fruit, stone nes |
| 603 | Fruit, tropical fresh nes |
| 406 | Garlic |
| 720 | Ginger |
| 507 | Grapefruit (inc. pomelos) |
| 560 | Grapes |
| 242 | Groundnuts, with shell |
| 839 | Gums, natural |
| 225 | Hazelnuts, with shell |
| 777 | Hemp tow waste |
| 336 | Hempseed |
| 677 | Hops |
| 277 | Jojoba seed |
| 780 | Jute |
| 310 | Kapok fruit |
| 263 | Karite nuts (sheanuts) |
| 592 | Kiwi fruit |
| 224 | Kola nuts |
| 407 | Leeks, other alliaceous vegetables |
| 497 | Lemons and limes |
| 201 | Lentils |
| 372 | Lettuce and chicory |
| 333 | Linseed |
| 210 | Lupins |
| 56 | Maize |
| 446 | Maize, green |

| FAO id | Commodity |
|---|---|
| 571 | Mangoes, mangosteens, guavas |
| 809 | Manila fiber (abaca) |
| 947 | Meat, buffalo |
| 1127 | Meat, camel |
| 867 | Meat, cattle |
| 1017 | Meat, goat |
| 977 | Meat, sheep |
| 568 | Melons, other (inc.cantaloupes) |
| 299 | Melonseed |
| 951 | Milk, whole fresh buffalo |
| 1130 | Milk, whole fresh camel |
| 882 | Milk, whole fresh cow |
| 1020 | Milk, whole fresh goat |
| 982 | Milk, whole fresh sheep |
| 79 | Millet |
| 449 | Mushrooms and truffles |
| 292 | Mustard seed |
| 702 | Nutmeg, mace and cardamoms |
| 75 | Oats |
| 254 | Oil palm fruit |
| 339 | Oilseeds nes |
| 430 | Okra |
| 260 | Olives |
| 403 | Onions, dry |
| 402 | Onions, shallots, green |
| 490 | Oranges |
| 600 | Papayas |
| 534 | Peaches and nectarines |
| 521 | Pears |
| 187 | Peas, dry |
| 417 | Peas, green |
| 687 | Pepper (piper spp.) |
| 748 | Peppermint |
| 587 | Persimmons |
| 197 | Pigeon peas |
| 574 | Pineapples |
| 223 | Pistachios |
| 489 | Plantains and others |
| 536 | Plums and sloes |

| FAO id | Commodity |
|---|---|
| 296 | Poppy seed |
| 116 | Potatoes |
| 394 | Pumpkins, squash and gourds |
| 754 | Pyrethrum, dried |
| 523 | Quinces |
| 92 | Quinoa |
| 788 | Ramie |
| 270 | Rapeseed |
| 547 | Raspberries |
| 27 | Rice, paddy |
| 836 | Rubber, natural |
| 71 | Rye |
| 280 | Safflower seed |
| 328 | Seed cotton |
| 289 | Sesame seed |
| 789 | Sisal |
| 83 | Sorghum |
| 236 | Soybeans |
| 373 | Spinach |
| 544 | Strawberries |
| 423 | String beans |
| 157 | Sugar beet |
| 156 | Sugar cane |
| 267 | Sunflower seed |
| 122 | Sweet potatoes |
| 305 | Tallowtree seed |
| 495 | Tangerines, mandarins, clementines, satsumas |
| 136 | Taro (cocoyam) |
| 667 | Tea |
| 826 | Tobacco, unmanufactured |
| 388 | Tomatoes |
| 97 | Triticale |
| 275 | Tung nuts |
| 692 | Vanilla |
| 463 | Vegetables, fresh nes |
| 420 | Vegetables, leguminous nes |
| 205 | Vetches |
| 222 | Walnuts, with shell |
| 567 | Watermelons |
| 15 | Wheat |
| 137 | Yams |
| 135 | Yautia (cocoyam) |

