Climate and Economics: Tropical Forests
Part V

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Integrated model of deforestation, rainfall and agriculture.

- Integrated model of deforestation, rainfall and agriculture.
- Deforestation for agriculture affects rainfall, which affects agricultural productivity.
    - Most deforestation in Amazon is for agriculture (cattle-ranching)
- Araujo [2023]
    - Model to measure the externality caused by land-use decisions on agricultural productivity via changes in rainfall.
    - Application: Effect of the state of the Amazon forest on agricultural productivity in Mato Grosso State, where 10% of world's soybeans are grown.
    - Counterfactual where farmers are allowed to deforest an important currently protected area.

Some relevant references

- Well known connection between deforestation and rainfall,]Salati et al. [1979],Spracklen et al. [2012]
- Measurement of externality, Araujo et al. [2023]
- Balboni et al. [2022]: Economics literature mostly overlooks feedback between land use decision and climate.
- Araujo [2023]
    - develops discrete choice model of land use that accounts for adaptation, which is missing from natural sciences models.
    - develops climate model of precipitation accounting for climate externalities that are absent in economic models.

Land use model I

- Farmer in plot i can:
  - Deforest and choose activity $c = 1, 2, 3$ (cattle, soybeans or soybeans + corn) with log payoff

    $$\hat{\pi}_i^c = \log r_i^c + \hat{\beta}_1^c R_i + \hat{k}^c + \hat{\epsilon}_i^c,$$

    where r_i^c is a measure of the value of sales of c in plot i, R_i is a measure of precipitation in plot i, k^c captures cost of production of activity c, and ϵ_i^c is a idiosyncratic shock.
- Keep plot i as forest and get log payoff

  $$\hat{\pi}^F = \hat{k}^F + \hat{\epsilon}_i^F.$$

- For $c = 1, 2$

  $$r_i^c = A_i^c(p^c - \tau_i^c)$$

Land use model II

- $$r_i^3 = A_i^2(p^1 - \tau_i^1) + A_i^{corn}(p^{corn} - \tau_i^{corn})$$
- A_i^1 is maximum cattle production in plot i,, A_i^2 is maximum soybean yield in plot i, and A_i^{corn} is maximum corn yield in plot i.
- $p^{\cdot}$, international market price;
- $\tau_i^{\cdot}$ is transportation cost from land i to the port.
- Farmer chooses $\max\{\max_c \hat{\pi}_i^c, \hat{\pi}^f\}$
- Assumption: Vector of unobservables follows a Generalized Extreme Value (GEV) with joint probability distribution:

$$\exp\left[-e^{-\frac{\hat{\epsilon}_i^F}{\sigma}} - \left(\sum_c e^{-\frac{\hat{\epsilon}_i^c}{\lambda\sigma}}\right)^{\lambda}\right] \tag{1}$$

Land use model III

  - if $\lambda \neq 1$ then non-forest shocks are correlated.
- Since rescaling payoffs has no choice consequences, let
  1. $\alpha := \frac{1}{\sigma}$
  2. $\beta_1^c := \frac{1}{\sigma}\hat{\beta}_1^c$
  3. $\dots$

  and rewrite log payoffs as:
-
$$\tilde{\pi}_i^c = \alpha \log r_i^c + \beta_1^c R_i + k^c + \epsilon_i,$$
-
$$\tilde{\pi}^F = \hat{k}^F + \hat{\epsilon}_i.$$
- and the distribution of unobservables is as in expression (1) with $\sigma = 1$.

Land use model IV

- Identification from observed behavior requires normalization of constants and coefficients of common variables.
- Set $(i)\, k^1 = 0$ and $(ii)\, \beta^1 = 0$.
- (i) is innocuous while (ii) has substance: Rain does not affect cattle productivity.
  - Would need a (probably dynamic) model of how rain affects cattle
- Application and (ii) motivates, R_i : total precipitation during growing season in Mato Grosso – September-March, on land i.

Choice probabilities

- Write $\pi_i^{\cdot}$ for $\tilde{\pi}_i^{\cdot}$ when $\epsilon_i^{\cdot} = 0$
- $$P_i(F) = \frac{e^{\pi_i^F}}{e^{\pi_i^F} + \left(\sum_c \frac{e^{\pi_i^c}}{\lambda}\right)^{\lambda}}$$
- $$P_i(c) = \frac{e^{\frac{\pi_i^c}{\lambda}} + \left(\sum_c e^{\frac{\pi_i^c}{\lambda}}\right)^{\lambda-1}}{e^{\pi_i^F} + \left(\sum_c \frac{e^{\pi_i^c}}{\lambda}\right)^{\lambda}}$$
- $$P_i(c|not\ F) = \frac{e^{\frac{\pi_i^c}{\lambda}}}{\sum_c e^{\frac{\pi_i^c}{\lambda}}}$$
- Each P_i function of precipitation R_i.

