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Unveiling Drivers of Deforestation: Evidence from the Brazilian Amazon

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Unveiling Drivers of Deforestation

Evidence from the Brazilian Amazon

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Abstract

The drivers of deforestation are the subject of many spatially explicit studies with considerable policy impact, yet few studies account for spatial dependence, thus neglecting spillover effects. In this work, we use high-resolution remotely sensed land cover change maps, extended with socioeconomic panel data for 141 municipalities in the state of Mato Grosso, Brazil, to investigate the role of agriculture in deforestation from 2006 until 2016. Our econometric model specifically accounts for spatial indirect effects from the dependent and explanatory variables, thus avoiding biased and inconsistent estimates. We identify indirect spillover effects from croplands and direct effects from cattle as significant deforestation drivers. Neglecting to explicitly account for spatial dependence considerably underestimates deforestation pressure of soy production. We conclude that spatial dynamics play a crucial role in deforestation and need to be considered in econometric studies, in order to facilitate informed policy decisions.

Keywords: *Deforestation, spillover effects, spatial econometrics, agriculture, soybean, land use change*

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1 Introduction

The Amazon rainforest is the world's largest forest and provides a wide range of ecosystem services. It is an unparalleled biodiversity hotspot, essential to the livelihoods of rural and indigenous peoples (Nepstad et al., 2014) and plays an important role in regional (Sampaio et al., 2007) and global climate (Malhi et al., 2008). Deforestation is a threat to the continued provision of these services and thus a primary focus of environmental policy (Meyfroidt et al., 2010). Yet, the rate of global forest loss has remained high (Global Forest Watch, 2019) and the topic is as relevant as ever.

Recent years have seen significant strides in environmental policy. Programs like REDD+ (United Nations, 2008) aim at setting up national strategies and institutions to successfully reduce emissions from deforestation, e.g. by establishing financial incentives. Regional implementations and approaches are very heterogeneous and target a variety of channels (see e.g. Gibbs et al., 2015). As a result, government efforts and their success differ wildly and commitments are often volatile. Since a peak in 2004 Brazil has long set the pace for curbing deforestation (BBC Reality Check, 2018). Conservation policies such as the Soy Moratorium and active enforcement by the executive branch of the Ministry of the Environment (IBAMA) were supported by innovations in the monitoring of deforestation via remote sensing (Achard et al., 2007). Latest developments, however, have led to a paradigm shift in Brazil. A significant rise in forest cover loss since 2016 (Global Forest Watch, 2019) goes along with increased deforestation (see Section 3 for a juxtaposition). Fritz et al. (2019) and Global Forest Watch (2018) discuss of diverging estimates between official and third party sources. The recent blaze of unprecedentedly vast forest fires in the Brazilian Amazon (McCoy, 2019) can be seen as a trend continuation. IBAMA and environmental policy in general have come under heavy criticism by the government (Escobar, 2019) and protection laws were revoked (BBC Latin America, 2018). Such a hands-off approach by the national government further stresses the need to understand the incentives and drivers, and thus the decision-making behind deforestation processes. Forests are generally understood to suffer from the tragedy of the commons (Ostrom et al., 2002), i.e. from publicly inefficient forms and extents of private use, and carry significant positive externalities. As such, forests play a crucial role in a variety of future challenges, ranging from climate change to socioeconomic issues Bonan (see e.g. 2008). An understanding of deforestation dynamics is necessary for actors at all levels to help achieve a cleaner, safer, and healthier environment.

The drivers of deforestation have been the topic of much research for decades. Different focal points, technical feasibility and changing drivers have shaped the academic discourse (see e.g. Hosonuma et al., 2012). In the case of Brazil, deforestation started out in the 1960s as a state-driven process, encouraged by infrastructure investment, coordinated settlement policies and financial incentives (Andersen et al., 2002). Early studies dealing with this period emphasise the effects of roads, population and credit availability (see e.g. Pfaff, 1999). Following this initial period of government intervention, market forces have become increasingly important in the dynamics of deforestation. In addition to the continued focus on infrastructure (see e.g. Pfaff et al., 2007), the impacts of large-scale cattle ranching, followed by expanding croplands were attributed more significance (Nepstad et al., 2009). Particularly the production of soybeans is associated with the agricultural frontier's expansion into previously forested areas. While large infrastructure projects remained a policy feature, political intent in general turned towards forest conservation. With the designation of protected areas, improved enforcement and the endorsement of policies such as the Soy Moratorium, the literature has concentrated on assessing the effectiveness of these policies Nepstad et al. (see 2014); Garrett et al. (see 2019). As such, Assunção et al. (2013) and Hargrave and Kis-Katos (2013) suggest that law enforcement, i.e. powerful responsible institutions, is an effective means for curbing deforestation. Research on protected areas and similar measures (see e.g. Soares-Filho et al., 2010; Gibbs et al., 2015) also find them to be effective, further highlighting the importance of conclusive policy coordination. Gasparri et al. (2013) call this into question, pointing out strong linkages of agriculture and macroeconomic shocks. Macedo et al. (2012) notes how the relative success of the Soy Moratorium has led to decoupling of deforestation and soy production. On the other hand, Arima et al. (2011) and Barona et al. (2010) document continued deforestation pressure from soy production, with the transmission now happening indirectly, as theorised by Meyfroidt et al. (2018). Their findings are corroborated by Richards et al. (2014), who find considerable, if declining, indirect impacts. Another area of active research is the impact of mineral extraction on deforestation (Sonter et al., 2017). Rapidly expanding consumption of minerals has led to extraction sites advancing into environmentally vulnerable areas (Bebbington et al., 2018). As can be seen, the literature on deforestation, even when limited to the Brazilian Amazon, is diverse in focal points and methodologies. Qualitative (Geist and Lambin, 2001) and quantitative (Busch and Ferretti-Gallon, 2017) meta-analyses shed some light on the issue. Especially in regards to tropical deforestation, the expansion of croplands and pasture appears pervasively as a driver. Geist and Lambin (2001) emphasise the interplay of several factors and also highlight the role of economic, political and institutional circumstances. Busch and Ferretti-Gallon (2017) find market forces to be the main drivers and prevention measures that insulate forest areas from them to be most effective.