## A4. Data summary statistics

| Statistic | N | Mean | St. Dev. | Min | Pctl(25) | Pctl(75) | Max |
|---|---|---|---|---|---|---|---|
| Agricultural land share | 4,272 | 0.352 | 0.251 | 0.000 | 0.137 | 0.523 | 0.971 |
| Commodity price index‡ | 3,034 | 1.602 | 0.580 | 0.626 | 1.279 | 1.787 | 6.293 |
| Population density (#/km$^2$) | 4,272 | 104.369 | 280.702 | 0.000 | 13.438 | 99.178 | 4,587.878 |
| Fertilizer use index | 3,548 | 170.790 | 492.189 | 0.000 | 87.951 | 140.527 | 8,917.735 |
| Growing Season Length (days/year) | 4,224 | 365.247 | 0.433 | 360.688 | 365.000 | 365.497 | 366.000 |
| Rain above 20 mm (days/year) | 4,224 | 140.774 | 57.862 | 0.675 | 97.395 | 180.229 | 307.242 |
| Ratio agricultural exports to Imports‡ | 4,111 | 0.984 | 0.697 | 0.014 | 0.545 | 1.268 | 10.306 |
| Rule of Law index | 3,870 | −0.570 | 0.731 | −2.606 | −1.042 | −0.279 | 1.923 |
| Corruption index | 3,870 | −0.507 | 0.716 | −1.869 | −0.996 | −0.255 | 2.326 |
| Voice and Accountability index | 3,870 | −0.365 | 0.787 | −2.233 | −0.994 | 0.156 | 1.507 |
| Terrestrial Biome Protection index | 4,208 | 64.274 | 30.487 | 0.000 | 35.891 | 91.801 | 100.000 |

*Note:* ‡Statistics for the variable transformed as 3-years-rolling-average

## A5. Commodity price index at the subnational level

We used the FAOSTAT database to obtain information on individual commodity prices to create our index. We then utilized the available land cover information within each AEZ-country region to obtain an index at the subnational level. The agricultural commodities included are related to three aggregated groups identified by FAO—primary crops, meat, and milk products (see A3).

Our starting point is to obtain subindices that account for the importance of each commodity in the agricultural sector. For this, we calculated weights, $\omega_{iat}$, representing each commodity's (*i*) importance in the total value of agricultural production ($V_{at}$). This calculation is done separately for each aggregated group of products (*a*), i.e., plant- and animal-based commodities. All the weights for plant-based products sum to unity, and the same result is obtained for animal-based products. For each commodity, we multiplied the weights with the ratio of current prices to the price of our base year (i.e., average of 2004 to 2006). We then summed all prices to obtain two subindices for each commodity group *a*. These steps are represented in Equations A5.1 to A5.4.

$$V_{at} = \sum_{i=1}^{N} V_{iat} \tag{A5.1}$$

$$\omega_{iat} = \frac{V_{iat}}{V_{at}}, and\ \sum_{i=1}^{N} \omega_{iat} = 1 \tag{A.5.2}$$

$$wP_{iat} = \frac{P_{iat}}{P_{iab}} * \omega_{iat} \tag{A5.3}$$

$$wP_{at} = \sum_{i=1}^{N} wP_{iat} \tag{A5.4}$$

Our next set of steps involves the calculation of the price index at the subnational level. For this, we used weights that reflect the period-average share of cropland and pasture to agricultural land allocated in each mesoregion. We multiplied the cropland weight by the subindex of plant-based commodities and the pasture weight by the subindex of animal-based commodities. We then summed both and multiplied by 100 to obtain our index for agricultural commodities. We summarize these steps in Equations A5.5 to A5.7 as follows:

$$\overline{AgrLand_i} = \frac{\sum_{t=1}^{N} AgrLand_{it}}{T};\ \overline{Pasture_i} = \frac{\sum_{t=1}^{N} Pasture_{it}}{T}; \overline{Cropland_i} = \frac{\sum_{t=1}^{N} Cropland_{it}}{T} \tag{A5.5}$$

$$w_c = \overline{Cropland}/\overline{AgrLand}; w_P = \overline{Pasture}/\overline{AgrLand} \tag{A5.6}$$

$$P_t = ((w_c * wP_{ct}) + (w_p * wP_{pt})) * 100 \tag{A5.7}$$

Finally, we convert the subnational agricultural price index to real terms by dividing it with the agricultural deflator in the FAOSTAT database.

$$RealP_t = \frac{P_t}{AgrDefl_t}$$

Our final price index, $RealP_t$, is then used to calculate a three-year average for each year (*t*), from *t*-1 to *t*-3. This is the final variable used in the econometric analysis, and it was used to calculate the land supply elasticities reported in the main text.

