Carbon prices and forest preservation over time and space in the Brazilian Amazon

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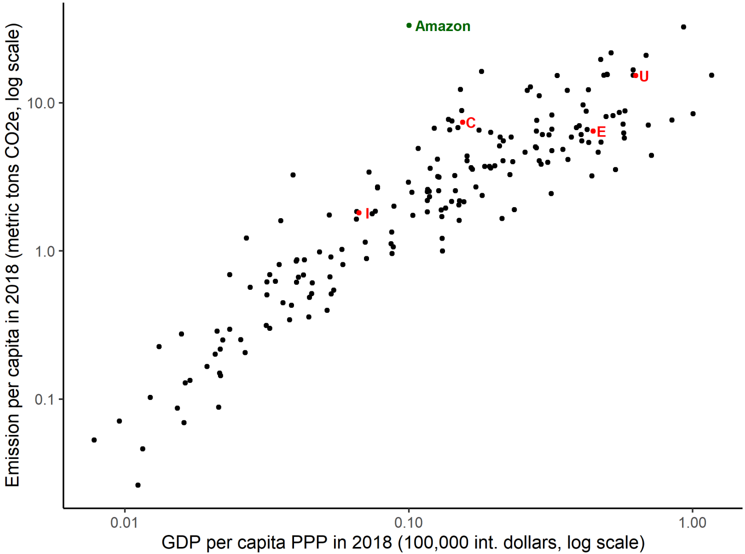
Based on work with Juliano Assunção (Climate Policy Initiative and PUC-Rio), Lars P. Hansen (University of Chicago), and Todd Munson (Argonne National Laboratories)

Motivation

- The Amazon forest contains 123$\pm$23 billion tons of captured carbon that can be released to the atmosphere.
- Brazilian Amazon occupies 60% of the 2.7 million square miles that comprise the Amazon.
- An area the size of Texas has been deforested in the Brazilian Amazon.
  - Logging
  - Currently mostly for cattle.
- Eastern Amazon has become a source instead of sink for carbon.

Emissions curve



This talk

- Discuss preliminary results on the optimal strategy of forest preservation over time and space in the Brazilian Amazon.
- Study the problem of a "social planner" (SP) who considers the economic value of deforested land and carbon-emission prices
  - SP internalizes the externalities resulting from deforestation.
  - Opens the door to the study of alternative ad hoc policies.
- Analyze a dynamic model across heterogeneous regions in Amazon
- Exploit a rich panel dataset that covers a cross-section of regions in the Amazon
- Use numerical methods to achieve a necessary degree of economic and environmental richness.
- Provide input into a broader project on "structuring better incentives for the Brazilian rain forest.

Challenges

- To accommodate the heterogeneity of subregions requires a large number of state variables and state-dependent control constraints that bind in optimum.
- Present results obtained using a method called model predictive controls (MPC) that allows for a large number of state variables and state dependent control constraints.
- Discuss the need to incorporate pervasive uncertainty on parameter-values into perspective of fictitious social planner.

State and control variables

- Sites are denoted $i = 1, \ldots, I$ and the state-vector by (Z, X, P^a).
  - $Z = (Z^1, \ldots Z^I)$, is the vector of site-specific hectares of land used for agriculture.
  - $X = (X^1, \ldots, X^I)$ is the vector of site-specific stocks of captured carbon
- P^a is an index of cattle prices in Brazil in 2017 USD.
  - 85% of deforested land is used for cattle raising.
- Control (U, V) where $U = (U^1, \ldots U^I)$ is a flow vector of increases in the stock of agriculture and $V = (V^1, \ldots V^I)$ is a flow vector of decreases in the stock of agriculture.

State and control constraints

- State constraints:
$$0 \leq Z_t^i \leq \bar{z}^i,$$
  where $\bar{z}^i$ is the area in site i.
- Control constraints:
$$U_t^i \geq 0 \qquad V_t^i \geq 0.$$

State dynamics

- Captured carbon dynamics

$$\dot{X}^i = -\gamma^i U^i - \alpha X^i + \alpha\gamma^i \left(\bar{z}^i - Z^i\right)$$

where $\gamma^i > 0$ and $\alpha > 0$.