Decisions on land use and land use change, of an inherently spatial nature, lie at the core of deforestation dynamics. As such, a large number of studies on deforestation take a spatially explicit approach, often employing econometric methods. Here, two issues arise – the first, pivotal, one stems from the spatial nature of the problem. Spatial dependence of observations is more likely than spatial independence (LeSage and Pace, 2009) and should therefore be accounted for. It is a crucial part of land use change literature (see Li et al., 2013), yet it is not systematically considered in most studies on deforestation (e.g. Fehlenberg et al., 2017). Disregard of spatial dependence may yield biased and inconsistent effect estimates of the explanatory factors (LeSage and Pace, 2009), severely limiting the validity of results. Ay et al. (2017) stress the importance of spatial dependence and give evidence of the improved predictive power of spatial models. Another virtue of this approach is the opportunity to gain insights into the spatial structure and transmission-effects of deforestation episodes. In this contribution, we address the spatial dimension of deforestation dynamics by applying a spatial Durbin model (SDM) to model forest loss changes over time. Our spatial econometric specification can account for both spatial autocorrelation as well as spatial heterogeneity and allows for inference on indirect, i.e. spillover, effects. The second issue that needs to be assessed is availability of suitable data. While information on forest loss or deforestation is generally available from remote sensing sources (e.g. Hansen et al., 2016), other data that would be required for a thorough analysis are scarce. Only few countries gather and publish statistics at the required level of detail, with Brazil and its National Institute of Statistics and Geography (IBGE) constituting a notable exception. We employ high-resolution, remotely sensed land cover change maps of the Brazilian state of Mato Grosso by Câmara et al. (2019) as primary data source. We use such data in an econometric study for the first time. Outstanding progress in the field (Gomez et al., 2016) has led to significantly improved resolutions and classification accuracy. Furthermore, new products are able to distinguish among many different land cover types (e.g. European Commission, 2019) and even individual crops (Câmara et al., 2019), relying exclusively on widely available satellite imagery and training data.

In this paper, we empirically assess the drivers of deforestation dynamics in Mato Grosso (Brazil), using econometric specifications that account for spatial dependence present in subnational data. The applied method avoids problems of bias and inconsistency in estimates of the effects of interest, which may be present in models that abstract from the explicit assessment of spatial spillovers. Our econometric modelling exercise is unique in several ways. To the best of our knowledge, this is the first application of an SDM to deforestation in Brazil, meaning this is the first study to allow for the measurement of both global and local spillover effects. We put emphasis on analysing these, a goal that is facilitated by our choice of spatial scale, i.e. the municipal level. This scale holds some key advantages, including straightforward interpretation, over any form of grid-level (see Section 3 for further information). Comparable studies focus only on singular spatial terms or do not fully explore the spatial structure (Aguiar et al., 2007; Hargrave and Kis-Katos, 2013; Richards et al., 2014). Last, we build upon a state-of-the-art remote sensing dataset that affords us considerable flexibility. Similar sources are often used for deforestation measures; we first additionally derive cropland and pasture variables for an econometric study.

The main contribution of this paper is a thorough quantitative investigation of the drivers of deforestation in Mato Grosso. Our consideration of spatial dependence safeguards the results from potential bias and inconsistency emanating from spatial dependence and attains improved model fits over conventional models. Furthermore, this approach allows us to gain additional insights into the spatial structure of deforestation drivers, with spillover effects modelled explicitly. Our model relies primarily on cutting-edge remotely sensed land cover change maps with a remarkable degree of accuracy and detail. We find considerable benefits from accounting for spatial dependence and are able to showcase the bias of conventional specifications. Our model identifies agriculture as a significant direct and indirect driver of deforestation in Mato Grosso.

The remainder of this paper is structured as follows. In Section 2 the econometric framework of our model is presented. Section 3 provides an overview of the data, variables and spatial weights used. Results are presented in Section 4 and discussed in Section 5. We conclude with Section 6.

2 Econometric Framework

Building on the theoretical basis of the land use literature Chakir and Parent (see e.g. 2009); Chakir and Le Gallo (see e.g. 2013), we model yearly deforestation as the results of land use allocation decisions. In this section, we present the underlying theory and econometric specification used in our analysis.

Land use allocation arises from the decision of individual landowners that generally happen at the parcel level. These landowners are assumed to base their decisions on simple profit maximisation strategies, i.e. they choose an allocation based on the present discounted value of each possible use, considering conversion costs (Chakir and Le Gallo, 2013). This valuation, in turn, is derived from a variety of factors, such as agricultural suitability, commodity prices, accessibility, resale value and legal constraints, as well as their enforcement. Hence, we assume that this process can be accurately represented by a function of observed and unobserved variables. In addition, we assume these variables to be sufficiently similar across different land use types, i.e. the factors determining the value of a certain use to hardly differ from other uses. Within this framework, we are interested in the transitions between forest use and any other use, i.e. deforestation. We operate at the municipal level and thus investigate the aggregated conversion, originating from a multitude of individual decisions. As such, we use information on the costs and benefits of aggregate uses to model the process of deforestation. This allows us to make use of generally applicable variables and gives us a method of controlling for unobservable effects at the regional level, such as policy or land quality (Baltagi, 2008). We account for spatial spillovers by specifying a spatial Durbin model (SDM), with deforestation as the response and aforementioned indicators as the explanatory variables. The specification takes the following form:

$$\mathbf{y}_t = \rho \mathbf{W} \mathbf{y}_t + \mathbf{X}_{t-1}\beta + \mathbf{W}\mathbf{X}_{t-1}\theta + \mu + \psi_t + \epsilon_t, \tag{1}$$
$$\epsilon_t \sim N(0, \sigma^2 \mathbf{I}_N).$$

In this model $\mathbf{y}_t$ denotes an $N \times 1$ vector of the deforestation at time t in N municipalities and $\mathbf{X}_{t-1}$ is an $N \times K$ matrix of K explanatory variables. $\mathbf{W}$ is an $N \times N$ spatial weights matrix that is used to impose a spatial structure. This matrix is non-negative with $w_{ii} = 0$ and $w_{ij} \geq 0$ for neighbouring regions i and j and is transformed to be row-stochastic (with $i, j = 1, ..., N$). The $K \times 1$ vectors β and θ contain parameters to be estimated and correspond to the reactions of $\mathbf{y}_t$ to $\mathbf{X}_t$ and $\mathbf{W}\mathbf{X}_t$, i.e. the explanatory variables and their spatial lag. The spatial autoregressive parameter $\rho \in (-1, 1)$ is associated with the spatially lagged dependent variable $\mathbf{W}\mathbf{y}_t$. It measures the strength of spatial autocorrelation. Note, that for $\rho = 0$ the model collapses to a classic linear model, without spatial spillovers from the dependent variable. Unobserved individual heterogeneity is controlled for via the region and time-specific fixed effects μ and ψ_t. The error term vector ϵ_t is assumed to follow a multivariate Gaussian distribution with zero mean and σ^2 variance.

