Global Spatially Explicit Land Supply Elasticity Estimates for Economic Modeling

GTAP 29th Annual Conference on Global Economic Analysis
Kyoto, Japan | June 19, 2026

Matthew Braaksma
University of Minnesota

Justin Johnson
University of Minnesota

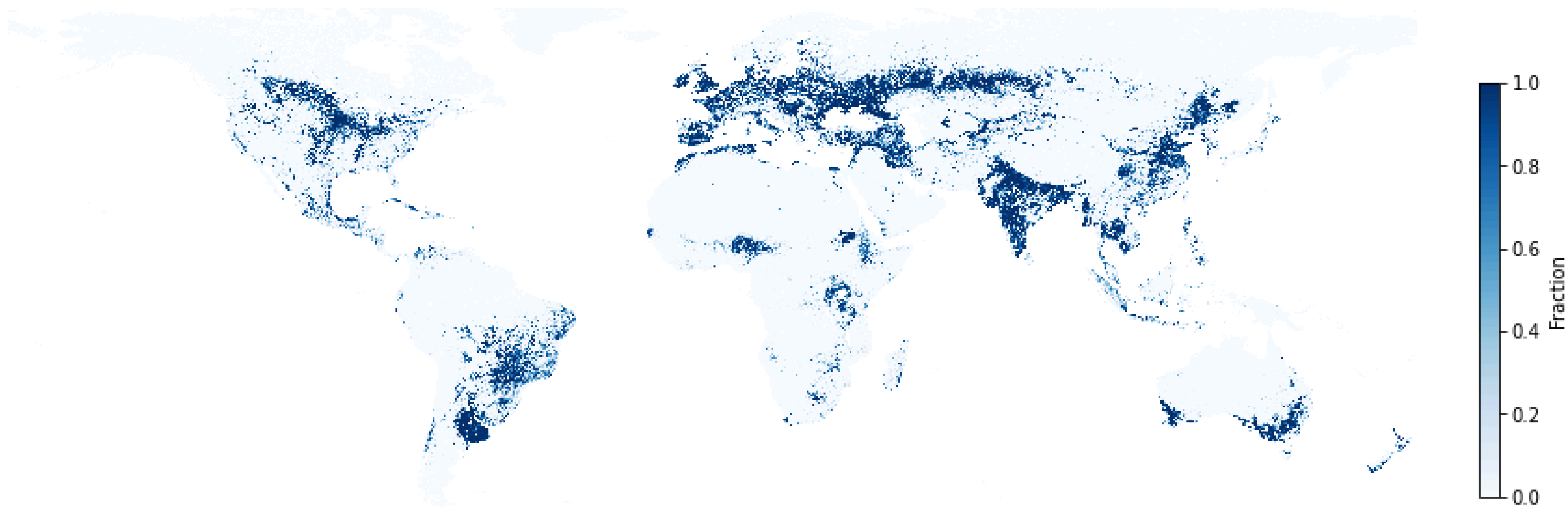
Willem-Jan van Zeist
Wageningen University & Research

Victor Nechifor
European Commission, Joint Research Centre

NatCap TEEMs
University of Minnesota

Motivation

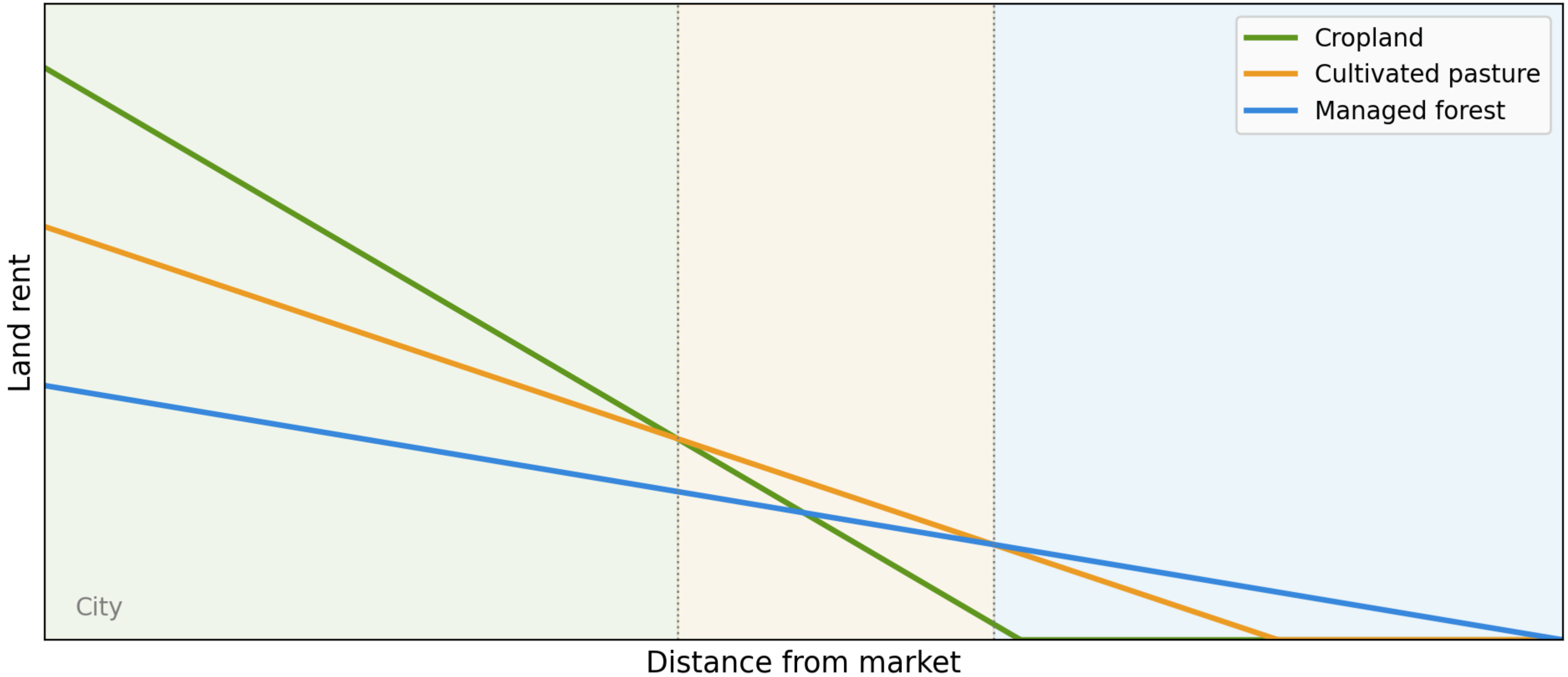
Where does agricultural expansion happen?



Agricultural land is not distributed uniformly; expansion concentrates along infrastructure corridors and at forest frontiers, not evenly across countries.