- Agricultural land dynamics

$$\dot{Z}^i = U^i - V^i$$

Price dynamics

- Presume an n state Markov chain with possible values for the agricultural price, $p_1^a, \ldots p_n^a$
- An infinitesimal generator given by $n \times n$ matrix $\mathbb{M} = [m_{\ell,\ell'}]$ with non-negative off-diagonal entries and

$$\sum_{\ell' \neq \ell} m_{\ell\ell'} = -m_{\ell\ell} > 0.$$

Outputs

- Agricultural output
$$A^i = \theta^i P^a Z^i$$
where $\theta^i \geq 0$ is a site specific productivity parameter.
- Net emissions
$$\kappa \sum_{i=1}^{I} Z_t^i - \sum_{i=1}^{I} \dot{X}_t^i$$
where $\kappa > 0$ measures the emissions per hectare of land induced by by agriculture.

Quadratic adjustment cost

- Aggregate investment/disinvestment in agriculture over sites

$$\sum_{i=1}^{I} \left(U^i + V^i\right)$$

- Quadratic costs

$$\frac{\zeta}{2}\left[\sum_{i=1}^{I} \left(U^i + V^i\right)\right]^2$$

Social Planner's Objective

- Planner maximizes

$$\int_0^\infty \exp(-\delta t)\mathcal{E}\left(\sum_{i=1}^{I}\left[P^e\left(\dot{X}_t^i - \kappa Z_t^i\right) + P_t^a \theta_i Z_t^i\right] - \frac{\zeta}{2}\left[\sum_{i=1}^{I}\left(U_t^i + V_t^i\right)\right]^2 \mid \mathfrak{F}_0\right) dt$$

- Planner chooses site-specific controls (U^i, V^i) subject to the state evolution equations and the initial states
- P^e, price of emissions, reflects a market for offsets and/or a planner's own valuation.

Calibration of Initial States

- Sites:
  - Fine grid of 1887 sites of $\approx$ 67 km $\times$ 67 km. Of these 1058 overlap with Amazon biome.
  - Course grid of 25 sites (featured in our results today): Aggregate 64 sites of fine grid to produce sites of $\approx$ 600km $\times$ 600km.
- Agricultural areas in 2017 (Z_0^i)
  - Source: MapBiomas
- Total land available in 2017 ($\bar{z}^i$)
  - Source: MapBiomas
- Stock of CO2e stored in forest in 2017 (X_0^i)
  - Source: Global Forest Watch (GFW) + MapBiomas

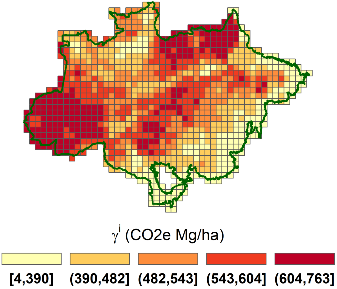
Calibration of Site-specific Parameter Calibration

- γ^i is measured as the average CO2e density stored on primary forests in 2000. Source: Global Forrest Watch (GFW)
- θ^i: average predicted value of cattle sold for slaughter per hectare of pasture. Source: 2017 Agricultural Census.
  - Regressors: pasture area, average precipitation and temperature, latitude, and longitude.
  - Heterogeneity reflects transportation cost and current technology.

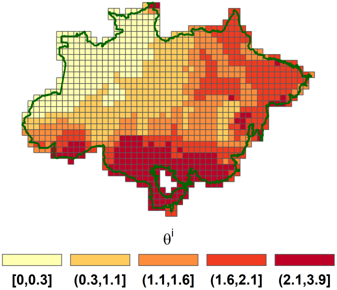
Calibration of Common Parameters

- Mean reversion coefficient, α, is calibrated so that if one lets the forest grow undisturbed in a deforested area, it would reach 99% of the maximal captured CO2e in 100 years. This is motivated by the conclusions of Heinrich (2021).
- Carbon intensity parameter, κ, is measured as the total net CO2e emissions from agricultural use divided by agricultural use area. Source: SEEG + MapBiomas.
- Adjustment cost parameter, ζ, is set so that the marginal cost of changing land use matches forest to pasture transition cost estimated by Araujo et al (2020).
- Agricultural price dynamics are constructed from monthly observations of cattle prices in Brazil using the 25% and 75% quantiles to infer a two-state transition matrix.

Site-specific Parameters γ^i and θ^i (1058 sites)

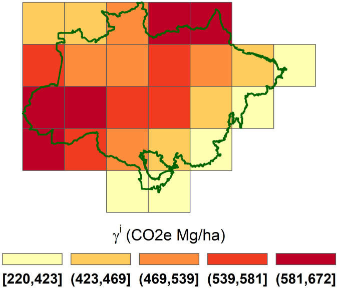


γ^i

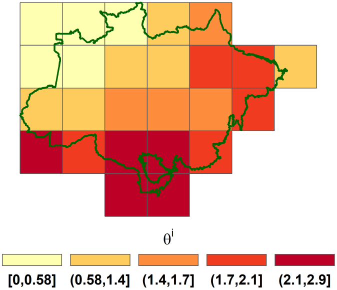


θ^i

Calibration - local parameter γ^i and θ^i (25 sites)