Empirical precipitation model I

- Time interval: month
- Use wind data from Copernicus [2017] from 1985 to 2018.
- Since wind data ($\sim 25km\,x\,25km$) is lower resolution than land use data ($.25km \times .25km$), map land use pixel into corresponding wind pixel.
- For each wind pixel o construct forest index I_o^m using average Mapbiomas status (forested $=$1, deforested $=$0) of the Mapbiomas pixels (30m x 30m) in wind pixel.
- Upwind exposure to the forest of a back trajectory is:

$$H_o^m := \sum_{\tilde{O}_o^m} I_{\tilde{o}}^m, \tag{2}$$

where $\tilde{O}_o^m$ is the set of wind pixels in back trajectory of wind that arrives at o in month m.

Empirical precipitation model II

- Ignores cascading (see Part III)

- Model of precipitation at climate pixel o as a function of upwind exposure to the forest,

$$R_o^m = \theta_m H_o^m + \epsilon_o^m \tag{3}$$

  - Precipitation in land plot only depends on wind pixel.
  - Aggregate (3) to growing season in Mato Grosso.

ML estimation

- Discrete time model estimated by maximum likelihood in two stages (Train [2009])
- Agriculture nest: ML estimate of parameters parameters $(\frac{\alpha}{\lambda}, \frac{\beta^c}{\lambda}, \frac{k_c}{\lambda})$.
- (log) likelihood

$$\sum_i \mathbb{I}_i^c \log P_i(c|C), , \tag{4}$$

where $P_i(c|C)$ is the conditional probability of activity c given theat the plot is not kept for forest and $\mathbb{I}_i^c = 1$ if c is chosen for plot i.

- Given the estimated parameters for agriculture nest obtained by maximizing expression 4 over choices of $(\frac{\alpha}{\lambda}, \frac{\beta_c}{\lambda}, \frac{k_c}{\lambda}$ choose parameters (k_f, λ) in the deforestation nest by maximizing
- (log) likelihood

$$\sum_i \mathbb{I}_i^F \log P_i(F) + (1 - \mathbb{I}_i^F) \log(1 - P_i(F)) \tag{5}$$

Equilibrium

- Land use choice is function of precipitation and precipitation depends on land use.
- Equilibrium is a land use that is consistent with the precipitation it generates.
    - For counterfactual needs to compute impact of changing area of allowed deforestation
- Write $P(F)$ for the vector of $P_i(F)$. From precipitation model, expected rain in plot i depends on $P(F)$.
- In turn plot choices and hence $P'(F)$ depends on expected rain vector.
- This defines mapping $P'(F) = T(P(F))$
- Equilibrium is a fixed point of T.
- Estimated parameter values imply that T is a contraction. (see Appendix B of paper).
- Equilibrium can be computed by making initial guess and iterating.

Data I

- Land use from Simoes et al. [2020]
  - annual land use from 2001-2017 for pixels of 250 meters in Mato Grosso state.
  - Drop cities and water
  - Equate all single cropping to soybeans and all double cropping to soybeans plus corn.
  - Treat all vegetation. wetland, cerrado, as forest.
- Transportation cost from Araujo et al. [2020] which uses transportation and freight data to estimate as in Donaldson [2018], least cost for transportation from a plot i to port with access to international markets.
- International agricultural prices from St. Louis Federal Reserve dataset FRED.

Data II

- A^c (maximum sustainable yield for crop c) from soil suitability from FAO project Global Ecological Zone. For cattle, use grass potential yield (FAO) and match average grass potential per hectare in Mato Grosso to average production per hectare in MT.
    - Data used previously *e.g.*, Costinot et al. [2016].
    - FAO measure affected by rain