Motivation

Land rent declines with distance from market

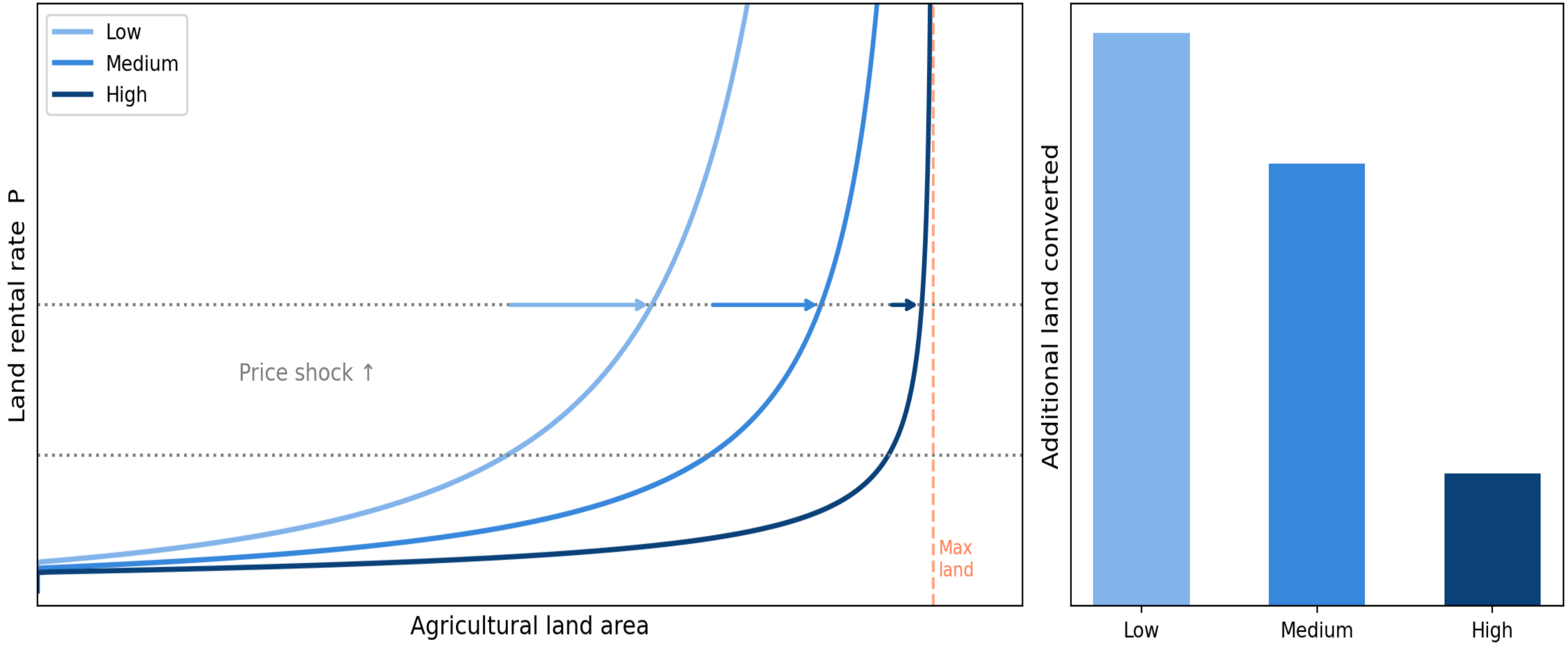


Von Thünen (Sinclair 1967): land use is determined by rent gradient intersections. Market access is our empirical proxy for land rent; the mechanism linking prices to land conversion (Chomitz and Gray 1996; Villoria and Liu 2018).

NatCap TEEMs
University of Minnesota

Motivation

Land supply responds to rental rates



$L = A - B/P^C$ where $E = C \cdot (A/L - 1)$ is the realized elasticity at the current operating point.

NatCap TEEMs
University of Minnesota

Motivation

The problem: uniform national elasticities

The standard approach

Data-constrained CGE models (GTAP, MAGNET, GTAP-InVEST) apply a single land supply elasticity E per country, uniformly across all land and land uses (Tabeau, Helming, and Philippidis 2017; Meijl et al. 2006).

- Sparse empirical data makes estimation difficult at subnational scale
- To ease model solving, $C = 1$ can be used as a working default (Woltjer et al. 2014)
- Single expansion parameter for all land uses

Prior work

- Villoria and Liu (2018) estimated pixel-level elasticities for the Americas at 5 arc-minute (~10 km) — the methodological foundation for this study
- Meijl et al. (2006) calibrated regional supply curves from biophysical data, showing EU E of 0.01–0.20 vs. Africa 0.5–3.0
- Dixon et al. (2016) demonstrated that policy shocks to the land supply asymptote (e.g. forest protection) interact critically with the local elasticity slope, motivating spatially explicit E

NatCap TEEMs
University of Minnesota

Contributions

Spatial Coverage

Dimension	This study
Coverage	Global
Resolution	10 arc-sec (~300 m)
Aggregation	Flexible (AEZ, country, watershed)
Land uses	cropland, cultivated grassland, managed forest
Estimation	block fractional logit

Data

Three economically relevant land uses

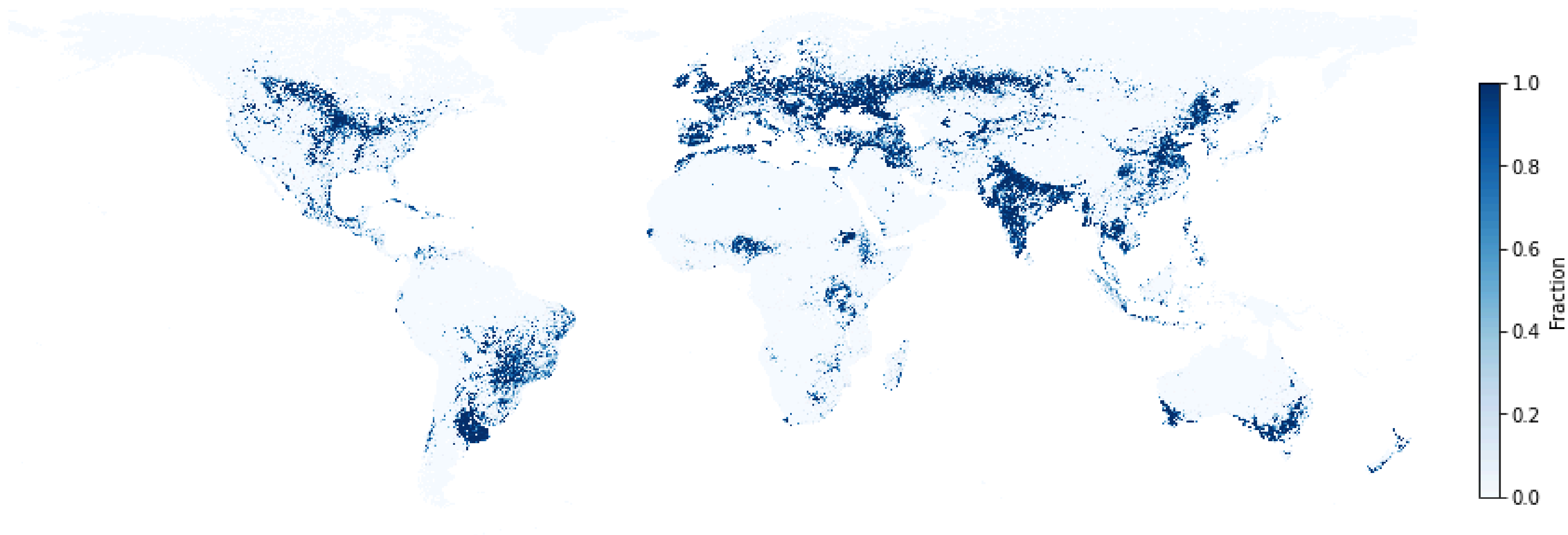
	Cropland	**Cultivated grassland**	**Managed forest**
Source	GLC_FCS30d (Zhang et al. 2023)	Global Pasture Watch (Parente et al. 2024)	Global Forest Management (Lesiv et al. 2022)
Resolution	30 m → 300 m fraction	30 m → 300 m fraction	100m → 300 m fraction
Definition	• rainfed cropland • herbaceous cover cropland • tree or shrub cover (orchard) cropland • irrigated cropland	• cultivated grassland	• planted forests • plantation forests • oil palm plantations • agroforestry

Each variable is a continuous fraction [0, 1] of the 300 m pixel, enabling fractional logit estimation of mixed land-use pixels.

