Global Spatially Explicit Land Supply Elasticity Estimates for Economic Modeling

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Abstract

National-level land supply elasticities mask crucial spatial heterogeneity in how land use responds to economic incentives. We develop high-resolution land supply elasticities at 300-meter global resolution, capturing variation in cropland, managed forest, and cultivated pastureland. We estimate fractional logit models relating land use fractions to market access and biophysical characteristics using a block regression approach applied to ~8.4 billion pixels. The resulting pixel-level elasticity database enables flexible aggregation to GTAP-AEZ zones, conservation regions, or gridded frameworks, replacing uniform national parameters with spatially explicit estimates capturing where conversion pressure concentrates. This extends prior continental analyses to global coverage and demonstrates computational feasibility of high-resolution econometric analysis at global scale.

Introduction

National-level land supply elasticities, estimates of how much land use responds to changes in agricultural prices, are fundamental parameters for economic models of land use change, deforestation, and agricultural expansion. Yet nearly all existing elasticity estimates are derived at the national level, implicitly assuming uniform price sensitivity across entire countries. This spatial aggregation masks crucial heterogeneity in how different regions respond to economic incentives.

The problem is substantial. Protected agricultural cores near infrastructure respond fundamentally differently to price signals than remote frontiers with poor market access. High-potential areas with good soils and established infrastructure exhibit different supply elasticities than marginal lands. Yet uniform national elasticities obscure where agricultural expansion actually occurs, systematically biasing predictions about land conversion hotspots, policy effectiveness, and conservation outcomes.

This spatial aggregation introduces three key biases. First, when expansion should concentrate in accessible frontiers with high supply elasticity, uniform national elasticities distribute predicted expansion proportionally across all land, obscuring conversion hotspots. Second, conservation priorities cannot distinguish between high-elasticity areas where protection avoids substantial conversion and low-elasticity areas where pressure is limited. Third, infrastructure investment decisions lack the spatial granularity to assess which investments mobilize substantial land supply versus where supply constraints limit responses.

We address this limitation by developing globally consistent, high-resolution land supply elasticities that capture within-country spatial heterogeneity in economic responses to agricultural incentives. Building on Villoria and Liu (2018), who estimated pixel-level elasticities for the Americas at 5 arc-minute (~10km) resolution, we extend coverage globally at 10 arc-second (~300m) resolution, a significant improvement in spatial detail that captures local variation in market access, biophysical suitability, and institutional constraints.

Our analysis advances prior work in three ways. First, we incorporate managed forest and cultivated pastureland alongside cropland, enabling explicit modeling of land use competition and substitution patterns. Second, we leverage temporal dynamics in land use (2000-2022) and evolving market access to capture how infrastructure development alters supply responsiveness over time. Third, we develop a computationally feasible block regression approach for global-scale high-resolution econometric analysis, overcoming the computational infeasibility of analyzing ~8.4 billion pixels simultaneously.

The resulting database of pixel-level elasticities supports flexible spatial aggregation to match different modeling frameworks. For GTAP-AEZ parameterization, elasticities can be aggregated to the model's 18 agro-ecological zones within each country, replacing uniform national parameters with zone-specific estimates capturing within-country heterogeneity. For gridded frameworks like SIMPLE-G, pixel-level elasticities can be directly applied at native resolution. For conservation applications, elasticities can be aggregated to priority regions or jurisdictions, enabling evidence-based conservation targeting.

Data and Methods

Land Use Data

We analyze three economically relevant land use categories, each at 300-meter resolution:

Cropland comes from the Global Land Cover (GLC_FCS30d) dataset (Zhang et al. 2023), a 30-meter resolution global classification combining Sentinel-2 imagery with machine learning. We combined the cropland classes (rainfed cropland, herbaceous cover cropland, tree or shrub cover (orchard) cropland, irrigated cropland) and resampled to 300m to create a continuous fraction representing the proportion of each pixel allocated to cropland.