The SDM can be seen as a generalisation of the spatial lag model, extending it to also include spatially lagged explanatory variables. The model delivers unbiased and consistent estimates in all common cases of spatial dependence and allows for local and global spatial spillover effects (Elhorst, 2010), leading to somewhat more complex interpretation of parameter estimates than for classical linear models. Due to the spatially lagged dependent, the assumption of independence of observations is violated. Hence, a marginal change in a single region has effects on the region itself and local spillover effects, affecting its direct neighbours, as well as global spillover effects for $\rho \neq 0$. The origin of these global spillovers is evident when rewriting Eq. (1) as

$$\mathbf{y}_t = (\mathbf{I}_N - \rho \mathbf{W})^{-1} (\mathbf{X}_{t-1}\beta + \mathbf{W}\mathbf{X}_{t-1}\theta + \mu + \psi_t + \epsilon_t). \tag{2}$$

Eq. 2 implies non-zero cross-partial derivatives, leading to spillovers across cross-sectional units. LeSage and Pace (2009) suggest the use of average direct effect and average indirect effect metrics to describe the effects embodied in the SDM. The average direct effect only considers changes in the region itself, i.e. diagonal elements of a derivative (with respect to a certain regressor), while the average indirect effect only accounts for changes in other regions, i.e. off-diagonal elements. This way additional insights into the spatial structure of the model at hand can be gained. The magnitude of spillovers then depends on the parameters ρ, β and θ, as well as the degree of connectivity implied by $\mathbf{W}$.

To deal with the potential correlation of unobservables in the specification, we decompose the error term into two systematic components, modelled as a fixed effect (Baltagi, 2008), and one random one. Whilst in the spatial setting this may induce an incidental parameter problem (Lee and Yu, 2010), the adequacy of the underlying assumptions of the random effect specification for the spatial context is controversial (see e.g. Elhorst, 2014). We follow Baltagi (2008) in formally assessing the presence of individual and time-specific effects as well as in the validation of our fixed effects specification.

Estimation is done in a Bayesian fashion, using Markov chain Monte Carlo (MCMC) methods (see Koop, 2003). Priors are chosen in accordance to the literature and are proper, but uninformative. The individual parameters in β and θ have a normal prior with mean 0 and variance 10^8, and an inverse gamma prior with shape and rate of 10 and 1, respectively is used for the error term variance. These prior choices yield known and tractable posterior distributions. For the autoregressive parameter ρ we employ an uninformative Beta(a_0, a_0) prior with a parameter value of $a_0 = 1.01$, following LeSage and Pace (2009). The parameter is sampled separately in a Griddy-Gibbs step (see e.g. Koch and LeSage, 2015). We present our parameter estimates in the fashion of LeSage and Pace (2009) and thus report overlaps of highest density posterior intervals (HDPI) with zero. For further information on Bayesian estimation and interpretation of results we refer to Koop (2003) and Kruschke and Liddell (2018). [1]

3 Data and Variables

The data used in this paper come from three sources. Land cover change maps from Câmara et al. (2019) are the primary data source, providing variables such as deforestation, forest cover, croplands and pasture areas. This information is further supplemented by municipal statistics and other data compiled and published by IBGE (2019). These include population data, gross domestic production (GDP), agricultural data, such as harvested areas, production, yields and headcounts, as well as maps of the municipal boundaries of Mato Grosso. The Standardised Precipitation-Evapotranspiration Index (SPEI), a multi-scalar drought index by Vicente-Serrano et al. (2010), is factored in to control for variations of climatic conditions. The data used in the model allows us to investigate the effects of agriculture, i.e. croplands and animal husbandry, on deforestation, while controlling for several other potential drivers. An overview of the variables used is provided in Table 1. Summary statistics are available in Appendix B2.

All data used in our analysis exhibit variation both across municipalities and over time: 1) the land cover maps are available yearly from 2001 until 2017 at the grid-level with 250 meter spatial resolution, 2) the SPEI covers the time period from 1955 on a monthly scale and is provided at the grid-level with $1°$ spatial resolution, 3) IBGE data is generally available from 2001 until 2017, with spatial detail on the municipal level. While we are able to cover and

[1] The code used for this work is openly available under the GNU General Public License (GPL-v3) at `https://github.com/fineprint-global/defor_sp`. All data used in our analysis are publicly available.

Variable	Description	Source
Forest area	Area classified as forest (km^2).	Câmara et al. (2019)
Forest change	Change of forest area (ha).	Câmara et al. (2019)
Pasture area	Area classified as pasture (km^2).	Câmara et al. (2019)
Crop area	Area including soy, cotton or sugarcane (km^2).	Câmara et al. (2019)
GDP per capita	Gross domestic product per capita (thousand 2010 BRL).	IBGE (2019)
Population density	Population count per area (capita per km^2).	IBGE (2019)
Cattle density	Cattle per pasture area (head per pasture).	IBGE (2019)
Soy yield	Yield per harvested area of soy (thousand BRL per ha).	IBGE (2019)
SPEI, Wet	Incidence of a particularly wet month (binary, three months).	Beguería et al. (2010)
SPEI, Dry	Incidence of a particularly dry month (binary, three months).	Beguería et al. (2010)

Table 1: Variables used in the analysis. All are available yearly from 2005 until 2016.

analyse the most important drivers, the necessity of temporal and spatial variation implies we cannot include, among others, infrastructure, which is rather persistent over time and hence captured by the regional fixed effects.

Mato Grosso's 141 municipalities with their political boundaries as spatial resolution have advantages over other levels. The political boundaries are likely to convey the regional heterogeneity that we control for via fixed effects. That not only in terms of terrain characteristics and infrastructure, but also by capturing persistent differences in policies implemented at the municipal level. The temporal aggregation level is straightforwardly set to years, since only the SPEI comes at a different timescale. Aggregation at the municipal level is necessary for the land cover maps and the SPEI and was performed in R (R Core Team, 2019) using the **raster** package (Hijmans, 2019). Due to the high resolution centroids were used for allocating grid-cells of the land cover maps, while the SPEI was weighted according to intersecting areas.

The municipality map comes from IBGE (2019) and is the most recent version, with 141 municipalities (see Appendix A1 for the map). The municipal structure of Mato Grosso had several changes in the early 2000s, including the creation of two new municipalities and some significant border changes. From 2005 onwards, changes are negligible; minor adjustments occur, e.g. due to changing riverbeds, but should not impact relevant data that is provided at the municipal level. Departing from this spatial structure, one needs to define a concept of neighbourhood to be imposed by $\mathbf{W}$, the spatial weights matrix. By treating $\mathbf{W}$ as given, the number of extra parameters to estimate is limited to ρ and θ, resulting in a parsimonious treatment of spatial dependence. The estimation results however, may be heavily influenced by the chosen spatial weights (Halleck Vega and Elhorst, 2015). This fact makes a proper theoretical foundation of the nature of spatial spillovers and robustness checks ever more important. Several approaches to the specification of the spatial linkage matrix exist in the literature, with contiguity, k-nearest neighbour and distance-based matrices as the most prominent forms (Anselin, 2013). Due to the landlocked nature of Mato Grosso and the rather regular shape of municipalities, we construct our spatial-weights matrices using Queen-contiguity (i.e. regions are considered neighbours if they share a border) as well as k-nearest neighbour algorithms with varying k.