NatCap TEEMs
University of Minnesota

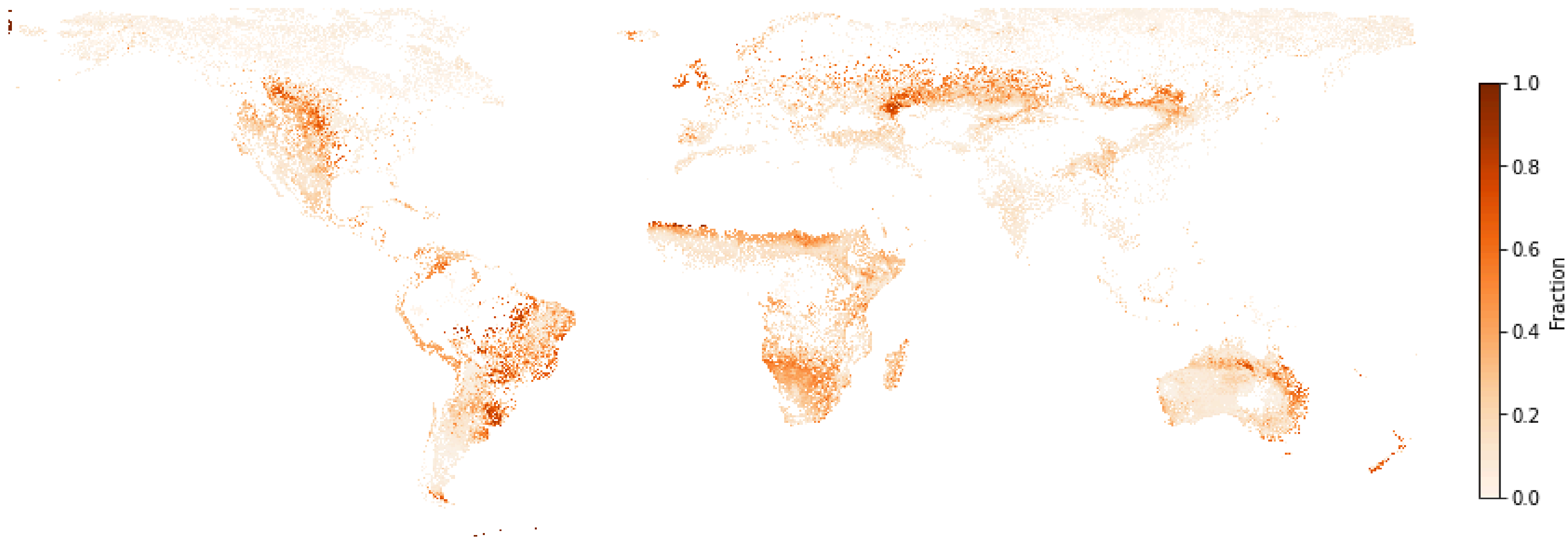
Data

Cropland coverage



Data

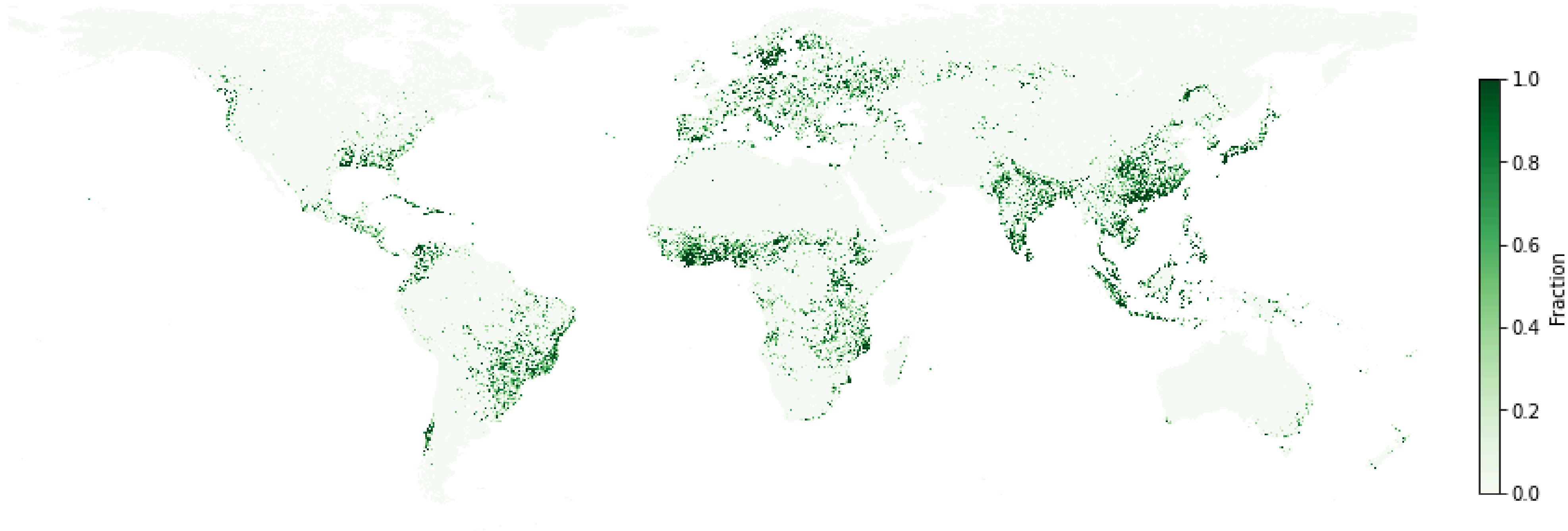
Cultivated grassland coverage



NatCap TEEMs
University of Minnesota

Data

Managed forest coverage



NatCap TEEMs
University of Minnesota

Data

Market access as a proxy for land rent

We assume spatial variation in land rents is driven by transportation costs[1]. At fine scales within a region, market access dominates land rent differences; biophysical controls absorb remaining variation (Sinclair 1967; Chomitz and Gray 1996).

Market access index:

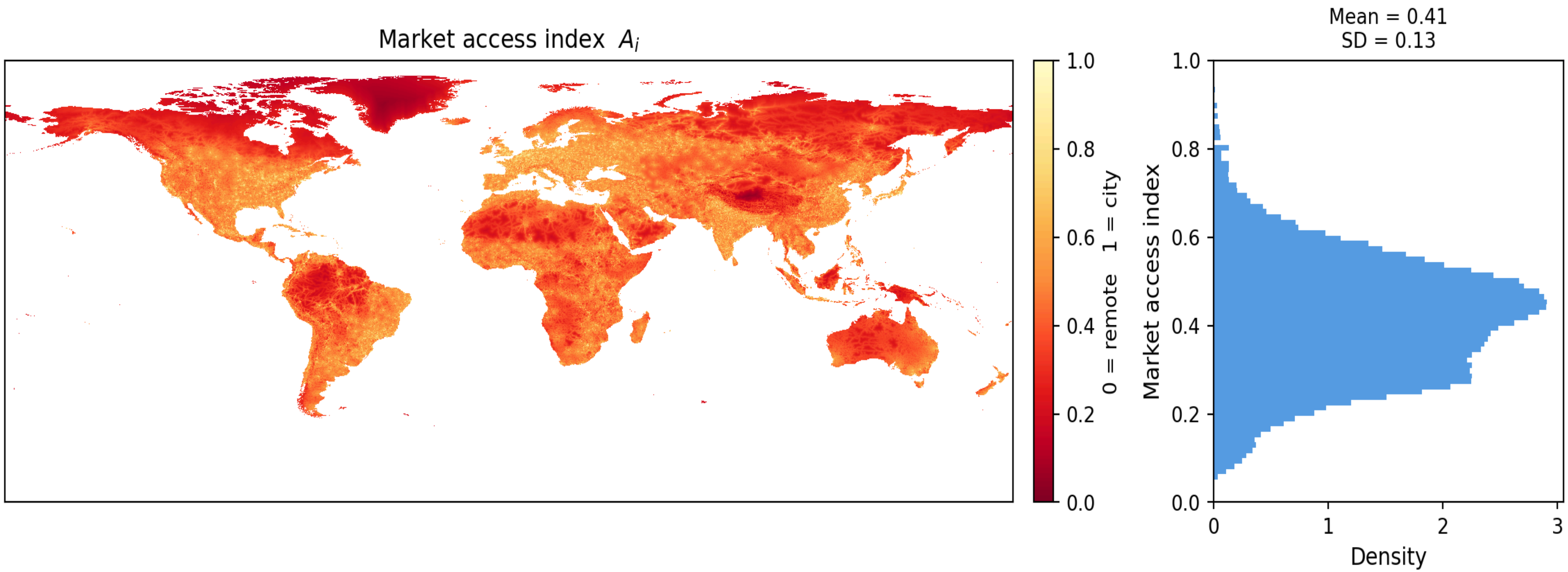
$$A_i = 1 - \frac{\ln(1 + t_i)}{\ln(1 + t_{\max})}$$

where t_i is travel time (minutes) to the nearest city with 50,000+ inhabitants (Weiss et al. 2018) and $t_{\max} = 50{,}000$ minutes. Log-scaling spreads variation across the populated range (0–240 min) rather than compressing it near 1.0.

NatCap TEEMs
University of Minnesota

Data

Market access index



NatCap TEEMs
University of Minnesota

Data

Biophysical and institutional controls

Biophysical *(log-transformed)*

- Temperature, precipitation (Fick and Hijmans 2017)
- Elevation, aspect (GEBCO Bathymetric Compilation Group 2023)
- Soils: sand, silt, clay, bulk density, CEC, organic carbon, pH (Hengl et al. 2017)
- Above-ground biomass (Johnson 2019)
- Wetlands presence (Gumbricht et al. 2017)
- Irrigation area (Siebert et al. 2010)
- Built-up surface area (Pesaresi and Politis 2023)

Institutional *(entered linearly)*

- Strict protected area status (Leberger et al. 2020)
- Population density (Lamarche et al. 2017)

Methods

Block regression and elasticity formula

Fractional logit per tile: (Papke and Wooldridge 1996)

$$E(Z_i) = \Lambda\left[\alpha_0^b + \alpha_1^b A_i + \sum_k \alpha_k^b \log S_{ki}\right]$$

- ~8.4 billion pixels, estimated in 1024×1024 pixel tiles (~300 km). Coefficients vary by tile, capturing regional heterogeneity.