## A6. Correlation matrix

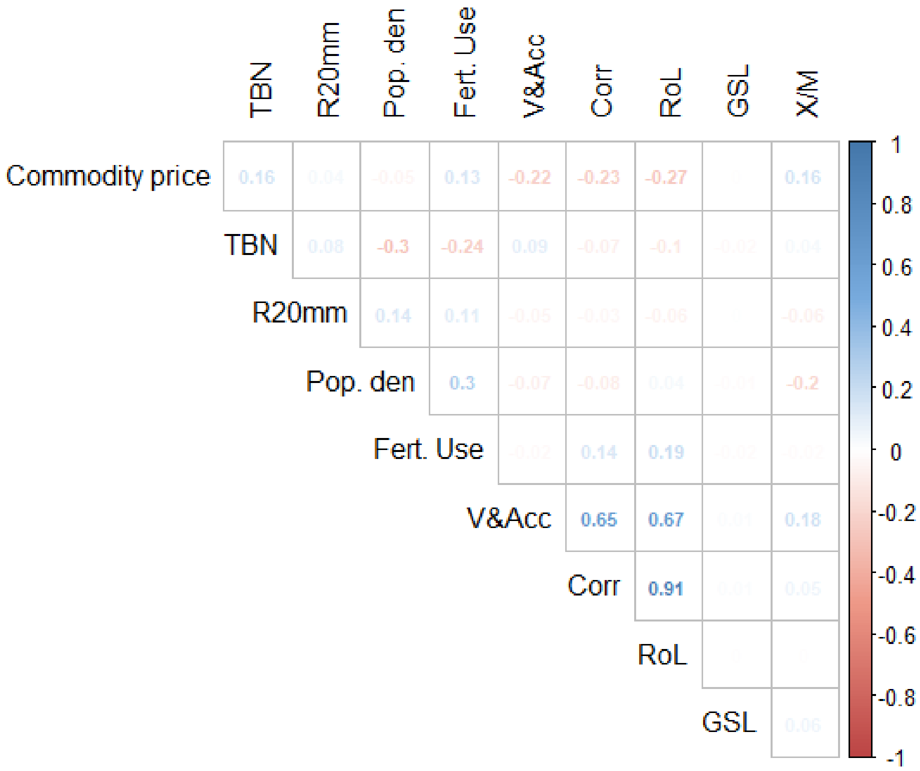


**Figure A6.1. Upper diagonal correlation matrix**

*Note*: Correlation matrix of the covariates used in the econometric analysis. The numbers represent the correlation coefficient, where stronger correlations are depicted with bolder colors.

# A7. Econometric models

## Table A7.1. Fractional response models

| | *Dependent variable:* | | |
|---|---|---|---|
| | Agricultural land share | | |
| | (1) | (2) | (3) |
| Commodity price | 0.062[a] | 0.069[a] | 0.066[a] |
| | (0.017) | (0.018) | (0.019) |
| Pop | 0.248[a] | 0.223[a] | 0.235[a] |
| | (0.082) | (0.080) | (0.087) |
| $Pop^2$ | −0.013[a] | −0.012[a] | −0.013[a] |
| | (0.004) | (0.004) | (0.004) |
| Fertilizer use | 0.022 | −0.015 | 0.015 |
| | (0.062) | (0.063) | (0.061) |
| GSL | 0.016[c] | 0.015[c] | 0.017[c] |
| | (0.009) | (0.009) | (0.009) |
| R20 mm | −0.0003 | −0.0002 | −0.0002 |
| | (0.0002) | (0.0002) | (0.0002) |
| X/M | −0.009 | −0.014 | −0.011 |
| | (0.010) | (0.011) | (0.011) |
| V&Acc | 0.014 | | |
| | (0.043) | | |
| Corr | | 0.005 | |
| | | (0.044) | |
| RoL | | | 0.039 |
| | | | (0.048) |
| TBN | −0.002[b] | −0.002[b] | −0.002[b] |
| | (0.001) | (0.001) | (0.001) |
| Time Effects | Yes | Yes | Yes |
| Regressor's period mean* | Yes | Yes | Yes |
| Observations | 2100 | 2100 | 2100 |