The land cover change dataset by Câmara et al. (2019) provides yearly land cover classifications from 2001 until 2017 for the state of Mato Grosso. The maps are based on MODIS image time series at 250 meter spatial resolution. The authors report strong correlation of their crop classifications with IBGE harvest estimates, which we confirm based on own calculations. Furthermore, they cross-check pixels classified as forest with the mapping of Hansen et al. (2013), and forest and pasture classifications with Parente et al. (2017), achieving an overall high accuracy. In our model we rely directly on forest cover, pasture area and an aggregate of the different crop classifications, dropping the Cerrado, water, urban and secondary vegetation classes. Note that agricultural intensification in Mato Grosso (Garrett et al., 2018) means that later crop classifications include more incidences of double-cropping. However, the most significant

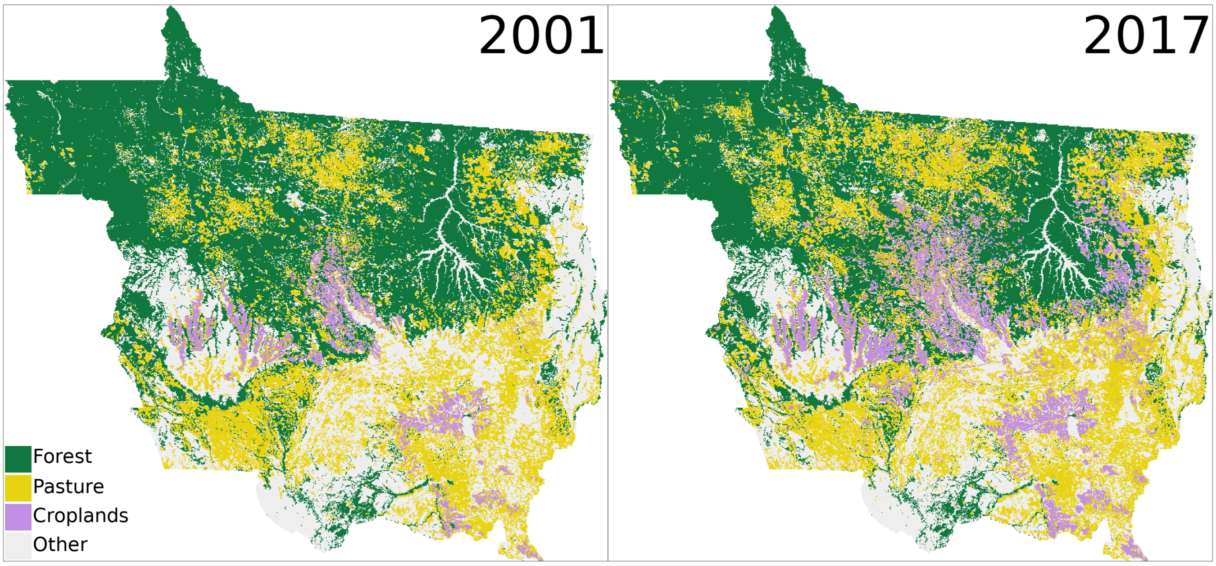

Figure 1: Land use cover maps of Mato Grosso, based on Câmara et al. (2019), 2001 and 2017

changes occur before the period cover by analysis and residual heterogeneity is captured by temporal and regional fixed effects in our modelling framework. It should also be noted that deforestation, the dependent variable of interest, is understood as the yearly change of forest cover. This means deforestation occurs when land is converted between forest use and any other use. As a result, negative deforestation may occur, but plays a minuscule role in practice. Furthermore, this definition includes all kinds of forest loss, also fire and forestry. Curtis et al. (2018) find forest loss in the Brazilian Amazon to be mainly caused by deforestation and shifting agriculture. Using the map output of Curtis et al. (2018) we find 92 percent of non-minor forest loss in our area of interest to be caused by deforestation and shifting agriculture. The vast Amazon fires in August 2019 fall outside the scope of our analysis. Figure 1 presents a visual comparison of the utilised classifications at the start and the end of the dataset. One can discern the expansion of croplands and their appearance in areas previously covered by forest or pasture. The area devoted to pasture has also risen considerably, replacing vast amounts of forest.

In addition, we source a variety of data from established IBGE (2019) statistics. In combination with deforestation maps, these data are regularly used in studies on deforestation in the Brazilian Amazon (see e.g. Aguiar et al., 2007). We primarily rely on this source for information on population and GDP time series[2]. IBGE (2019) provides precise population data from the 2000, 2007 and 2010 censuses and estimates for the remaining years. Furthermore, we use some of the available census data[3] to better cover agricultural actualities. We consider the soy-yield in Brazilian real (BRL) per harvested area as an additional variable. As an alternative, we also use the maximum achievable yield by any crop. The former measure is preferred since a) soy is by far the most significant crop in Mato Grosso, both in terms of yield and area (IBGE, 2019) and b) the yields of some arguably unimportant crops distort the data significantly. Since soy is not produced in every region at every point in time, we estimate the observations corresponding to missing values in a two-step procedure: 1) regions with some missing values are filled based on available values and time trends; 2) regions without any soy production are filled with values from contiguous regions. As supplementary information on livestock, we consider the density of cattle per pasture area and the yields from milk production. The latter is dropped due to the relatively small milk production and the spatial divergence of milk cows and cattle in general.

Busch and Ferretti-Gallon (2017) assess the impact of climatic conditions on deforestation. They find excessively wet and dry regions to experience less deforestation, possibly due to the restricted use of machinery and poor agricultural suitability. We use the SPEI (Vicente-Serrano et al., 2010) to further consider these potential drivers. This drought

[2] See *Censo Demográfico*, *Estimativas de População* and *Produto Interno Bruto dos Municípios* (IBGE, 2019).

[3] See *Censo Agropecuário*, *Produção Agrícola Municipal* and *Pesquisa da Pecuária Municipal* (IBGE, 2019).

index is based on precipitation rates and potential evapotranspiration, and improves upon similar measures by including temperature data. It is available in different time scales; short ones are related to soil water content and headwater discharges, medium ones to reservoir storage and river discharges and long ones to groundwater storage (Beguería et al., 2010). We consider short-term and medium-term timescales (three, six and twelve months), settling on the three-months scale. To capture the material information of extreme climatic conditions we use the index to build two binary variables that indicate the incidence of at least one particularly wet or dry month, defined as SPEI values below or above the critical values of -2 and 2.

4 Estimation Results

The estimates of the model given by equation 1 are reported in Table 2. Estimation was performed using MCMC with $25,000$ iterations, $15,000$ of which were discarded as burn-in, and a Griddy-Gibbs step with $2,000$ iterations. Convergence was assessed via trace plots and the convergence diagnostic in Geweke (1991). The p-values in Table 2 refer to the overlap of the highest density posterior credible intervals (HDPI) with zero. The HDPIs are provided in Appendix B5. We compare results from our chosen SDM specification to the ones obtained from classical linear panel models without accounting for spatial autocorrelation, as well as those corresponding to SAR and SEM Anselin (see 2013) specifications. In addition to the model estimates discussed here, we also entertained alternative specifications. The estimation results for these alternative models are available in Appendix B3 and B4.