Elasticity per pixel (after algebraic simplification):

$$\varepsilon_i = \hat{\alpha}_1 \cdot A_i \cdot (1 - \hat{Z}_i)$$

- $\hat{\alpha}_1$: tile responsiveness to market access
- A_i: pixel market access [0,1]
- $(1 - \hat{Z}_i)$: saturation, already-converted land cannot expand further
- Only positive pixels used for supply parameterization; $\varepsilon = 0$ assigned to zero-LULC land

NatCap TEEMs
University of Minnesota

Methods

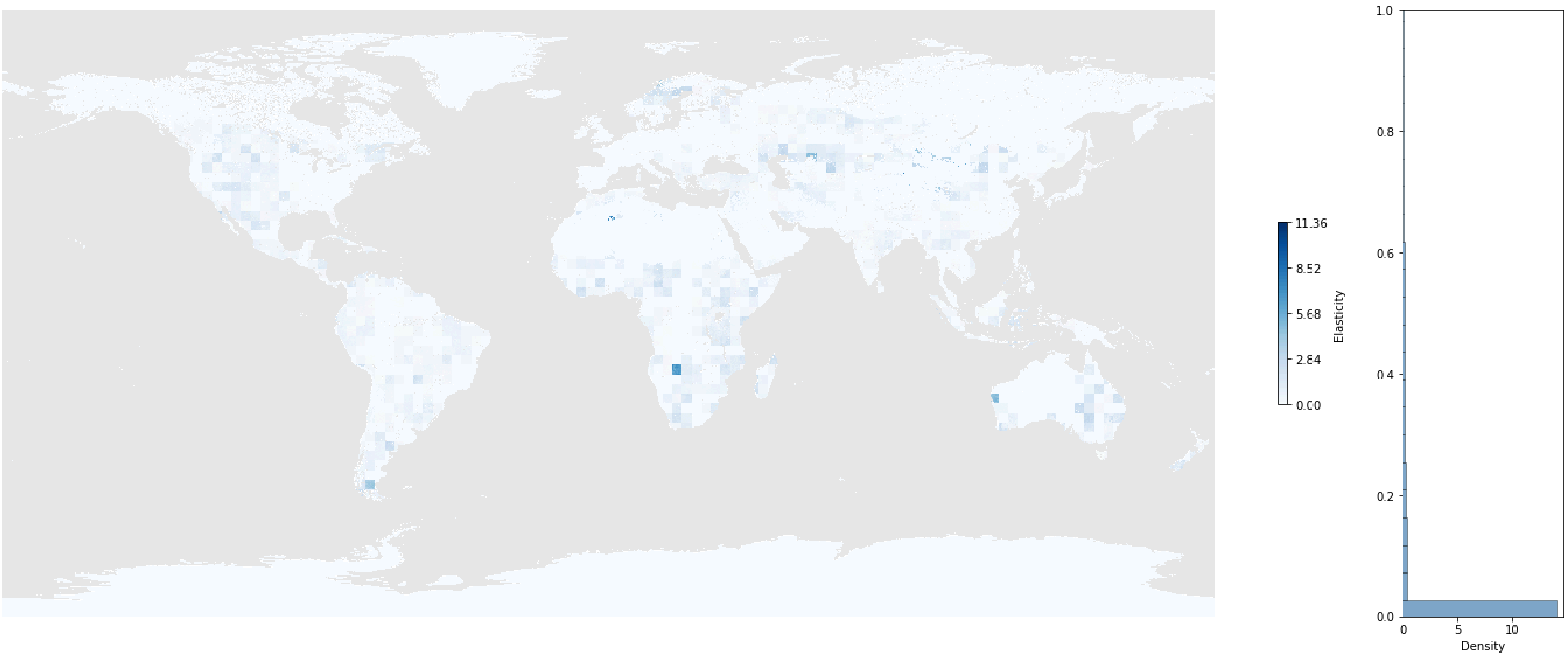
Interpreting the elasticity values

Range	Interpretation	Typical context
$\varepsilon > 1$	Highly elastic	Uncultivated frontier with recent road access
$0.1 < \varepsilon \leq 1$	Moderately elastic	Active agricultural frontier — where conversion concentrates
$0 < \varepsilon \leq 0.1$	Near-inelastic	Saturated farmland, biophysical constraints, or protected areas
$\varepsilon = 0$	Inelastic	Zero current LULC fraction, no supply response at extensive margin

NatCap TEEMs
University of Minnesota

Cropland Elasticity Results

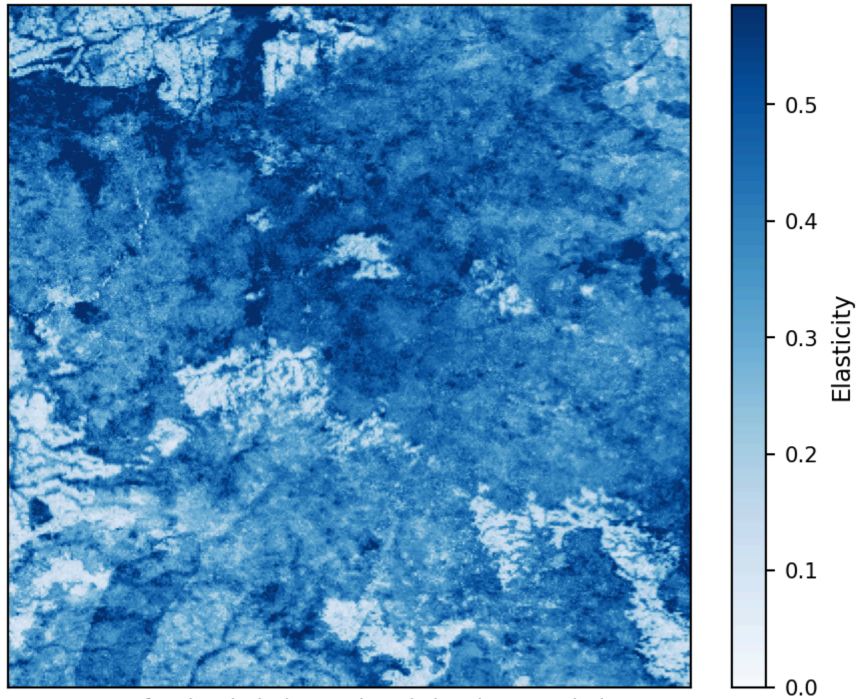
Global Distribution



NatCap TEEMs
UNIVERSITY OF MINNESOTA

Cropland Elasticity Results

Brazilian Cerrado frontier (~16-18S, 52-55W)