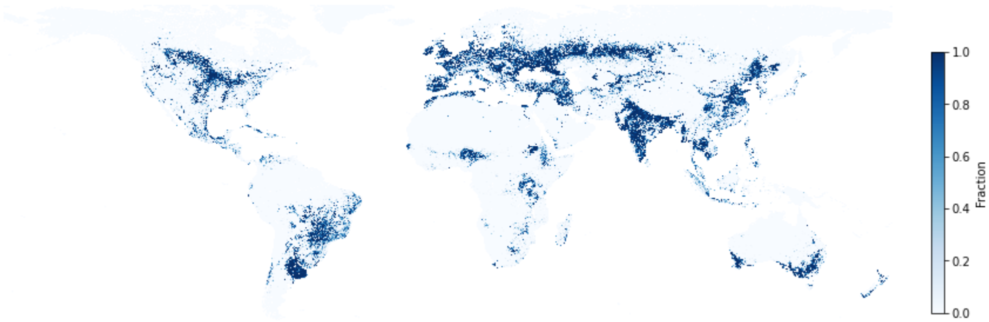

Figure 1: Fraction of Pixel for Cropland

Cultivated grassland (managed pastureland) is derived from Global Pasture Watch (Parente et al. 2024), a 30-meter resolution annual product that distinguishes managed pasture from natural grassland and other vegetation through spectral and seasonal analysis of multi-year Sentinel imagery. We isolated cultivated grassland and resampled to 300m as a continuous fraction.

Figure 2: Fraction of Pixel for Grassland

Managed forest is classified using the Global Forest Management dataset (Lesiv et al. 2022), which identifies forests with evidence of economic management (logging activity, planted forests, and forestry plantations) at 100-meter resolution by integrating multiple satellite datasets (Landsat, Sentinel, and Tandem-X). We combined the managed forest classes (planted forests, plantation forests, oil palm plantations, agroforestry) and resampled this 100-meter managed forest indicator to 300m. Each land use variable represents the fractional coverage (0–1) within each 300-meter pixel, enabling a fractional dependent-variable econometric approach that naturally handles mixed-use pixels.

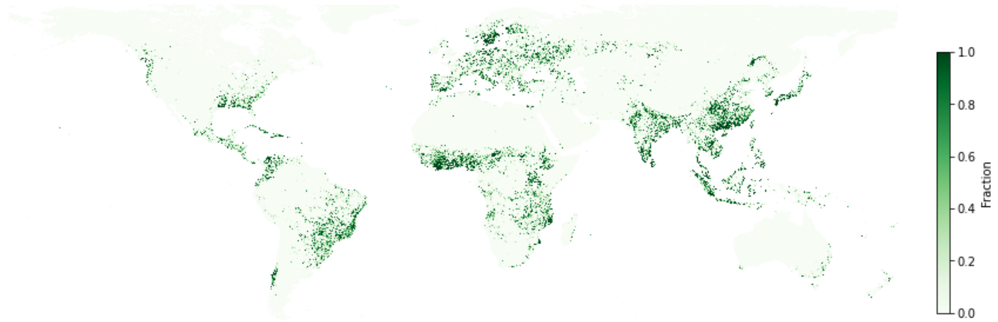

Figure 3: Fraction of Pixel for Managed Forest

Covariates

Following von Thünen's spatial economics framework (Sinclair 1967), as applied by Chomitz and Gray (1996), we estimate land rents at fine spatial scales by attributing spatial variation in economic returns entirely to differences in transportation costs. Accordingly, our primary regressor is:

Market access: Measured as travel time (in minutes) to the nearest city with 50,000+ inhabitants (Weiss et al. 2018). We transformed this travel time variable to a market access index on the [0,1] scale using the transformation $A_i = 1 - \tanh(\text{travel\_time}/10000)$, where higher values indicate closer proximity to markets.

Biophysical covariates capture land suitability and productivity constraints:

- **Climate**: Temperature and precipitation from WorldClim v2.1 (Fick and Hijmans 2017)
- **Topography**: Elevation and aspect from GEBCO (GEBCO Bathymetric Compilation Group 2023)
- **Soils**: Sand, silt, and clay fractions; bulk density; cation-exchange capacity; organic carbon; and pH from SoilGrids v2.0 (Hengl et al. 2017), all at 250-meter resolution resampled to 300m
- **Vegetation**: Above-ground biomass carbon from GEDI (Johnson 2019)
- **Hydrology**: Wetlands presence from the Global Wetlands Map (Gumbricht et al. 2017)

These biophysical variables were log-transformed in the regression analysis to capture nonlinear dose-response relationships typical in agricultural production functions.