Change (ha / km^2)	SDM-QU		SDM-K7		SAR-QU		SEM-QU	CLM
~	Direct	Indirect	Direct	Indirect	Direct	Indirect		
Forest (%)	-14.433 ***	-10.371 *	-14.131 ***	-10.293 **	-12.339 ***	-23.07 ***	-17.04 ***	-17.007 ***
Pasture (%)	-0.752 *	-0.005	-0.663 *	-1.007	-1.064 ***	-1.99 ***	-0.715 *	-0.703
Croplands (%)	-0.134	-10.907 ***	-0.239	-9.043 ***	-1.708 ***	-3.195 ***	-2.378 ***	-2.367 ***
Population density	-0.002	0.012	0	-0.003	0	0	-0.003	-0.003
GDP per capita	0.001	0.005	0.001	0.004	0.001	0.002	0.001	0.001
Cattle density	-0.003 ***	-0.007	-0.003 ***	-0.007	-0.003 ***	-0.006 ***	-0.004 ***	-0.004 ***
Soy yields	0.138 ***	0.05	0.127 ***	0.008	0.131 ***	0.244 ***	0.149 ***	0.148 ***
Wet	0.125 **	0.293	0.093	0.23	0.15 ***	0.28 ***	0.26 ***	0.259 ***
Dry	-0.054 **	-0.02	-0.042	0.01	-0.056 ***	-0.104 ***	-0.056 ***	-0.056 **
ρ	0.774 ***		0.749 ***		0.696 ***		0.582 ***	
R^2	0.816		0.805		0.8		0.659	0.659
$RMSE_p$	0.23		0.236		0.24		0.314	0.314
$RMSE_d$	0.244		0.251		0.254		0.332	0.332
BIC	2976.733		2906.194		2876.808		2846.606	2727.977

Table 2: Estimation results for 141 municipalities, 2006-2016. Models are SDM, SAR, SEM and the classical linear model, with *QU* and *K7* indicating spatial weights matrices constructed via queen-contiguity and a 7-nearest-neighbours algorithm. ***, ** and * correspond to HDPI covering 99, 95 and 90 percent of the posterior. Root-mean-square errors are reported point-wise ($RMSE_p$) and over the whole posterior ($RMSE_d$). $n = 1551$.

The estimation results presented in Table 2 are robust to the use of different spatial weights. Initial forest endowment have a significantly negative effect on subsequent deforestation across all specifications, implying within-municipality convergence of forest cover rates. At first glance, the impact of pastures appears negligible, with low significance and even different signs of the effect between SDM and other specifications. However, the impact of cattle ranching and expanding pastures appears to be captured by the density of cattle per pasture. The corresponding coefficients are consistently negative and highly significant in the own region. Deforestation pressure originating from these drivers does not tend to spill over into other municipalities. On the other hand, we find croplands to be a significant driver of indirect deforestation. Our model estimates indicate that higher rates of deforestation should be observed in regions neighbouring those where a large amount of land is devoted to crops (i.e. soy production). This relationship is particularly prominent in our SDM specifications. The SAR specification also features significant global spillovers, but the total effects are split between direct and indirect ones. In the SDM case, all related impacts are indirect and stem from local and global spillovers. The coefficients for soy yields are consistently positive, albeit small, across all specifications. Again, the SAR captures direct as well as indirect effects, whilst for this variable the SDM finds exclusively direct effects. Climatic variables also have significant effects – regions with at least one excessively wet month tend to feature significantly lower rates of deforestation, while deforestation tends to be higher in dry climatic conditions. After controlling for these effects, none of the models capture any additional significant effects from population density or GDP per capita. We find highly significant, positive estimates of the spatial autoregressive parameter, ρ, for virtually all specifications (see also Appendix B3 and B4). Deforestation in neighbouring regions is thus an important predictor of deforestation in a given municipality, strongly indicating the presence of spatial autocorrelation in the deforestation data. Hence, our model features global spillover effects, which are captured by our summary statistics of direct and indirect effects. This result also means that specifications neglecting to take spatial dependence of deforestation into account yield biased and inconsistent estimators.

The relevance of spatial autocorrelation in our data is further underpinned by the common measures of Moran's I and Geary's C (see Appendix B1). Both of the statistics indicate the presence of spatial autocorrelation at every reasonable level of significance. The competing model specifications are also tested with Lagrange Multiplier (LM) tests (Anselin, 1988), which point towards modelling spatial autocorrelation rather than heterogeneity. This is in line with the results of our SDM and SAR specifications, which feature significant estimates of the spatial autoregressive parameter. The spatial lag of the explanatory variables in the SDM plays a considerable role as explanatory factor of deforestation patterns in Mato Grosso. In regards to spatial heterogeneity, the SEM specification yields significant values of λ, the measure of spatial autocorrelation in the error term. Beside the aforementioned LM tests, we also calculated Moran's I for the residual values of the classical specification, but did not find evidence in favour of spatial heterogeneity. Our choice of considering individual and temporal heterogeneity, as well as the suitability of fixed effects were assessed using standard test statistics (Hausman, 1978; Honda, 1985). In addition, we also considered the possibility of a structural break in the drivers of deforestation. With the Soy Moratorium and changes in the political and economic climate in mind, we applied the Chow (1960) test to check for changes in the driver relationships. We are able to discard this hypothesis for our examined period, with insignificant test statistics.

We also perform an out-of-sample forecasting exercise in order to validate the different models entertained. The SDM specifications consistently yield low root-mean-square error (RMSE) values in sample and perform also well out of sample. In particular, the SDM specification based on the Queen contiguity matrix exhibits the best statistics in terms of out-of-sample predictive ability. A heatmap of yearly RMSE values, calculated across the full posterior, for considered models is provided in Appendix A2.