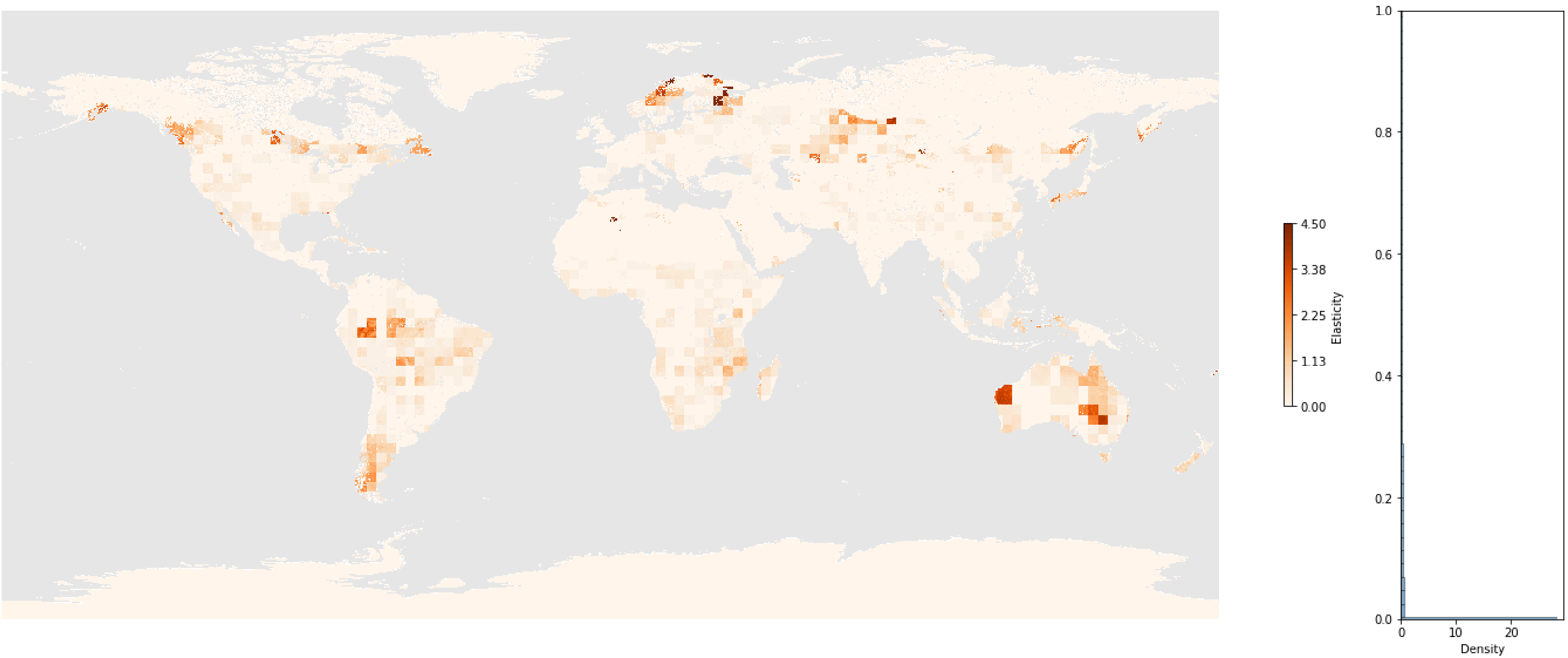


100% frontier pixels | ~307 km window | 300 m pixels

NatCap TEEMs
University of Minnesota

Cultivated Grassland Elasticity Results

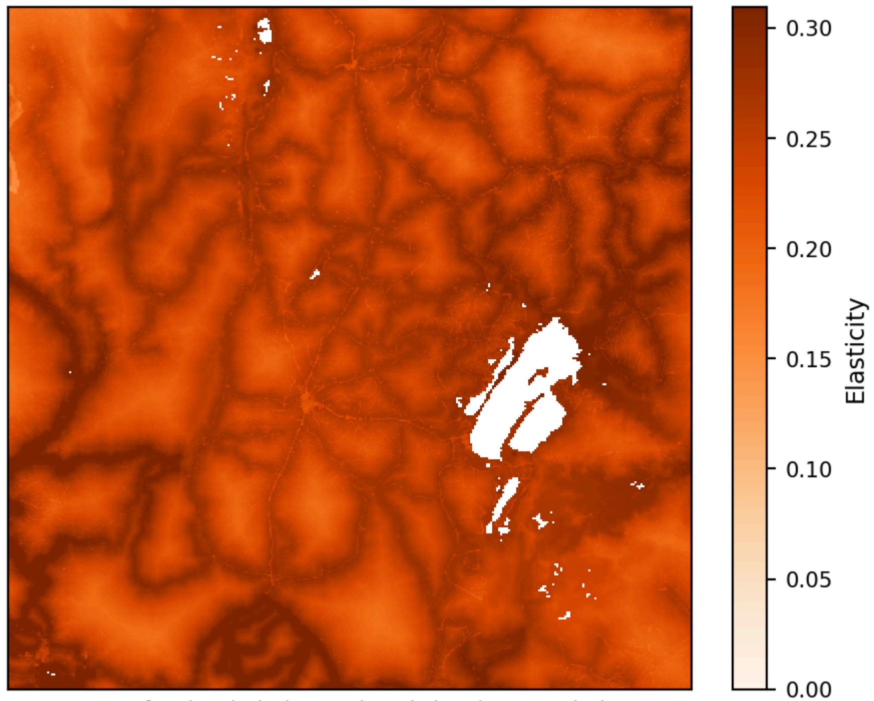
Global distribution



NatCap TEEMs
University of Minnesota

Cultivated Grassland Elasticity Results

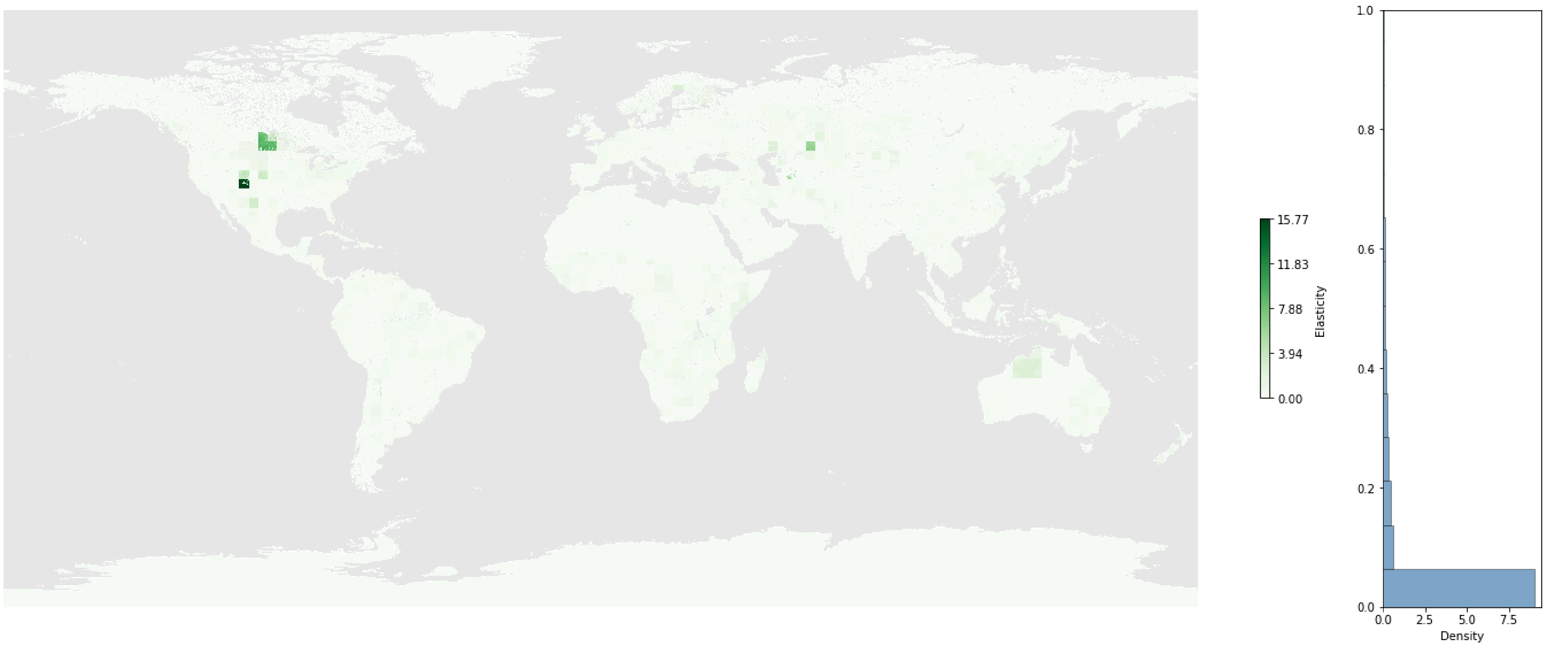
Miombo woodland frontier (~10-12S, 28-31E)



100% frontier pixels | ~307 km window | 300 m pixels

Managed Forest Elasticity Results

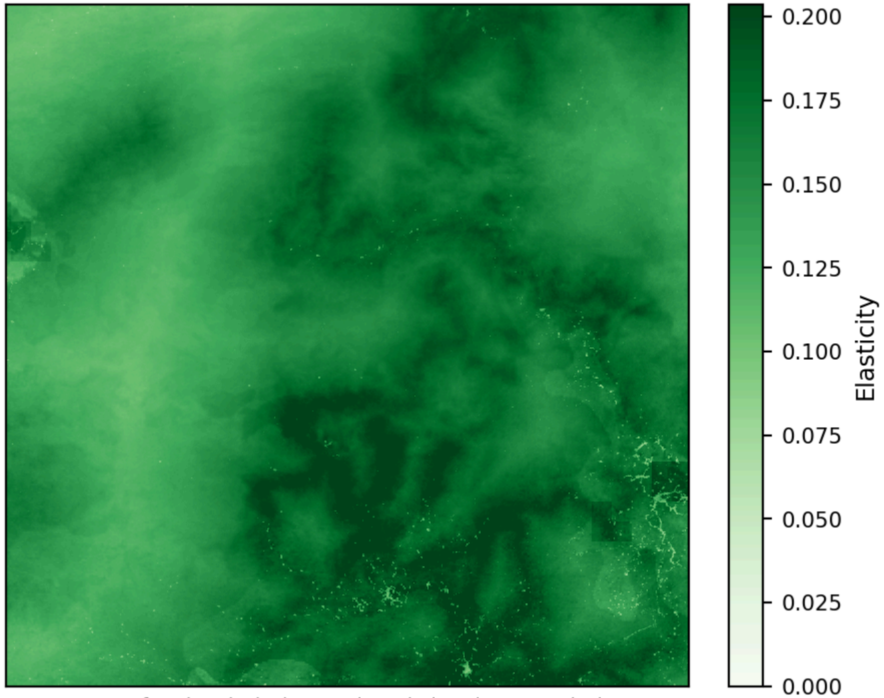
Global distribution



NatCap TEEMs
University of Minnesota

Managed Forest Elasticity Results

Kalimantan palm frontier (~0-2N, 113-116E)



100% frontier pixels | ~307 km window | 300 m pixels

NatCap TEEMs
University of Minnesota

Discussion

From pixel elasticities to model parameters

Step 1. Estimate

Fractional logit per tile yields pixel-level $\hat{\varepsilon}_i = \hat{\alpha}_1 \cdot A_i \cdot (1 - \hat{Z}_i)$

- Positive pixels: frontier expansion potential
- Negative pixels: urban displacement, excluded from supply parameterization
- Separate estimates for cropland, grassland, and managed forest

Step 2. Calibrate to FAO

Following Villoria and Liu (2018), scale pixel means to observed national land changes (FAOSTAT 2000–2015):

$$\text{scale}_r = \frac{\varepsilon_r^*}{\bar{\varepsilon}_r}$$

ε_r^* from FAO-derived or JRC (2017) realized elasticity (Tabeau, Helming, and Philippidis 2017); $\bar{\varepsilon}_r$ = arithmetic mean of positive pixels in country r. Scale factors capped at 3× in all displayed results (maps and comparison chart) to prevent a handful of data-sparse countries from distorting the scale; uncapped pixel-level spatial patterns are unaffected.