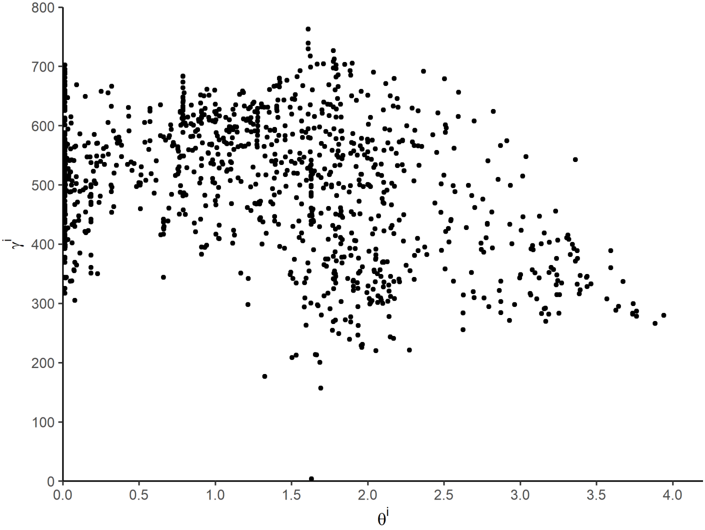


γ^i



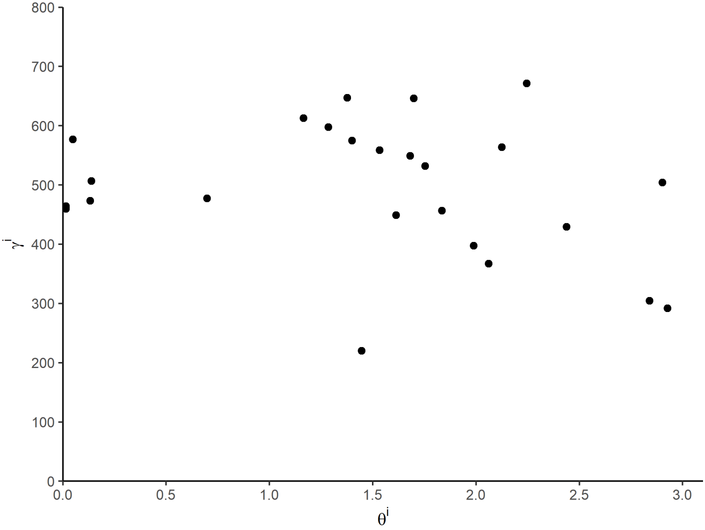
θ^i

Scatterplot $\gamma^i \times \theta^i$ (1058 sites)



The correlation between γ^i and θ^i is -0.35.

Scatterplot $\gamma^i \times \theta^i$ (25 sites)



The correlation between γ^i and θ^i is -0.23.

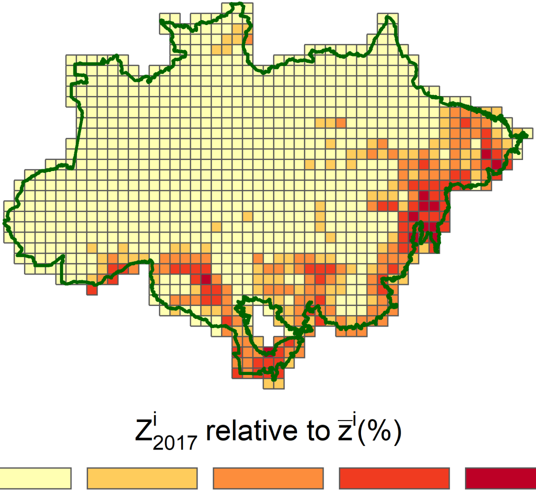
Computational Challenges

- Parameter heterogeneity across sites
- Inequality constraints on controls and states
- Results today based on the 25 aggregated states
- Planner eventually allocates no land to agriculture except in a few sites (state constraints bind).
- Optimality of no agricultural activity in most sites is even more likely with finer grids.