*Note: Columns 1–3 represent different estimations using V&Acc, corruption, and RoL as conventional governance indicators, respectively. a Significant at the 1% level. b Significant at the 5% level. c Significant at the 10% level. ∗The P&W (2008) model includes this set of covariates to control for unobserved heterogeneity. Robust standard errors clustered at the country level are presented in parentheses.*

## A8. Individual elasticities

### Table A8.1. AEZ-country elasticities

| AEZ code | Country | Mod. V&Acc | Mod. Corr | Mod. RoL |
|---|---|---|---|---|
| 3 | Argentina | 0.151 | 0.168 | 0.160 |
| 4 | Argentina | 0.153 | 0.171 | 0.162 |
| 5 | Argentina | 0.157 | 0.174 | 0.166 |
| 6 | Argentina | 0.157 | 0.175 | 0.166 |
| 2 | Australia | 0.102 | 0.135 | 0.115 |
| 3 | Australia | 0.109 | 0.143 | 0.123 |
| 4 | Australia | 0.124 | 0.163 | 0.140 |
| 5 | Australia | 0.121 | 0.159 | 0.137 |
| 4 | Bangladesh | 0.047 | 0.048 | 0.049 |
| 5 | Bangladesh | 0.072 | 0.077 | 0.076 |
| 5 | Belize | 0.097 | 0.101 | 0.098 |
| 6 | Belize | 0.101 | 0.105 | 0.102 |
| 3 | Bolivia | 0.119 | 0.130 | 0.124 |
| 4 | Bolivia | 0.127 | 0.140 | 0.134 |
| 5 | Bolivia | 0.134 | 0.147 | 0.141 |
| 6 | Bolivia | 0.140 | 0.153 | 0.147 |
| 2 | Brazil | 0.142 | 0.154 | 0.149 |
| 3 | Brazil | 0.147 | 0.159 | 0.154 |
| 4 | Brazil | 0.155 | 0.169 | 0.163 |
| 5 | Brazil | 0.169 | 0.183 | 0.178 |
| 6 | Brazil | 0.183 | 0.199 | 0.193 |
| 6 | Brunei | 0.113 | 0.147 | 0.136 |
| 2 | Burkina Faso | 0.074 | 0.087 | 0.080 |
| 3 | Burkina Faso | 0.075 | 0.088 | 0.081 |
| 4 | Burkina Faso | 0.089 | 0.104 | 0.097 |
| 4 | Burundi | 0.089 | 0.096 | 0.095 |
| 5 | Burundi | 0.077 | 0.083 | 0.083 |
| 4 | Cambodia | 0.095 | 0.101 | 0.102 |
| 5 | Cambodia | 0.087 | 0.093 | 0.094 |
| 2 | Cameroon | 0.064 | 0.069 | 0.069 |
| 3 | Cameroon | 0.062 | 0.067 | 0.067 |
| 4 | Cameroon | 0.088 | 0.095 | 0.095 |
| 5 | Cameroon | 0.093 | 0.100 | 0.100 |
| 6 | Cameroon | 0.089 | 0.095 | 0.096 |
| 4 | China | 0.013 | 0.017 | 0.014 |
| 5 | China | 0.084 | 0.094 | 0.094 |
| 6 | China | 0.073 | 0.083 | 0.083 |

*Note: The table presents the calculated individual elasticities using the different specifications presented in Table A7.1. These specifications vary depending on the conventional governance indicator employed. The acronyms are defined as follows: V&Acc=voice and accountability; Corr=corruption; RoL=rule of law.*