Step 3. Aggregate

Two paths into CGE models:

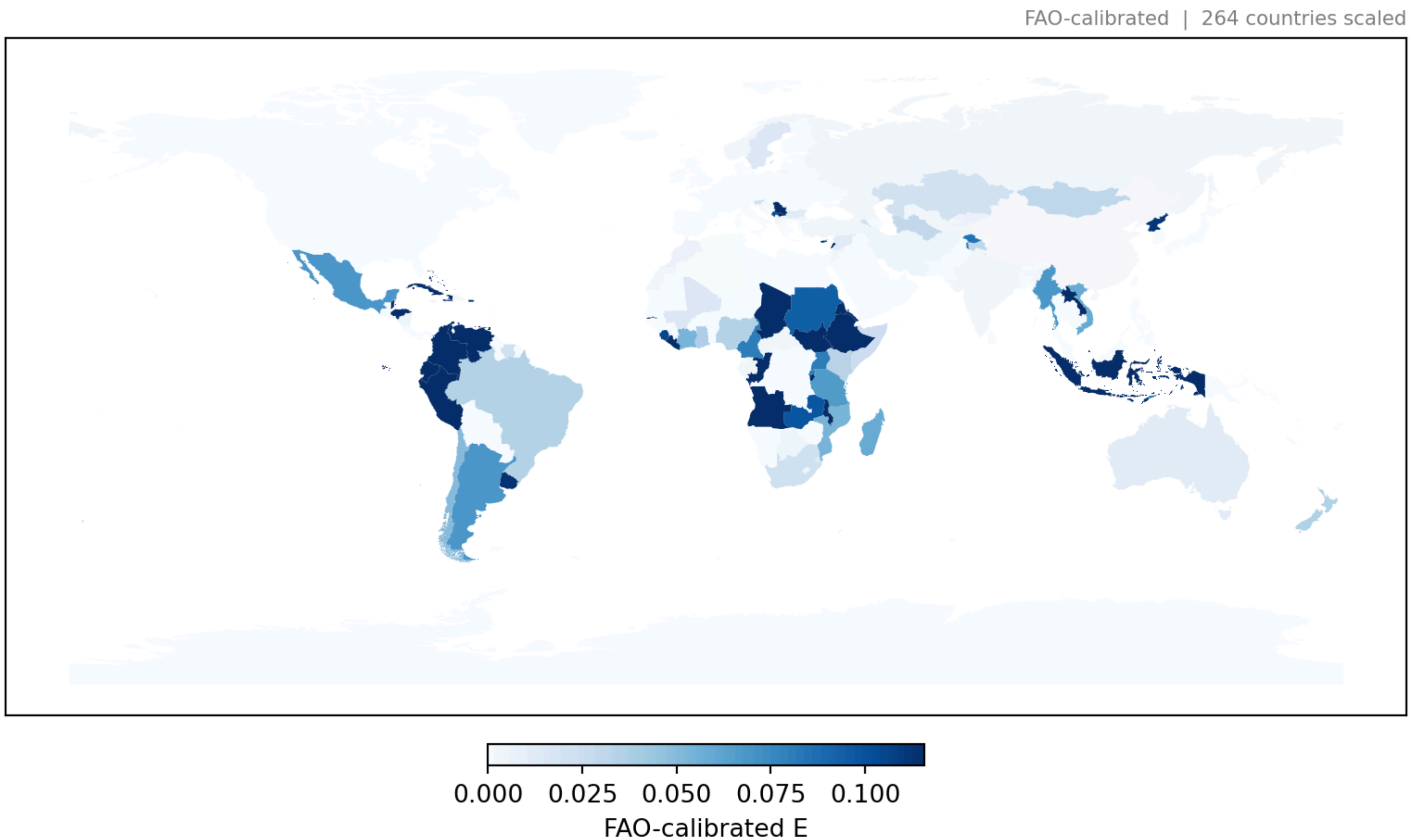
A. Exogenous land supply shift: use pixel elasticities to pre-compute land entering the agricultural pool between periods. Compatible with any dynamic CGE without model modification.

B. Aggregate supply curve: Sort pixels by $\hat{\varepsilon}$ to reconstruct a nonlinear aggregate supply curve at any spatial scale (country, AEZ, watershed), or collapse to a single area-weighted mean for direct LANDPOW/C parameterization in MAGNET and GTAP-InVEST (Woltjer et al. 2014).

NatCap TEEMs
University of Minnesota

Cropland Results

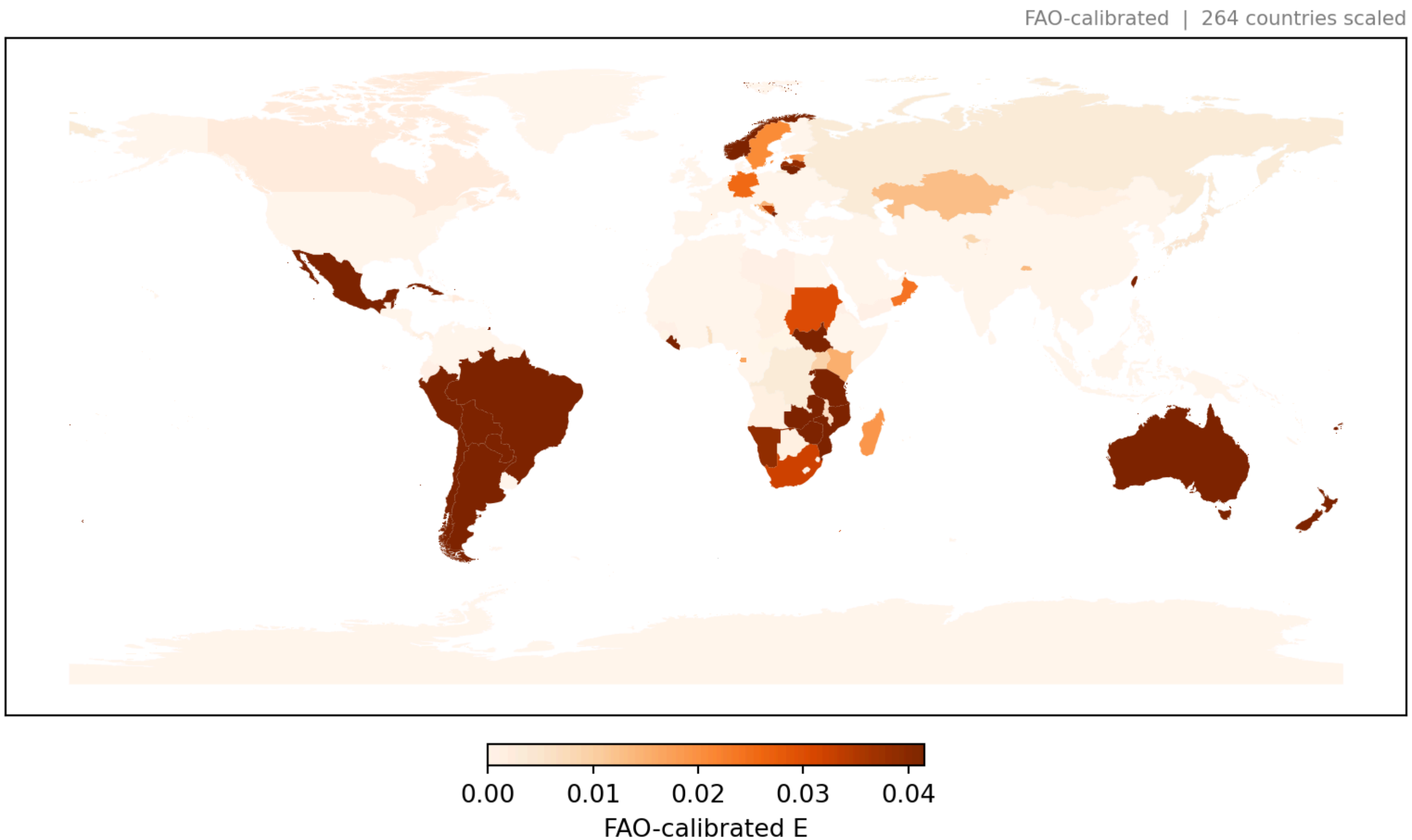
Aggregated elasticities (FAO-calibrated)



Scaled using FAOS's cropland area and value of agricultural production per area, rent proxy.

