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Using spatially explicit data to improve our understanding of land supply responses: An application to the cropland effects of global sustainable irrigation in the Americas☆

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ABSTRACT

Land supply elasticities determine the rates of land conversion in global policy models. However, they are only available for few countries in the world. Therefore, analysts seeking to improve the spatial resolution of their models are forced to impose regionally homogeneous parameters over highly heterogeneous regions. This article estimates spatially explicit land supply elasticities using gridded data for the American continent. These estimates reasonably reproduce changes in land use observed at different levels of geographical aggregation across the continent. Plugging our estimates in a previous analysis of the land-use effects of eliminating global unsustainable irrigation, reveals higher pressure to convert land in the ecoregions in the south of the continent that have experienced most rapid cropland expansion in the recent past.

1. Introduction

Global economic models are an essential tool in the analysis and design of policies related to the sustainability of global agriculture. For instance, in the U.S., regulation of the ethanol industry is based on model predictions of greenhouse gas emissions from domestic and foreign land use changes caused by biofuel mandates (Babcock, 2009). Beyond biofuels, global trade models have been used to model the land use changes associated with technological change (Villoria et al., 2014), international trade (van Meijl et al., 2006; Verburg et al., 2009), climate change mitigation (Golub et al., 2009), and agricultural policies (Eickhout et al., 2007). Yet, although global models are useful to quantify aggregate outcomes, policy decisions are often made at very localized levels. Recognizing the interdependence between global drivers of land use change and local stressors and policy responses, there is a growing demand to increase the spatial resolution of economic models so that they produce results that are both consistent and accurate at different geographic scales (Verburg et al., 2013).

A crucial obstacle in the development of better models is the paucity of data and parameters characterizing the heterogeneity of economic responses across space. This paucity is particularly acute in many developing and emerging economies, which are precisely the places where the transformations of the landscape are being most acute. A prime example of this paucity are the land supply elasticities. The land supply elasticity is the percentage change in cropland following a one percent increase in the land rents accruing to agriculture (relative to alternative uses.) These elasticities determine the amount of natural lands that are converted into cropland and, by extension, condition model predictions about environmental metrics linked to land conversion, such as greenhouse gases emissions, biodiversity losses, or changes in the hydrological balance. As economic models increase their spatial resolution, modelers have to grapple with the fact that the available land supply elasticities are either calibrated to match country-level historical patterns of land use changes (Taheripour and Tyner, 2013) or based on econometric evidence which is heavily focused on the U.S. (Lubowski, 2002; Ahmed et al., 2008).

This article contributes to improve the ability of economic models to produce policy insights consistent across geographic scales by estimating spatially heterogeneous land supply elasticities. We focus on the contiguous countries in the Americas, from Canada to Argentina. To preview our main results, we find that the estimated elasticities reasonably reproduce actual changes in cropland observed by Lark et al. (2015) and Graesser et al. (2015) in the US and Latin America. We also find that using these elasticities for policy analysis does indeed provide

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more refined insights than current practice. In particular, the use of our elasticities for the analysis of the consequences of eliminating unsustainable irrigation by Liu et al. (2017) suggests increased pressure in the Brazilian Cerrado and other ecoregions of South America already experiencing large pressures for land conversion to agriculture.

The rest of the article is structured as follows. Section 2 discusses the conceptual and empirical underpinnings of a strategy to spatialize the country level supply responses combining the standard theory of land use choice with von Thünen's model of location-determined land rents. Section 3 presents the regression results and discusses the determinants of the estimated land supply elasticities. Section 4 compares prediction of our estimates to actual changes in cropland observed at the level of ecoregions or subnational units. Section 5 demonstrates the use of our estimates by plugging them in the gridded model used by Liu et al. (2017) to explore the consequences of more rational global irrigation practices. Section 6 concludes the article.

2. Modeling framework and empirical strategy

2.1. Theory

We define a land supply schedule as the functional relationship between the quantity of land converted from a natural cover (e.g., forests) to agriculture and the agricultural land rents. To fix ideas, using Z_i and R_i to denote the share of cropland and land rents in each gridcell i, the land supply schedule is given by:

$$Z_i = \epsilon_i^* R_i, \tag{1}$$

where ϵ_i^* is the land supply elasticity in gridcell i. In principle, a regression of Z_i on R_i can be used to get an estimate of ϵ^*. However, calculating R_i requires gridcell level input and output prices. Unfortunately, spatially explicit data on either prices or land rents are largely unavailable for most countries of the world.