Institutional covariates represent policy constraints:

- **Protected areas**: Strict protection status (IUCN categories Ia, Ib, II) from the World Database on Protected Areas (Leberger et al. 2020)
- **Population density**: From high-resolution gridded population estimates (Lamarche et al. 2017)

All covariate rasters were aggregated or interpolated to 300-meter resolution using bilinear resampling for continuous variables and nearest-neighbor for categorical variables.

Econometric Framework

Model Specification

We estimate fractional logit models relating land use share to market access and biophysical characteristics:

$$E(Z_i \mid A_i, \mathbf{S}_i) = \Lambda \left[\alpha_0 + \alpha_1 A_i + \sum_{k=1}^{K} \alpha_k S_{ki} \right]$$

where:

- i indexes pixels
- $Z_i \in [0, 1]$ is the land use fraction (cropland, grassland, or managed forest)
- A_i is the market access index
- S_{ki} are biophysical and institutional covariates
- $\Lambda(\cdot) = \exp(\cdot)/[1 + \exp(\cdot)]$ is the logistic cumulative distribution function
- $\alpha_0, \alpha_1, \alpha_k$ are coefficients to be estimated

The fractional logit specification, developed by Papke and Wooldridge (1996), naturally handles dependent variables bounded on [0,1] and is particularly well-suited for land use fractions where multiple land covers coexist within pixels.

For cropland and grassland, which have multi-year coverage, we will extend this to a panel specification with pixel and year fixed effects to control for time-invariant unobserved heterogeneity (e.g., local institutions, historical land rights) and capture technological change or management intensification over time. Managed forest, limited to cross-sectional data, uses the pooled fractional logit specification.

Estimation Strategy: Block Regression Approach

Global estimation at 300-meter resolution involves approximately 8.4 billion pixels globally, far exceeding the computational and memory constraints of simultaneous estimation. Rather than subsample or aggregate data into large regions (which reintroduces the spatial aggregation problem we aim to solve), we employ a block regression approach that preserves spatial heterogeneity while remaining computationally tractable.

The workflow proceeds as follows:

1. **Spatial tiles**: The global land surface is divided into regular tiles (blocks) of 1,000×1,000 pixels (~300km × 300km at the equator). This block size represents a balance: large enough to include sufficient variation in market access and biophysical conditions for stable coefficient estimation, yet small enough to capture meaningful regional heterogeneity.

2. **Tile-level estimation**: For each tile, we estimate the fractional logit model independently using all valid pixels within that tile. This yields tile-specific coefficient vectors $\hat{}_{\text{tile}}$. Parallel computation distributes tile estimation across multicore processors, reducing wall-clock time substantially.

3. **Block-level results**: Tile-specific coefficients, standard errors, pseudo-R², and residual diagnostics are recorded to a summary table. This provides a geographic view of how estimated relationships vary spatially, for example, whether market access effects are stronger in developed regions than frontier regions.

4. **Pixel-level elasticity calculation**: Using block-level coefficients, we calculate pixel-specific elasticities (described below) at native 300-meter resolution. This step preserves subpixel spatial variation by using local covariates, not tile averages.

This approach implicitly controls for regional heterogeneity (different tiles may have different β coefficients reflecting different institutional, climatic, or economic contexts) while avoiding the computational infeasibility of full-data estimation.

Elasticity Calculation

Pixel-level price elasticities of land supply are calculated from block-level coefficients as:

$$\epsilon_i = \frac{\partial \hat{Z}_i}{\partial A_i} \times \frac{A_i}{\hat{Z}_i} = \lambda \left[\hat{\alpha}_0 + \hat{\alpha}_1 A_i + \sum_k \hat{\alpha}_k \log(S_{ki}) \right] \hat{\alpha}_1 \times \frac{A_i}{\hat{Z}_i}$$

where:

- λ is the logistic probability density at the fitted index

- The coefficient $\hat{\alpha}_1$ captures the elasticity with respect to market access (our empirical proxy for land rents)
- The ratio $A_i/\hat{Z}_i$ introduces saturation effects: elasticity decreases with land use intensity

This formulation captures three economically meaningful patterns: (1) elasticity increases with market access (better-connected areas respond more elastically to price incentives), (2) elasticity decreases with current land use intensity (saturation effects already converted areas have less remaining conversion potential), and (3) elasticity peaks at intermediate land use shares, reflecting the greatest potential for marginal conversion.