Cultivated Grassland Results

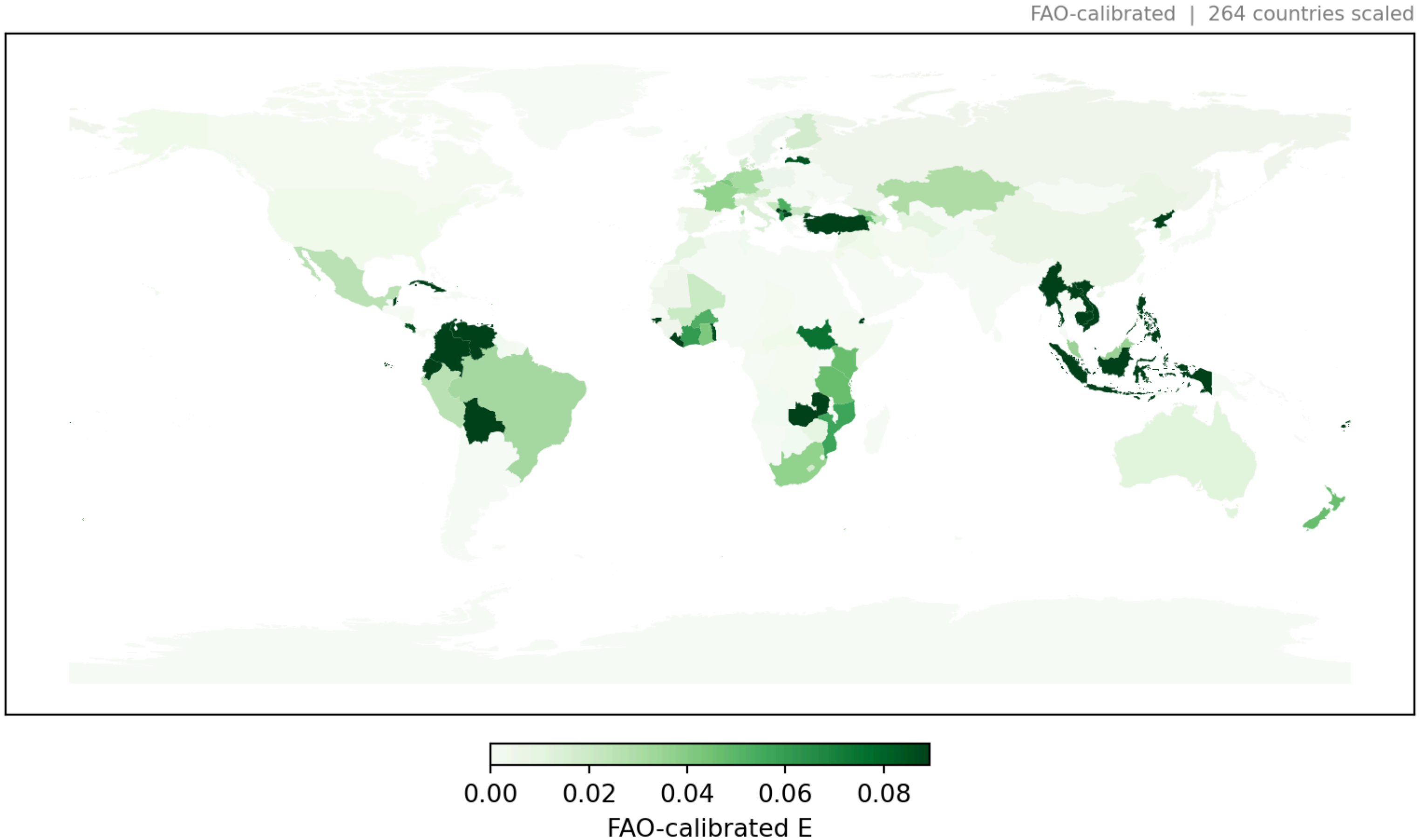
Aggregated elasticities (FAO-calibrated)



Scaled using FAO's permanent meadows & pastures and the same rent proxy.

Managed Forest Results

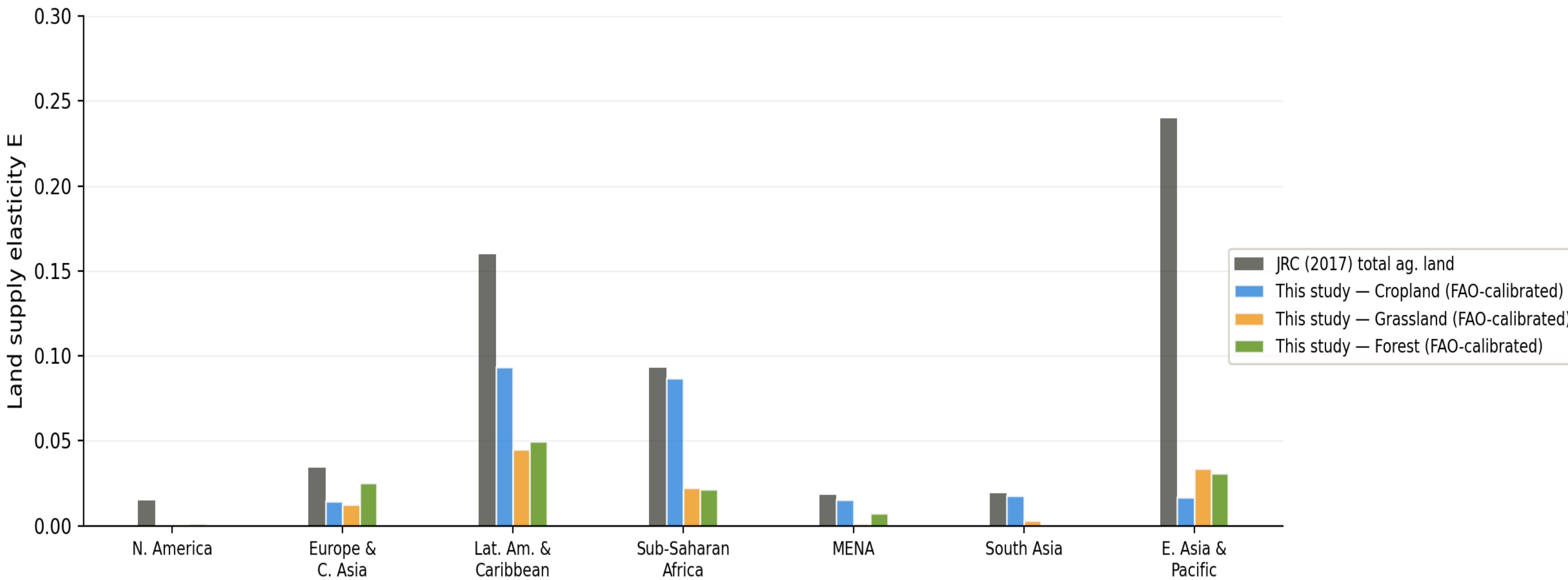
Aggregated elasticities (FAO-calibrated)



Scaled using FAO's forest land area and the same rent proxy.

Discussion

Elasticities comparison



NatCap TEEMs
University of Minnesota

Conclusion

Contributions and next steps

Contributions

- First globally consistent pixel-level land supply elasticity database at 300 m: cropland, cultivated grassland, and managed forest separately
- Standard elasticity definition directly parameterizes curve (MAGNET, GTAP-InVEST, DEMETRA, SIMPLE-G), two integration paths into CGE models
- Calibrated to FAO observed land use changes; consistent with Villoria and Liu (2018)
- Core contribution: spatial heterogeneity at 300 m that national parameters cannot capture

Potential extensions

- Panel estimation (2000–2022) for cropland and grassland
- Formal validation against historical price shocks
- MAGNET/GTAP-InVEST/DEMETRA parameterization workflows
- Tile boundary smoothing refinements

References

Citations

Chomitz, K. M., and D. A. Gray. 1996. "Roads, Land Use, and Deforestation: A Spatial Model Applied to Belize." Article. *World Bank Economic Review* 10 (3): 487–512. https://doi.org/10.1093/wber/10.3.487.

Dixon, Peter B., Hans van Meijl, Maureen T. Rimmer, Lindsay Shutes, and Andrzej Tabeau. 2016. "RED Versus REDD: Biofuel Policy Versus Forest Conservation." *Economic Modelling* 52: 366–74. https://doi.org/10.1016/j.econmod.2015.08.030.

Fick, Stephen E, and Robert J Hijmans. 2017. "WorldClim 2: New 1-Km Spatial Resolution Climate Surfaces for Global Land Areas." *International Journal of Climatology* 37 (12): 4302–15.

GEBCO Bathymetric Compilation Group. 2023. "The GEBCO_2023 Grid - a Continuous Terrain Model of the Global Oceans and Land." NERC EDS British Oceanographic Data Centre NOC. https://doi.org/10.5285/f98b053b-0cbc-6c23-e053-6c86abc0af7b.