### Table A8.1. AEZ-country elasticities (continue)

| AEZ code | Country | Mod. V&Acc | Mod. Corr | Mod. RoL |
|---|---|---|---|---|
| 2 | Colombia | 0.107 | 0.117 | 0.112 |
| 3 | Colombia | 0.081 | 0.089 | 0.084 |
| 4 | Colombia | 0.075 | 0.084 | 0.078 |
| 5 | Colombia | 0.129 | 0.142 | 0.136 |
| 6 | Colombia | 0.149 | 0.164 | 0.158 |
| 5 | Costa Rica | 0.120 | 0.139 | 0.128 |
| 6 | Costa Rica | 0.121 | 0.140 | 0.128 |
| 3 | Côte d'Ivoire | 0.112 | 0.127 | 0.123 |
| 4 | Côte d'Ivoire | 0.116 | 0.133 | 0.128 |
| 5 | Côte d'Ivoire | 0.112 | 0.127 | 0.123 |
| 6 | Côte d'Ivoire | 0.101 | 0.116 | 0.112 |
| 3 | Dominican Republic | 0.088 | 0.091 | 0.090 |
| 4 | Dominican Republic | 0.086 | 0.089 | 0.088 |
| 5 | Dominican Republic | 0.062 | 0.064 | 0.063 |
| 6 | Dominican Republic | 0.062 | 0.064 | 0.063 |
| 2 | Ecuador | 0.116 | 0.126 | 0.121 |
| 3 | Ecuador | 0.074 | 0.080 | 0.076 |
| 4 | Ecuador | 0.114 | 0.123 | 0.119 |
| 5 | Ecuador | 0.132 | 0.142 | 0.138 |
| 6 | Ecuador | 0.158 | 0.171 | 0.166 |
| 6 | Egypt | 0.093 | 0.104 | 0.105 |
| 4 | El Salvador | 0.053 | 0.058 | 0.053 |
| 2 | Ethiopia | 0.083 | 0.100 | 0.095 |
| 3 | Ethiopia | 0.084 | 0.101 | 0.096 |
| 4 | Ethiopia | 0.093 | 0.112 | 0.107 |
| 5 | Ethiopia | 0.086 | 0.104 | 0.099 |
| 5 | Fiji | 0.088 | 0.102 | 0.096 |
| 6 | Fiji | 0.080 | 0.094 | 0.087 |
| 3 | Gambia | 0.048 | 0.057 | 0.055 |
| 3 | Ghana | 0.090 | 0.104 | 0.097 |
| 4 | Ghana | 0.097 | 0.111 | 0.104 |
| 5 | Ghana | 0.095 | 0.109 | 0.102 |
| 6 | Ghana | 0.088 | 0.101 | 0.094 |
| 3 | Guinea | 0.094 | 0.104 | 0.101 |
| 4 | Guinea | 0.097 | 0.107 | 0.104 |
| 5 | Guinea | 0.106 | 0.117 | 0.114 |
| 5 | Guyana | 0.065 | 0.069 | 0.068 |
| 6 | Guyana | 0.036 | 0.038 | 0.038 |