5 Discussion of the Results

The deforestation drivers identified by our model are consistent with those highlighted in previous literature (Busch and Ferretti-Gallon, 2017), but our analysis provides some valuable additional results. Following the Soy Moratorium's relative success, the role of croplands in continued deforestation was questioned (Macedo et al., 2012). Nepstad et al. (2014) attribute decreasing rates in forest cover loss in part to this supply chain intervention. Still, soy production has increased, stemming from the use of previously cleared areas, and zero-deforestation commitments remain the subject of debate (Garrett et al., 2019). This fact is central to the discussion of indirect deforestation impacts from soy production, of which Arima et al. (2011) first provide statistical evidence. Hitherto, these dynamics have not been investigated in depth using econometric methods. Barona et al. (2010), for example, base their conclusion of indirect impacts on an inverse correlation of soybeans and pasture. Fehlenberg et al. (2017) apply a similar panel regression model to deforestation in the South American Chaco, but do not consider spatial dynamics beyond simple control variables. Our model reveals significant deforestation spillovers arising from croplands and thus, soy production. Arima et al. (2011) note that increasing production has to be considered a driver of forest cover change, even if it merely takes place on former pastures or savannah. Our results for the cattle sector are also in line with this interpretation – actual pastures are not captured as driver, but rather the density of cattle per existing pasture. Zalles et al. (2019) find that cropland expansion is fuelled by repurposed pastures, with existing (potentially growing) herds being driven into greener pastures. This interpretation matches our model results well. Beside the agricultural focus of our investigation, we find impacts of the SPEI-derived climatic variables. Excessive dryness is associated with higher deforestation, which is unsurprising in the face of slash-and-burn land clearance. The indicator of extreme wetness can be interpreted along the lines of Busch and Ferretti-Gallon (2017), i.e. as a hindrance to deforestation due to its impact on machinery. Overall, climatic conditions deserve close attention, since deforestation is known to significantly impact regional climate. On the other hand, the lack of effect of population density and GDP per capita is hardly surprising, given Mato Grosso's unique land use dynamics. The frontier state is shaped by international market forces (Lambin et al., 2001; Lambin and Meyfroidt, 2011), with economic incentives related to soy and beef playing a particularly central role as determinant of land use. Indeed, Mato Grosso presents a prime example for trade-driven deforestation, as discussed by Pendrill et al. (2019). This observation is hard to reconcile with the notion of an environmental Kuznets curve for deforestation (see e.g. Crespo Cuaresma et al., 2017), and, in fact, casts doubts on the concept in this particular context. Production of both beef and soy are partly driven by land-intensive diets in countries with high income levels. This is evident in the case of soy, most of which gets processed into feedstuff, e.g. soybean cake, and subsequently ends up on international markets (based on Bruckner et al., 2019b). The same goes for beef, with an even more direct pathway. Evaluation of trade patterns, e.g. via consumption-based approaches (Rothman, 1998), is vital for proper analyses. For a full picture, investigations of environmental Kuznets curves will need to consider displacement to remote regions (Muradian et al., 2002), such as Mato Grosso. This effect appears to be especially pervasive in regard to land use (see e.g. Bruckner et al., 2019a).

Perhaps the most crucial finding of this paper is the presence and importance of spatial dependence in the context of deforestation. We are able to showcase issues, namely bias and inconsistency, arising from negligence, that cast doubt on the findings of previous econometric studies based on subnational units (see e.g. Busch and Ferretti-Gallon, 2017). Our methodological approach allows us to gain new insights into the spatial structure of deforestation patterns, uncovering considerable influence of global factors, as discussed by Lambin and Meyfroidt (2011). The limitations of the method and data used imply that certain aspects of the linkage between deforestation and its determinants cannot be fully explored. The chosen spatial level of municipalities is a natural one, but may not be the optimal granularity to correctly capture the impacts of certain variables. Spillover effects can occur at all scales, including parcel and national levels. Our framework captures parcel-level spillovers as direct effects, while coarse spillovers, e.g. at the state-level, are not captured directly. This caveat should be kept in mind when interpreting our results.

Further research steps that build upon our analysis could concentrate on other areas, thus informing about the potentially specific nature of some of the results found for Mato Grosso. Investigations of the impacts of mining activities, certain policies and interventions could provide new important insights to inform policymaking. Further accounting for uncertainty in the nature of spatial interactions (see e.g. Halleck Vega and Elhorst, 2015; Crespo Cuaresma and Feldkircher, 2013) is also a potentially fruitful avenue of further research.

6 Conclusion

Our analysis concentrated on modelling spatial dependence and spillovers in the study of the drivers of deforestation dynamics. We applied a spatial econometric model to assess the impacts of agriculture in Mato Grosso. The model includes spatial lags of explanatory and dependent variables, allowing for local and global spillover effects, that we analysed explicitly. We employed remotely sensed land cover change data at the 250 meter grid-level, national statistics on the municipality level and grid-level climatic control variables. Estimation was performed using Bayesian methods, based on a dataset spanning the period 2006-2016 for 141 municipalities.

Our results indicate the presence of strong spatial dependence, which is supported by common test statistics. We are able to demonstrate the importance of accounting for this first hand, comparing results from our spatial econometric model with more naive specifications concerning the modelling of spillovers. Neglect of spatial spillovers leads to the underestimation of the role of croplands as a driver of deforestation in our reference models. Additionally, we manage to gain insights into the underlying spatial structure of forest cover dynamics, allowing us to identify indirect spillover effects across municipalities arising from croplands. Other deforestation drivers feature direct effects and include cattle density, dry climate and initial forest cover. Moreover, no significant effects from population density and GDP per capita can be found. This is hard to reconcile with the notion of a deforestation Kuznets curve, stressing the need for moving beyond local indicators for environmental performance. Our findings have major implications for future studies and policy evaluation exercises. The needs to examine spatial dependence and potentially control for it in studies aiming at assessing the drivers of deforestation is the first implication. Considering both direct and indirect drivers of forest cover change appears particularly important in models aimed at informing policymakers. For Mato Grosso, for instance, our results imply that deforestation pressure from soybean production is indirect and would not have been unveiled using standard linear regression without an explicit assessment of spatial dependence.