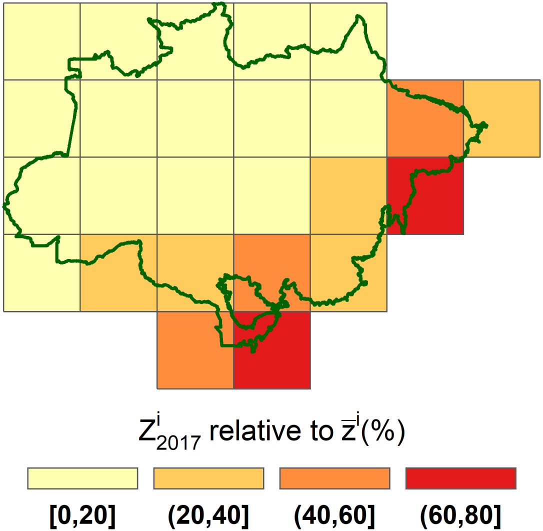
Computational Approach

- Modified Predictive Control:
  - Discrete-time approximation
  - Finite-horizon approximation with two horizons:
    - a relatively short uncertainty horizon where controls are computed as a function of potential shock realizations (we use six periods);
    - a longer horizon where the control solutions are approximated by eliminating shocks beyond the control horizon (we use fifty periods).
  - Solve the model again in subsequent periods with the same uncertainty horizon.
- Interior Point Method: inequalities are approximated with logarithmic penalty functions.

Land Allocation to Production (2017)



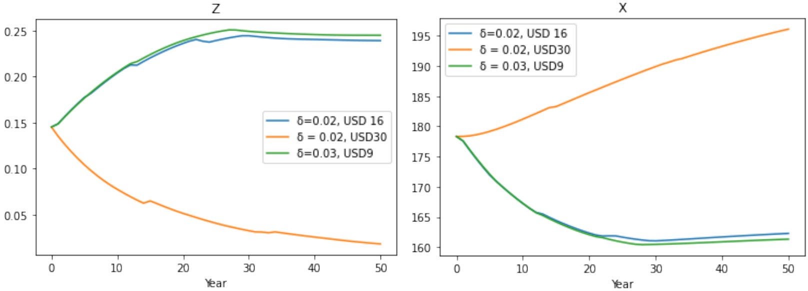
Initial Land Allocation to Production Z_0^i (25 sites)



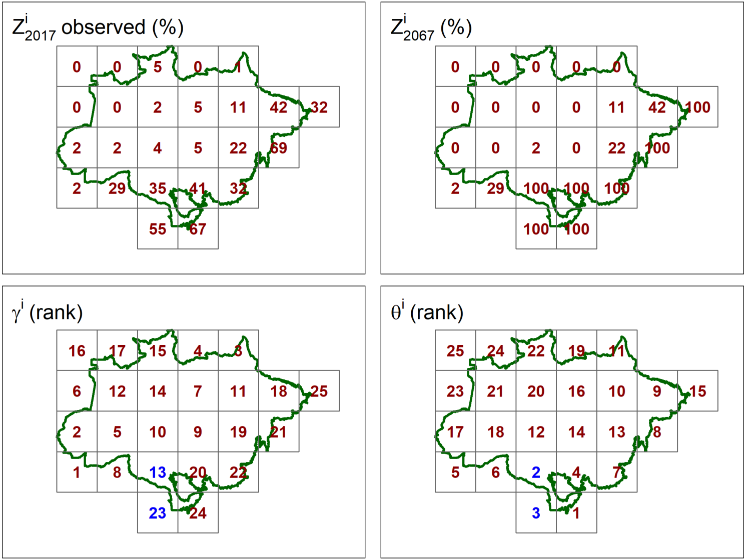
Planner's own valuation - Inferred shadow price of carbon from behavior from 1973 to 2017

- Assuming technology did not change from 1973
  - Possible technical progress during this period would lower shadow price.
- $\delta = 2\%$: USD 16.
- $\delta = 3\%$: USD 9.
- Lower price associated to higher δ, because cost of deforestation is instantaneous while benefits from agriculture have long duration
- These are the average implied prices until 2017, expect much lower under Bolsonaro.
- Also include runs with $\delta = 2\%$ and USD 30.

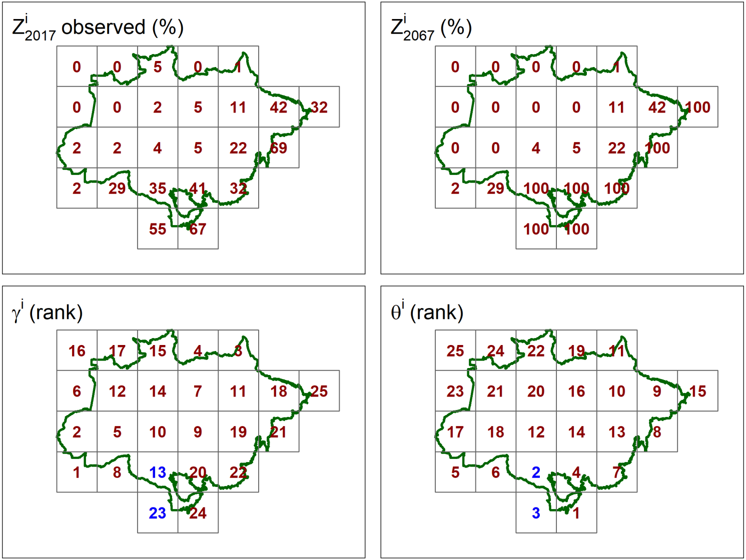
Aggregate Dynamics: Business as usual x $\delta = 2\%$; USD 30