**Table A8.1. AEZ-country elasticities (continue)**

| AEZ code | Country | Mod. V&Acc | Mod. Corr | Mod. RoL |
|---|---|---|---|---|
| 4 | Honduras | 0.088 | 0.093 | 0.092 |
| 5 | Honduras | 0.089 | 0.094 | 0.093 |
| 6 | Honduras | 0.101 | 0.107 | 0.106 |
| 2 | India | 0.054 | 0.055 | 0.055 |
| 3 | India | 0.056 | 0.058 | 0.057 |
| 4 | India | 0.048 | 0.051 | 0.050 |
| 5 | India | 0.059 | 0.062 | 0.061 |
| 3 | Indonesia | 0.139 | 0.151 | 0.148 |
| 4 | Indonesia | 0.160 | 0.173 | 0.170 |
| 5 | Indonesia | 0.089 | 0.099 | 0.095 |
| 6 | Indonesia | 0.169 | 0.183 | 0.180 |
| 3 | Jamaica | 0.052 | 0.057 | 0.052 |
| 4 | Jamaica | 0.077 | 0.083 | 0.078 |
| 2 | Kenya | 0.102 | 0.105 | 0.106 |
| 3 | Kenya | 0.107 | 0.110 | 0.112 |
| 4 | Kenya | 0.096 | 0.098 | 0.099 |
| 5 | Kenya | 0.072 | 0.074 | 0.074 |
| 6 | Kenya | 0.083 | 0.085 | 0.086 |
| 2 | Madagascar | 0.108 | 0.125 | 0.117 |
| 3 | Madagascar | 0.139 | 0.162 | 0.151 |
| 4 | Madagascar | 0.147 | 0.171 | 0.160 |
| 5 | Madagascar | 0.148 | 0.171 | 0.160 |
| 6 | Madagascar | 0.136 | 0.157 | 0.148 |
| 3 | Malawi | 0.094 | 0.106 | 0.107 |
| 4 | Malawi | 0.103 | 0.116 | 0.117 |
| 6 | Malaysia | 0.168 | 0.211 | 0.199 |
| 2 | Mali | 0.068 | 0.072 | 0.071 |
| 3 | Mali | 0.067 | 0.071 | 0.070 |
| 4 | Mali | 0.070 | 0.074 | 0.073 |
| 2 | Mexico | 0.065 | 0.071 | 0.066 |
| 3 | Mexico | 0.079 | 0.086 | 0.082 |
| 4 | Mexico | 0.084 | 0.091 | 0.087 |
| 5 | Mexico | 0.090 | 0.097 | 0.093 |
| 6 | Mexico | 0.081 | 0.089 | 0.084 |
| 6 | Morocco | 0.064 | 0.074 | 0.071 |
| 2 | Mozambique | 0.085 | 0.093 | 0.091 |
| 3 | Mozambique | 0.086 | 0.093 | 0.091 |
| 4 | Mozambique | 0.087 | 0.095 | 0.092 |
| 5 | Mozambique | 0.084 | 0.091 | 0.089 |

**Table A8.1. AEZ-country elasticities (continue)**

| AEZ code | Country | Mod. V&Acc | Mod. Corr | Mod. RoL |
|---|---|---|---|---|
| 2 | Namibia | 0.095 | 0.113 | 0.104 |
| 3 | Namibia | 0.096 | 0.115 | 0.105 |
| 4 | Nicaragua | 0.079 | 0.086 | 0.084 |
| 5 | Nicaragua | 0.100 | 0.110 | 0.107 |
| 6 | Nicaragua | 0.113 | 0.123 | 0.121 |
| 2 | Niger | 0.064 | 0.069 | 0.067 |
| 3 | Niger | 0.077 | 0.084 | 0.082 |
| 2 | Nigeria | 0.052 | 0.054 | 0.055 |
| 3 | Nigeria | 0.058 | 0.061 | 0.061 |
| 4 | Nigeria | 0.067 | 0.070 | 0.071 |
| 5 | Nigeria | 0.044 | 0.047 | 0.047 |
| 6 | Nigeria | 0.047 | 0.050 | 0.050 |
| 5 | Panama | 0.122 | 0.132 | 0.128 |
| 6 | Panama | 0.119 | 0.128 | 0.125 |
| 2 | Paraguay | 0.138 | 0.140 | 0.145 |
| 3 | Paraguay | 0.140 | 0.142 | 0.146 |
| 4 | Paraguay | 0.145 | 0.148 | 0.152 |
| 5 | Paraguay | 0.148 | 0.151 | 0.155 |
| 6 | Paraguay | 0.139 | 0.141 | 0.146 |
| 2 | Peru | 0.109 | 0.121 | 0.114 |
| 3 | Peru | 0.111 | 0.124 | 0.115 |
| 4 | Peru | 0.140 | 0.155 | 0.148 |
| 5 | Peru | 0.144 | 0.160 | 0.152 |
| 6 | Peru | 0.133 | 0.149 | 0.140 |
| 4 | Philippines | 0.062 | 0.068 | 0.065 |
| 5 | Philippines | 0.060 | 0.066 | 0.064 |
| 6 | Philippines | 0.084 | 0.090 | 0.088 |
| 5 | Republic of Congo | 0.142 | 0.157 | 0.156 |
| 6 | Republic of Congo | 0.128 | 0.141 | 0.140 |
| 2 | Senegal | 0.060 | 0.069 | 0.065 |
| 3 | Senegal | 0.077 | 0.087 | 0.083 |
| 2 | South Africa | 0.091 | 0.104 | 0.096 |
| 3 | South Africa | 0.084 | 0.097 | 0.089 |
| 4 | South Africa | 0.086 | 0.098 | 0.090 |
| 5 | South Africa | 0.076 | 0.087 | 0.080 |
| 3 | Sri Lanka | 0.086 | 0.101 | 0.097 |
| 4 | Sri Lanka | 0.093 | 0.109 | 0.106 |
| 5 | Sri Lanka | 0.092 | 0.109 | 0.105 |
| 6 | Sri Lanka | 0.055 | 0.068 | 0.064 |