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Appendix

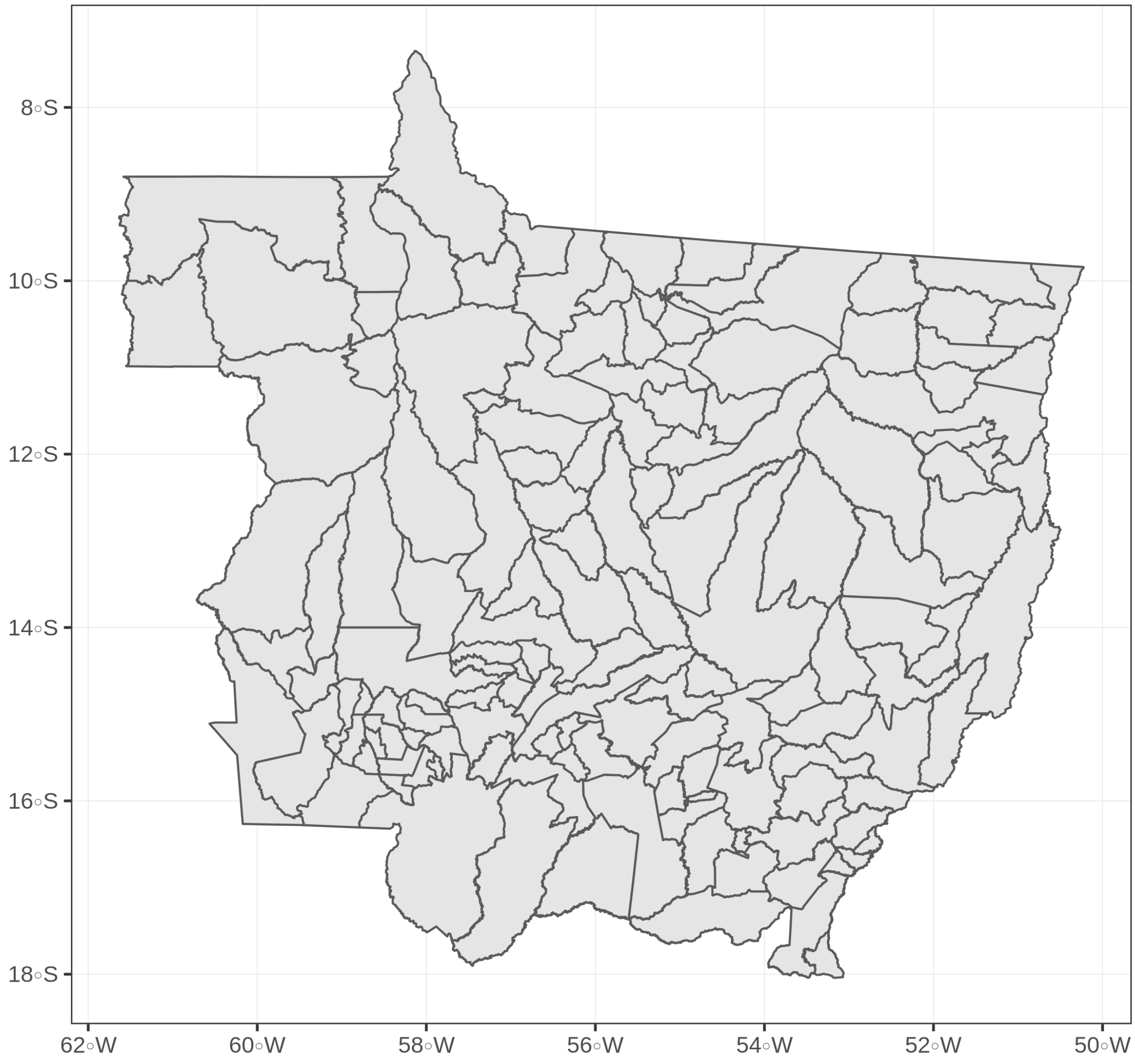

Figure A1: Municipality structure of Mato Grosso in 2018 (IBGE, 2019).

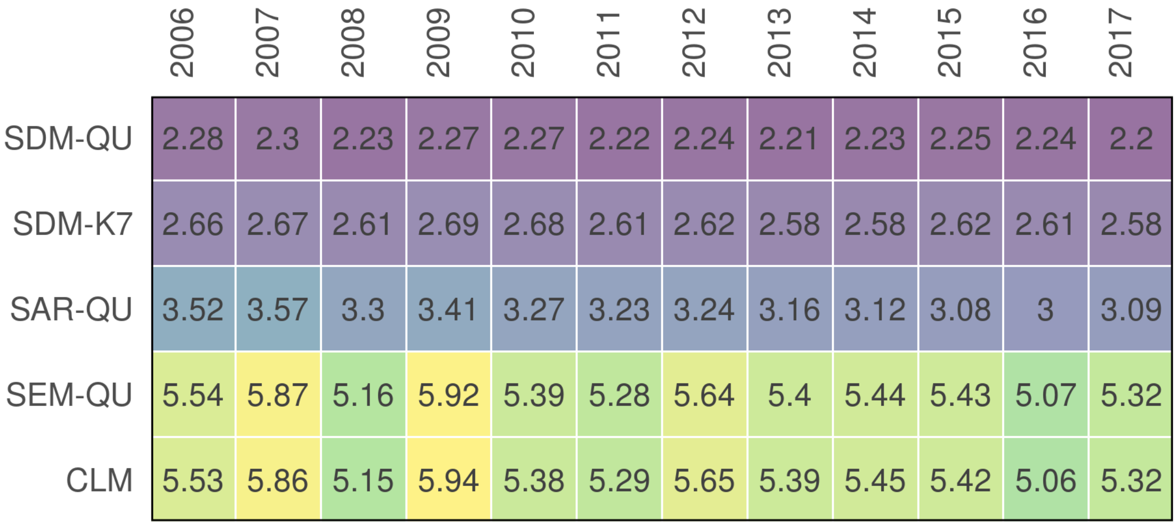

Figure A2: RMSE across models over time, with 2017 being out-of-sample. Models are SDM, SAR, SEM and CLM with *QU* and *K7* indicating spatial weights matrices constructed via queen-contiguity and using a 7-nearest-neighbours algorithm.

Weights	Moran's I	p-value	Geary's C	p-value
Queen-contiguity	0.5852	$<$ 2.2e-16	0.3693	$<$ 2.2e-16
5-nearest-neighbours	0.6273	$<$ 2.2e-16	0.4315	$<$ 2.2e-16
7-nearest-neighbours	0.5871	$<$ 2.2e-16	0.4447	$<$ 2.2e-16

Table B1: Results of Moran's and Geary's test for spatial autocorrelation in the dependent variable. Note that k-nearest-neighbour matrices where transformed to $1/2(\mathbf{W} + \mathbf{W}')$ for the calculation of Geary's C.

	Min	1st Quintile	Mean	Median	4th Quintile	Max
Forest change	-4.2254	-0.5533	-0.3061	-0.0743	0.0000	1.5440
Forest	0.0000	0.0185	0.2521	0.1786	0.4920	0.9398
Pasture	0.0285	0.1843	0.3819	0.3652	0.5431	0.9680
Croplands	0.0000	0.0006	0.0893	0.0200	0.1607	0.6483
Population density	0.2495	0.9905	6.7675	2.2185	5.4662	255.2953
GDP per capita	3.2442	7.8993	19.8416	13.6227	27.5596	158.1428
Cattle density	11.3329	64.6990	110.6767	101.5618	158.6439	266.0772
Soy yields	0.1117	1.0944	1.7760	1.7829	2.4338	3.7300
SPEI wet	0.0000	0.0000	0.0322	0.0000	0.0000	1.0000
SPEI dry	0.0000	0.0000	0.3417	0.0000	1.0000	1.0000

Table B2: Summary statistics of the variables used.