Gumbricht, Thomas, Rosa Maria Roman-Cuesta, Louis Verchot, Martin Herold, Florian Wittmann, Ethan Householder, Nadine Herold, and Daniel Murdiyarso. 2017. "An Expert System Model for Mapping Tropical Wetlands and Peatlands Reveals South America as the Largest Contributor." *Global Change Biology* 23 (9): 3581–99.

Hengl, Tomislav, Jorge Mendes de Jesus, Gerard BM Heuvelink, Maria Ruiperez Gonzalez, Milan Kilibarda, Aleksandar Blagotić, Wei Shangguan, et al. 2017. "SoilGrids250m: Global Gridded Soil Information Based on Machine Learning." *PLoS One* 12 (2): e0169748.

Johnson, Justin Andrew. 2019. "Globally Harmonized Carbon Storage Data."

Lamarche, Céline, Maurizio Santoro, Sophie Bontemps, Raphaël d'Andrimont, Julien Radoux, Laura Giustarini, Carsten Brockmann, Jan Wevers, Pierre Defourny, and Olivier Arino. 2017. "Compilation and Validation of SAR and Optical Data Products for a Complete and Global Map of Inland/Ocean Water Tailored to the Climate Modeling Community." *Remote Sensing* 9 (1): 36.

Leberger, Roxanne, Isabel MD Rosa, Carlos A Guerra, Florian Wolf, and Henrique M Pereira. 2020. "Global Patterns of Forest Loss Across IUCN Categories of Protected Areas." *Biological Conservation* 241: 108299.

Lesiv, Myroslava, Dmitry Schepaschenko, Marcel Buchhorn, Linda See, Martina Dürauer, Ivelina Georgieva, Martin Jung, et al. 2022. "Global Forest Management Data for 2015 at a 100 m Resolution." *Scientific*

NatCap TEEMs
University of Minnesota

Data 9 (1): 199.

Meijl, Hans van, Teunis van Rheenen, Andrzej Tabeau, and Bas Eickhout. 2006. "The Impact of Different Policy Environments on Agricultural Land Use in Europe." *Agriculture, Ecosystems & Environment* 114 (1): 21–38. https://doi.org/10.1016/j.agee.2005.11.006.

Papke, Leslie E, and Jeffrey M Wooldridge. 1996. "Econometric Methods for Fractional Response Variables with an Application to 401 (k) Plan Participation Rates." *Journal of Applied Econometrics* 11 (6): 619–32.

Parente, Leandro, Lindsey Sloat, Vinicius Mesquita, Davide Consoli, Radost Stanimirova, Tomislav Hengl, Carmelo Bonannella, et al. 2024. "Annual 30-m Maps of Global Grassland Class and Extent (2000–2022) Based on Spatiotemporal Machine Learning." *Scientific Data* 11 (1): 1303.

Pesaresi, Martino, and Panagiotis Politis. 2023. "GHS-BUILT-S R2023A – GHS Built-up Surface Grid, Derived from Sentinel-2 Composite and Landsat, Multitemporal (1975-2030)." European Commission, Joint Research Centre. https://doi.org/10.2905/9F06F36F-4B11-47EC-ABB0-4F8B7B1D72EA.

Siebert, Stefan, Joanne Burke, Jean-Marc Faures, Karen Frenken, Jippe Hoogeveen, Petra Döll, and Felix T. Portmann. 2010. "Groundwater Use for Irrigation – a Global Inventory." *Hydrology and Earth System Sciences* 14: 1863–80. https://doi.org/10.5194/hess-14-1863-2010.

Sinclair, Robert. 1967. "Von Thünen and Urban Sprawl." *Annals of the Association of American Geographers* 57 (1): 72–87.

Tabeau, Andrzej, John Helming, and George Philippidis. 2017. "Land Supply Elasticities: Overview of Available Estimates and Recommended Values for MAGNET." JRC106592, EUR 28626 EN. Joint Research Centre, European Commission. https://doi.org/10.2760/852141.

Villoria, Nelson B, and Jing Liu. 2018. "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." *Land Use Policy* 75: 411–19.

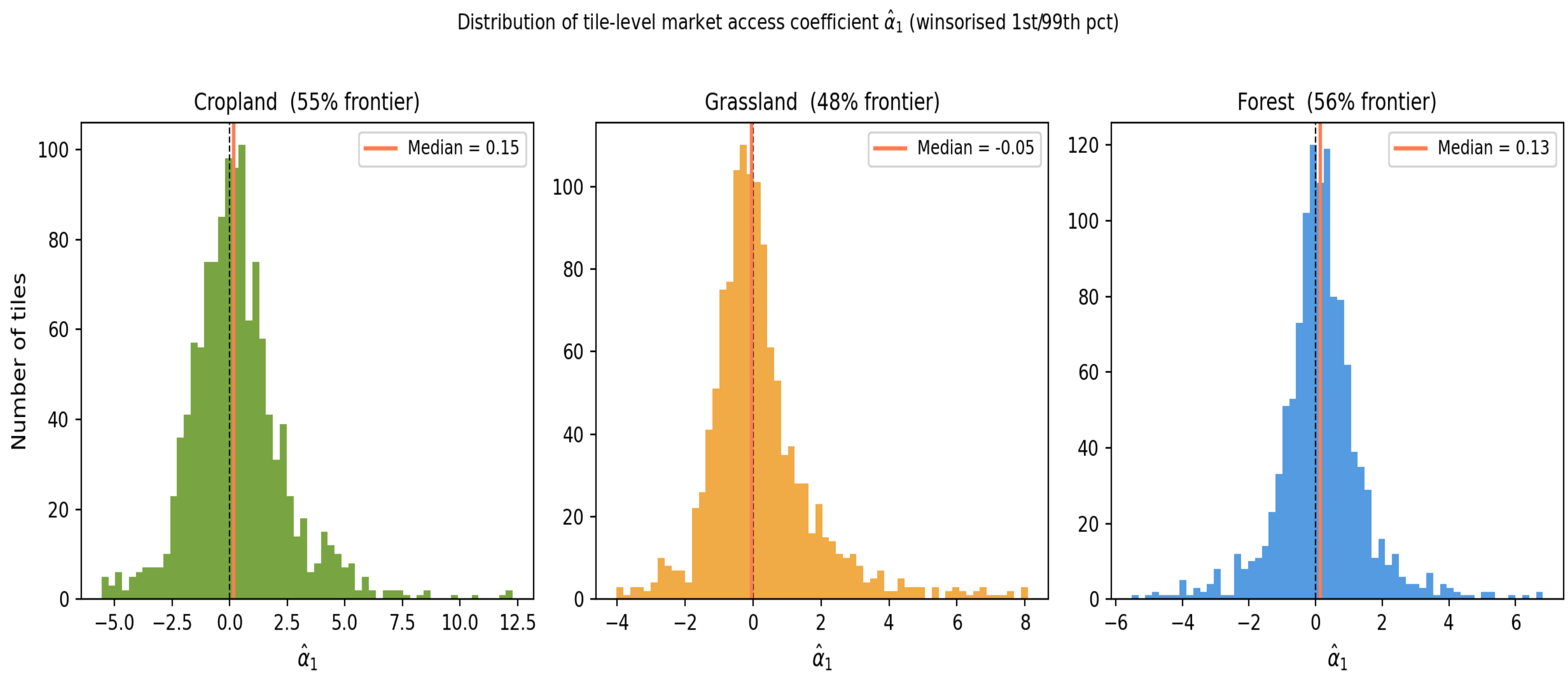
Weiss, D J, Andy Nelson, HS Gibson, W Temperley, Stephen Peedell, Allie Lieber, Matt Hancher, et al. 2018. "A Global Map of Travel Time to Cities to Assess Inequalities in Accessibility in 2015." *Nature* 553 (7688): 333–36.

Woltjer, Geert, Marijke Kuiper, Aikaterini Kavallari, Hans van Meijl, Jeff Powell, Martine Rutten, Lindsay Shutes, and Andrzej Tabeau. 2014. "The MAGNET Model: Module Description." LEI 14-057. LEI Wageningen UR. https://edepot.wur.nl/308014.

Zhang, Xiao, Tingting Zhao, Hong Xu, Wendi Liu, Jinqing Wang, Xidong Chen, and Liangyun Liu. 2023. "GLC_FCS30D: The First Global 30-m Land-Cover Dynamic Monitoring Product with a Fine Classification System from 1985 to 2022 Using Dense Time-Series Landsat Imagery and Continuous Change-Detection Method." *Earth System Science Data Discussions* 2023: 1–32.

Appendix

Tile-level market access coefficient



Frontier % = share of tiles with positive $\hat{\alpha}_1$. Forest shows highest frontier share; cropland and grassland show more displacement near urban centres.

NatCap TEEMs
UNIVERSITY OF MINNESOTA