**Table A8.1. AEZ-country elasticities (continue)**

| AEZ code | Country | Mod. V&Acc | Mod. Corr | Mod. RoL |
|---|---|---|---|---|
| 6 | Suriname | 0.128 | 0.141 | 0.134 |
| 3 | Tanzania | 0.107 | 0.119 | 0.117 |
| 4 | Tanzania | 0.107 | 0.119 | 0.117 |
| 5 | Tanzania | 0.105 | 0.117 | 0.116 |
| 6 | Tanzania | 0.120 | 0.134 | 0.132 |
| 4 | Thailand | 0.093 | 0.110 | 0.106 |
| 5 | Thailand | 0.113 | 0.131 | 0.127 |
| 6 | Thailand | 0.112 | 0.130 | 0.126 |
| 3 | Togo | 0.067 | 0.076 | 0.075 |
| 4 | Togo | 0.074 | 0.083 | 0.082 |
| 5 | Togo | 0.081 | 0.091 | 0.090 |
| 6 | Trinidad and Tobago | 0.094 | 0.110 | 0.100 |
| 4 | United States | 0.102 | 0.130 | 0.115 |
| 5 | United States | 0.045 | 0.067 | 0.053 |
| 2 | Venezuela | 0.153 | 0.168 | 0.156 |
| 3 | Venezuela | 0.131 | 0.146 | 0.134 |
| 4 | Venezuela | 0.181 | 0.198 | 0.186 |
| 5 | Venezuela | 0.190 | 0.208 | 0.195 |
| 6 | Venezuela | 0.234 | 0.257 | 0.243 |
| 4 | Vietnam | 0.055 | 0.064 | 0.063 |
| 5 | Vietnam | 0.072 | 0.081 | 0.082 |
| 6 | Vietnam | 0.099 | 0.110 | 0.111 |

## A9. Commodity price index in the period of study

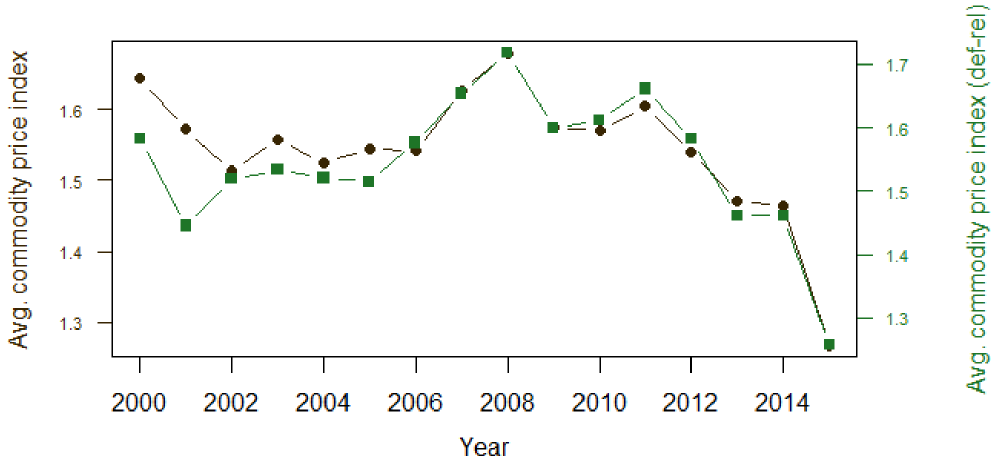


Figure A9.1. Commodity price indexes

*Note*: The graph depicts the yearly average values for the agricultural commodity price (dark brown) used in the study, and each is composed of commodities related to deforestation (green) in the tropics (Goldman et al., 2020).