Change (ha / km^2)	SDM-QU		SDM-K7		SAR-QU		SAR-K7		SEM-QU	CLM
$\sim$	Direct	Indirect	Direct	Indirect	Direct	Indirect	Direct	Indirect		
Forest (%)	-14.368 ***	-10.419	-14.081 ***	-10.067 *	-12.159 ***	-24.695 ***	-12.149 ***	-22.507 ***	-16.87 ***	-16.855 ***
Pasture (%)	-0.742 *	-0.454	-0.65 *	-1.151	-1.233 ***	-2.506 ***	-1.216 ***	-2.252 ***	-0.86 **	-0.865 **
Croplands (%)	0.031	-11.452 ***	-0.054	-8.978 ***	-1.69 ***	-3.433 ***	-1.582 ***	-2.932 ***	-2.44 ***	-2.443 ***
Cattle density	-0.003 ***	-0.008	-0.003 ***	-0.007	-0.003 ***	-0.006 ***	-0.003 ***	-0.006 ***	-0.004 ***	-0.004 ***
Soy yields	0.129 ***	0.01	0.122 ***	-0.023	0.121 ***	0.245 ***	0.125 ***	0.231 ***	0.134 ***	0.133 ***
ρ	0.798 ***		0.769 ***		0.715 ***		0.681 ***		0.601 ***	
R^2	0.817		0.806		0.799		0.791		0.652	0.652
$RMSE_p$	0.23		0.236		0.241		0.246		0.318	0.318
$RMSE_d$	0.243		0.25		0.255		0.26		0.335	0.335
BIC	2923.149		2849.813		2850.167		2790.414		2827.481	2699.447

Table B3: Alternative model specifications.

Change (ha / km^2)	SDM-QU		SDM-K7		SAR-QU		SAR-K7		SEM-QU	CLM
$\sim$	Direct	Indirect	Direct	Indirect	Direct	Indirect	Direct	Indirect		
Forest (%)	-13.899 ***	-7.57	-13.708 ***	-6.547	-11.673 ***	-22.421 ***	-11.616 ***	-21.703 ***	-16.252 ***	-16.297 ***
Pasture (%)	0.001	2.33	0.071	1.634	-0.401	-0.771	-0.385	-0.719	0.118	0.114
Croplands (%)	0.528	-8.349 ***	0.43	-6.059 **	-1.065 **	-2.047 **	-0.948 **	-1.772 **	-1.675 ***	-1.68 ***
Population density	0	0.002	0.001	-0.007	0.001	0.002	0.002	0.004	-0.002	-0.002
Wet	0.134 **	0.271	0.094 *	0.251	0.145 ***	0.279 ***	0.115 ***	0.215 **	0.256 ***	0.255 ***
ρ	0.787 ***		0.761 ***		0.702 ***		0.682 ***		0.592 ***	
R^2	0.813		0.802		0.796		0.787		0.65	0.65
$RMSE_p$	0.232		0.238		0.243		0.248		0.319	0.319
$RMSE_d$	0.246		0.253		0.257		0.262		0.336	0.336
BIC	2922.935		2851.418		2851.147		2788.59		2822.301	2699.267

Table B4: Alternative model specifications.

	SDM-QU								SDM-K7							
	Direct				Indirect				Direct				Indirect			
	99%	95%	5%	1%	99%	95%	5%	1%	99%	95%	5%	1%	99%	95%	5%	1%
Forest (%)	-16.841	-16.167	-12.801	-12.373	-27.117	-22.189	0.463	3.447	-16.355	-15.695	-12.472	-12.119	-25.239	-21.319	-0.302	2.196
Pasture (%)	-1.822	-1.549	0.037	0.239	-6.037	-4.401	4.391	5.952	-1.653	-1.422	0.112	0.323	-7.114	-5.414	3.212	4.346
Croplands (%)	-1.676	-1.290	1.084	1.449	-20.966	-17.857	-3.988	-2.265	-1.720	-1.435	0.887	1.326	-18.071	-15.440	-2.320	-0.766
Population density	-0.021	-0.017	0.012	0.018	-0.142	-0.107	0.130	0.172	-0.017	-0.014	0.014	0.018	-0.150	-0.109	0.110	0.140
GDP per capita	-0.003	-0.002	0.004	0.004	-0.022	-0.015	0.025	0.033	-0.002	-0.001	0.004	0.005	-0.024	-0.018	0.026	0.036
Cattle density	-0.005	-0.004	-0.002	-0.001	-0.019	-0.017	0.001	0.004	-0.005	-0.004	-0.002	-0.001	-0.019	-0.016	0.002	0.005
Soy yields	0.022	0.055	0.224	0.245	-0.610	-0.417	0.573	0.711	0.019	0.042	0.210	0.244	-0.679	-0.498	0.504	0.663
Wet	-0.028	0.006	0.241	0.282	-0.324	-0.188	0.732	0.923	-0.049	-0.018	0.201	0.241	-0.395	-0.232	0.713	0.855
Dry	-0.124	-0.107	-0.002	0.014	-0.264	-0.207	0.156	0.222	-0.107	-0.096	0.010	0.029	-0.226	-0.157	0.177	0.220
ρ	0.702	0.722	0.825	0.839					0.680	0.695	0.799	0.815				
	SAR-QU								SEM-QU				CLM			
	Direct				Indirect											
	99%	95%	5%	1%	99%	95%	5%	1%	99%	95%	5%	1%	99%	95%	5%	1%
Forest (%)	-14.432	-13.992	-10.753	-10.266	-32.080	-29.183	-17.219	-16.069	-19.233	-18.549	-15.202	-14.900	-19.221	-18.653	-15.287	-14.779
Pasture (%)	-1.997	-1.792	-0.349	-0.095	-3.972	-3.441	-0.563	-0.131	-1.753	-1.540	0.090	0.345	-1.749	-1.543	0.103	0.384
Croplands (%)	-3.103	-2.732	-0.673	-0.407	-6.172	-5.334	-1.183	-0.606	-3.880	-3.510	-1.128	-0.897	-3.859	-3.569	-1.252	-0.826
Population density	-0.018	-0.013	0.013	0.017	-0.034	-0.024	0.026	0.032	-0.020	-0.018	0.011	0.018	-0.022	-0.018	0.012	0.017
GDP per capita	-0.002	-0.001	0.003	0.004	-0.004	-0.002	0.007	0.008	-0.003	-0.002	0.003	0.004	-0.003	-0.002	0.003	0.004
Cattle density	-0.005	-0.004	-0.002	-0.001	-0.009	-0.008	-0.003	-0.002	-0.005	-0.005	-0.002	-0.002	-0.005	-0.005	-0.002	-0.002
Soy yields	0.029	0.050	0.211	0.238	0.037	0.089	0.409	0.466	0.044	0.059	0.239	0.266	0.029	0.055	0.241	0.275
Wet	0.037	0.059	0.238	0.269	0.056	0.106	0.467	0.535	0.122	0.157	0.362	0.390	0.126	0.152	0.357	0.396
Dry	-0.105	-0.092	-0.018	-0.008	-0.214	-0.178	-0.033	-0.016	-0.111	-0.096	-0.019	-0.005	-0.109	-0.100	-0.016	0.000
ρ	0.628	0.649	0.744	0.753					0.515	0.533	0.642	0.650				

Table B5: Credible intervals of results reported in Table 2.

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