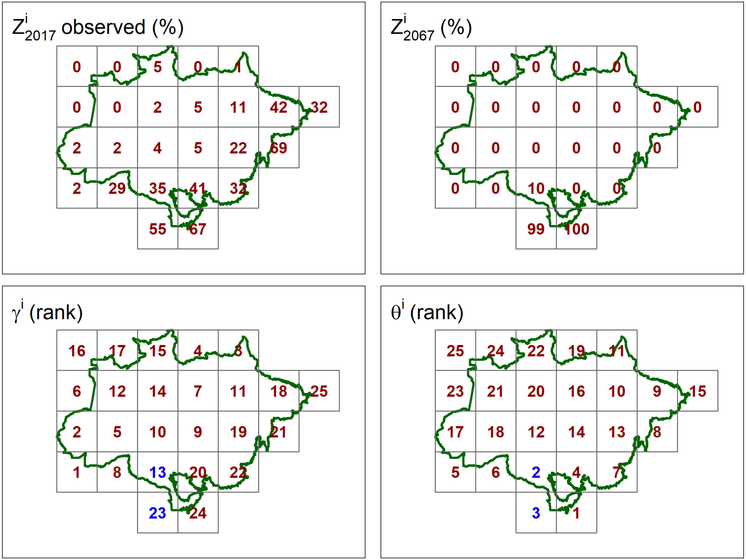
Business as usual: $\delta = 2\%$; $P^e = 16$



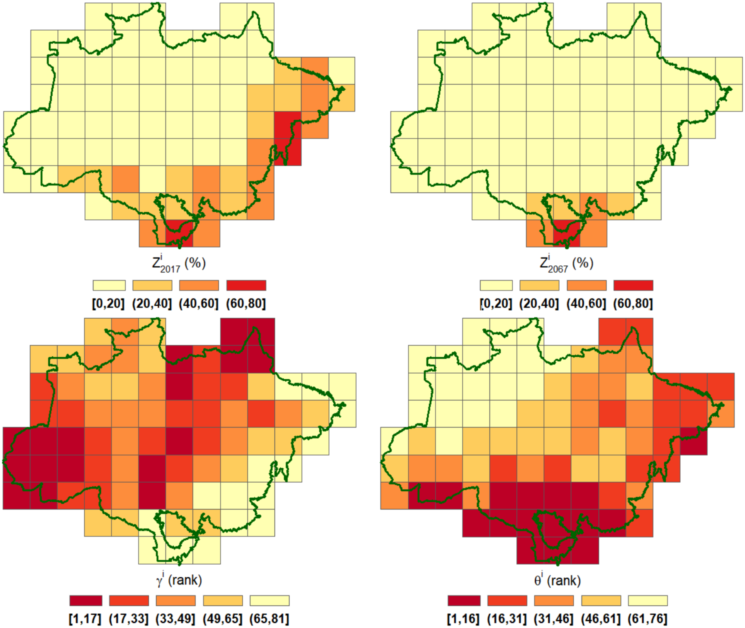
Business as usual: $\delta = 3\%$; $P^e = 9$



Adding payment of \$14 per ton: $\delta = 2\%$; $P^e = 30$



$\delta = 2\%$; $P^e = 19.2$; 81 Sites



Parameter uncertainty

- Explore uncertainty on γ, θ, $\zeta_1 \ldots$ in the cross section.
- Study the dynamic implications of uncertain technological improvements in agriculture in the future.
- Consider alternative specifications of the social cost of emissions.

Conclusions

- Posed explicit dynamic model across heterogeneous regions in the Amazon to assess the potential adverse impact of deforestation.
- Exploited a rich panel data set that covers cross-section of regions in the Amazon
- Computational challenge because the heterogeneity of subregions requires a large number of state variables and state-constraints that bind at the optimum.
- With modest prices for CO2e, Amazon has excessive deforestation and in wrong places.
- Planner solution will serve as a benchmark for comparing alternative ad hoc policies.