We report two elasticity metrics:

- **Unscaled elasticities**: Direct model output, reflecting relative responsiveness but not yet calibrated to match observed macro elasticities
- **Scaled elasticities** (future work): Calibrated to FAO country-level land use changes following the methodology of Villoria and Liu (2018), ensuring consistency with observed national-level land supply responses

Spatial Resolution and Aggregation

All analysis is conducted at native 300-meter resolution. The resulting global pixel-level elasticity rasters can be flexibly aggregated to match different modeling frameworks:

- **For GTAP-AEZ**: Elasticities are aggregated to the 18 agro-ecological zones within each country by area-weighted averaging
- **For gridded frameworks**: Pixel-level elasticities are directly applied at their native resolution
- **For conservation applications**: Elasticities are aggregated to priority regions, watersheds, or administrative jurisdictions as needed

Results

Overview and Data Coverage

Our analysis spans the global land surface at 300-meter resolution, yielding approximately 8.4 billion pixels. After removing pixels with missing covariate data or zero land use fractions, the effective sample captures substantial regional variation across all three land use categories. Detailed sample sizes by region and coverage statistics are detailed in supplementary materials.

Cropland Elasticity Results

Global Distribution

Cropland elasticity exhibits substantial spatial heterogeneity, reflecting differences in market access, biophysical constraints, and institutional factors. High elasticity concentrates in peri-urban areas and infrastructure corridors where market access drives conversion potential. Intermediate elasticity characterizes agricultural frontiers in sub-Saharan Africa, South America, and Southeast Asia. Low elasticity appears in saturated agricultural regions and protected areas where conversion is institutionally constrained.

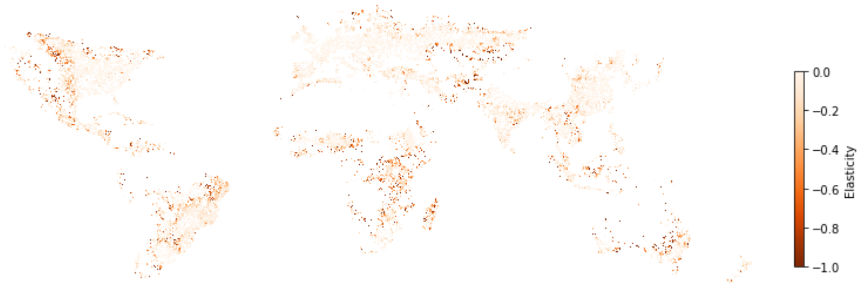

Figure 4: Cropland Land Supply Elasticity

Quantitative elasticity distributions and regional summaries are to be provided in supplementary materials.

Regional Variation

Cropland elasticity varies substantially across World Bank regions, reflecting differences in infrastructure development, agricultural intensity, and institutional constraints. Regional analysis is presented in supplementary materials.

Comparison to Prior Estimates

Validation of our estimates against prior work and observational land use changes is ongoing. Future analysis will compare our Americas estimates at matching resolution to prior studies and validate predictions against observed land use responses to historical price shocks.

Grassland (Cultivated Pasture) Elasticity Results

Global Distribution

Cultivated grassland elasticity exhibits different spatial patterns than cropland, reflecting the distinct economics of pastureland. Elasticity is notably higher in frontier regions with extensive pastoral systems and lower in intensively managed pasture regions and areas with biophysical conversion constraints.

Figure 5: Grassland Land Supply Elasticity

Grassland elasticity is notably higher in frontier regions with lower infrastructure development, particularly in Africa and South America, reflecting the extensive (low-input) nature of pastoralism. Elasticity is lower in intensively-managed pasture regions (e.g., Europe, temperate South America) and in desert regions where conversion potential is limited by biophysical constraints.

Regional Patterns

Quantitative distributions and regional summaries for grassland elasticity are to be provided in supplementary materials.

Managed Forest Elasticity Results

Global Distribution

Managed forest elasticity shows variation reflecting both infrastructure access and forest management economics. High elasticity concentrates in frontier forest regions with recent infrastructure development, while low elasticity appears in established forest management regions and areas where forests are strictly protected.