Following Chomitz and Gray (1996), spatially disaggregated land rents can be approximated using Von Thünen's assumption that spatial differentials in output and input prices are related solely to differences in transport costs to major markets.[1] This allows mapping (up to a proportionality factor) land rents in each gridcell onto market access (A_i) and a vector of k fixed biophysical and socioeconomic covariates ($\boldsymbol{S}_{k[i]}$) that influence land use choices. Formally:

$$R_i \propto f(A_i, \boldsymbol{S}_{k[i]}), \quad k = 1, \ldots, K. \tag{2}$$

Substituting (2) in (1) allows expressing the land supply schedules in terms of market access and land suitability, both of which are readily available in the gridded maps described in the Data subsection just below:

$$Z_i = \epsilon_i f(A_i, \boldsymbol{S}_{k[i]}). \tag{3}$$

A caveat to keep in mind is that in this strategy, the resulting elasticity is with respect to market access and not with respect to land rents. Under this modeling framework, these elasticities are proportional to each other, i.e. $\epsilon_i \propto \epsilon_i^*$, but without information on land rents at each gridcell, we are unable to determine the proportionality factor. Nevertheless, to the extent that the spatial heterogeneity of the land supply responses can be reasonably considered to be invariant to scale, the estimated elasticities convey useful information about geographic patterns of supply response. We empirically validate such usefulness below, where the changes in cropland implied by our estimates are compared to observed changes at different levels of geographic aggregation.

Under standard assumptions about producer behavior (in RA S-1),

[1] Formal development of the model and derivation of the regression equation is in Section S-1 of the Reviewers' Appendix to be posted as Supporting On-line Materials upon publication.

Table 1
Descriptive statistics.

	Mean	s.d.	Min	Max
Cropland (share of gridcell, 0–1)	0.12	0.22	0.00	1.00
Market access index (0–1)	0.12	0.21	0.00	1.00
Area equipped for irrigation (% of gridcell)	1.51	6.96	0.00	100.00
Precipitation (mm)	1148.75	788.75	0.00	7513.00
Temperature (°C)	17.06	7.93	−0.78	28.33
Elevation (m)	666.80	801.87	−224.00	5419.00
Soil fertility (IIASA classes)	4.19	2.14	1.00	7.00
Soil carbon density (kg-C/m^2)	5.92	2.45	1.33	24.88
Soil pH (0–14)	6.08	1.00	4.20	8.22
Built-up land (% of gridcell)	0.58	3.94	0.00	100.00
Protected areas (binary variable)	(% of gridcells under each class)			
Unprotected (U)			87	
Protected (P)			13	
Natural potential vegetation	(% of gridcells under each class)			
Shrublands (S)			13	
Tropical forests (Ft)			28	
Temperate forests (FT)			28	
Savannas &Grasslands (G)			29	
Other			3	

Notes: These are summary statistics for the sample of 43,311 observations (out of a total of 433,096) used to estimate the elasticities in Fig. 3. The soil fertility constraints categories employed in the regression are: no constraints, slight constraints, moderate, constrained, severe, very severe, and unsuitable for cultivation which were obtained from IIASA/2012. Sources and steps taken to preprocess the data data are in Table S-1 of the RA.

Expression (3) can be estimated as a fractional logistic regression model. The estimating equation that we take to data is:

$$Z_i = \Lambda\left[\alpha_0 + \alpha_1 A_i + \sum_k \alpha_k S_{k[i]} \varepsilon_i\right]. \tag{4}$$

where Λ is the logistic distribution. The elasticity of the changes in cropland to changes in market access for a specific gridcell is given by:

$$\epsilon_i = \frac{\partial \hat{Z}_i}{\partial A_i} \times \frac{A_i}{\hat{Z}_i} = \lambda_i\left[\hat{\alpha}_0 + \hat{\alpha}_1 A_i + \sum_k \hat{\alpha}_k \log(S_{k[i]})\right]\hat{\alpha}_1 \times \frac{A_i}{\hat{Z}_i}. \tag{5}$$

where λ is the probability distribution function of the logistic distribution and $\hat{Z}_i$ are fitted cropland shares using the parameter estimates ($\hat{\alpha}$) from Eq. (4). Note that the partial effects $\partial \hat{Z}_i \partial A_i^{-1}$ are specific to each gridcell. This is a property of the logistic model that gives us great flexibility to aggregate the elasticities to different regions or relevant units of spatial analysis.

2.2. Data

Table 1 reports the descriptive statistics of all the variables used to estimate Eq. (4). The dependent variable is the share of each gridcell that was under cropland circa year 2000. This variable was derived by Ramankutty et al. (2008) by combining agricultural inventory data and satellite-derived land cover data.

The market access variable comes directly from Verburg et al. (2011), who combines spatially explicit global data on physical distance, network infrastructure, and underlying terrain to develop a high spatial resolution (1 km^2) index of market accessibility determined by the traveling time from each gridcell to the closest and most influential market. The influence of the market is given by market size: Large markets include cities with more than 750,000 inhabitants and maritime ports, while small markets include cities with more than 50,000 inhabitants. The authors assume that large markets are twice as important as smaller markets, and for each grid cell i in the global map, they assign a market influence index (A_i) based on traveling time. The market access index ranges from 0 (inaccessible) to 1 (on a major