Figure 6: Managed Forest Land Supply Elasticity

High elasticity concentrates in frontier forest regions with recent infrastructure development (e.g., Brazil, Indonesia, Central Africa). Low elasticity appears in established forest management regions and areas where forests are strictly protected.

Regional Patterns

Detailed quantitative distributions and regional aggregations are to be provided in supplementary materials.

Discussion

Key Findings

This paper presents what we believe are the first global pixel-level land supply elasticity estimates at 300-meter spatial resolution, extending prior work from the Americas to global coverage and incorporating three economically distinct land use categories. Our results confirm substantial within-country spatial heterogeneity in supply responsiveness, with coefficient of variation across pixels substantially exceeding the variation captured by national-level estimates. Market access emerges as a robust driver of conversion elasticity across regions and land use types, consistent with von Thünen spatial economic theory.

The three-land-use approach reveals important land use competition dynamics obscured by cropland-only analyses. Grassland exhibits higher frontier elasticity but lower saturation elasticity than cropland, reflecting the extensive nature of pasture systems. Managed forest elasticity patterns suggest non-linear responses driven by land legalization costs and infrastructure-dependent timber market access.

Computational Innovation

A key methodological contribution is demonstrating the feasibility of block regression for global-scale high-resolution econometric analysis. Our tile-based approach maintains spatial heterogeneity while overcoming the computational infeasibility of estimating ~8.4 billion pixels simultaneously. This approach may be adapted for other high-resolution global economic analyses, particularly where spatial heterogeneity in parameters is substantively important.

Implications for Economic Modeling

These pixel-level elasticity estimates directly enable more nuanced economic modeling of land use change. For GTAP-AEZ, aggregating to the 18 agro-ecological zones within each country generates zone-specific elasticity parameters that replace uniform national values, capturing known within-country heterogeneity in supply responses. The quantified variation (which can reach 5–10x between high-elasticity frontier zones and low-elasticity core zones) should improve the realism of model predictions about where expansion occurs within countries.

For conservation applications, high-elasticity identification enables targeting of protection efforts: prioritizing conservation of high-elasticity areas maximizes avoided conversion per dollar invested. Conversely, low-elasticity zones where conversion pressure is weak can potentially support development with lower conservation risk.

For infrastructure planning, spatial elasticity heterogeneity identifies where road or market infrastructure improvements will mobilize substantial land supply versus where supply constraints are biophysical or institutional. This informs cost-benefit analysis of land-use related infrastructure investments.

Limitations and Future Work

This submission presents preliminary results flagged for early conference feedback. Several important limitations require attention before final publication:

Calibration to Observational Elasticities (In Progress)

Our current results report unscaled elasticities from the regression model. Following Villoria and Liu (2018), we plan to calibrate these to match observed FAO country-level land use changes, ensuring consistency with macro-level land supply responses. This calibration will be completed before submission to a peer-reviewed journal and will enable direct comparison of our estimates to existing CGE model parameterizations.

Temporal Dynamics (Future Work)

The abstract highlighted leveraging temporal dynamics in land use (2000–2022) and market access evolution; this temporal dimension is not yet incorporated. Panel estimation with pixel-year fixed effects will be conducted for cropland and grassland to capture technological change, land use policy shifts, and how infrastructure development over time altered supply responsiveness.

Validation Against Policy Shocks (Future Work)

Future work will validate these elasticity estimates through retrospective policy simulation: comparing predictions of land use change under uniform national elasticities versus pixel-level elasticities against observed changes during past price shocks. This will quantify the predictive improvement from spatial heterogeneity.

Applications Development (Future Work)

We plan to develop integration workflows with GTAP-AEZ, DEMETRA, and SIMPLE-G frameworks, demonstrating practical implementation of pixel-level elasticities in operational economic models.

Conclusion

We present global pixel-level land supply elasticity estimates as a preliminary contribution to improve parameterization of economic models of land use change. Spatial heterogeneity is substantial and economically meaningful, averaging across countries to national parameters discards crucial information about where supply responses concentrate. These estimates are offered early to the GTAP community for feedback on data quality, econometric approach, and practical implementation pathways before final scientific publication. We welcome engagement on validation approaches, regional refinements, and integration with modeling frameworks.

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