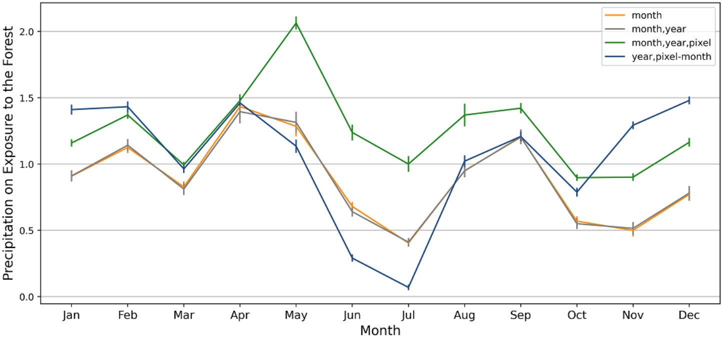
Estimation of model parameters

Table: Parameter Estimation

Panel A		Panel B	
Coefficient	Estimate	Coefficient	Estimate
$\frac{\alpha}{\lambda}$	0.56	λ	0.85
	(0.01)		(0.03)
$\frac{\beta_{singlecrop}}{\lambda}$	0.98	k_F	3.14
	(0.03)		(0.01)
$\frac{\beta_{doublecrop}}{\lambda}$	2.58		
	(0.03)		
$\frac{k_{singlecrop}}{\lambda}$	-3.68		
	(0.02)		
$\frac{k_{doublecrop}}{\lambda}$	-4.51		
	(0.02)		

Notes: Standard errors in parentheses computed with block bootstrap clustered at the pixel level. All estimates have p-value ¡ 0.01. Pane4l A - number of observations: 3,185,987; number of unique pixels: 379,902. Pannel B number of observations: 7,265,252; number of unique pixels: 727,750.

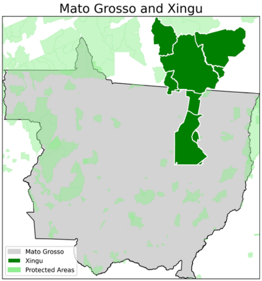
Estimation of empirical rain model 3



- All specifications include control of length of back trajectory over land.
- Standard errors clustered at the pixel level
- Small vertical lines show 95% interval
- 487,560 observations

Counterfactual: Effect of allowing farming in protected indigenous territories in Xingu region

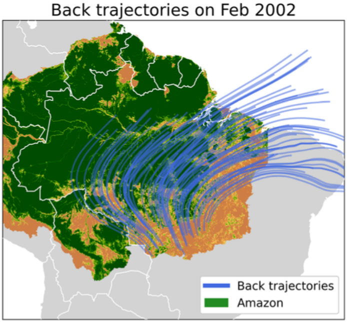
(A)



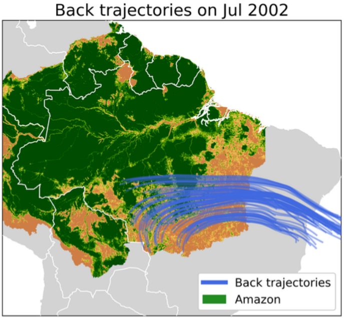
(B)

Figure: (A) shows the location of the Amazon Rainforest and of the Brazilian State of Mato Grosso. (B) shows the location of the indigenous territories of the Xingu River Basin and the locations of other protected areas in the State of Mato Grosso.

Counterfactual: Wind trajectories arriving in Mato Grosso



(C)



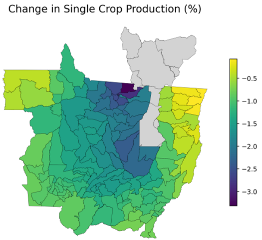
(D)

Figure: (C) and (D) show a sample of back trajectories for the months of February and July 2002 arriving in Mato Grosso.

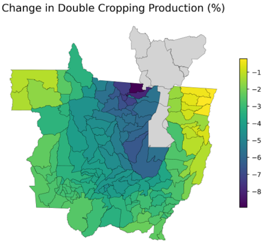
Counterfactual: Effect of allowing farming in protected indigenous territories in Xingu region

- Use average wind exposure in data to predict change in rainfall.
- Allowing farmers in protected Xingu river results in, 57,841 km^2 (43%) of deforestation.
  - Cattle ranching responsible for 73% of deforestation
  - A bit lower but not that different then average cattle-share in Brazilian Amazon
- For regions outside Xingu single and double cropping expected payoffs decrease by 2%,, with some regions reaching 8%.
  - Farmers outside protected areas in Xingu pay for farmers that invade Xingu.
  - Effect heavily driven by double cropping
  - Double cropping much more sensitive to rain change.
- Losses do not account for emissions of 2.8 Gigatons of CO2 (90 billion USD at $25/ton).
- Do not account for biodiversity loss.

Counterfactual: Change in single and double cropping expected payoffs



(A)



(B)

Figure: (A) Change in single crop expected payoff and (B) Change in double cropping expected payoff due to the endogenous change in rainfall caused by the deforestation in the Xingu

Counterfactual: Distribution of losses across years

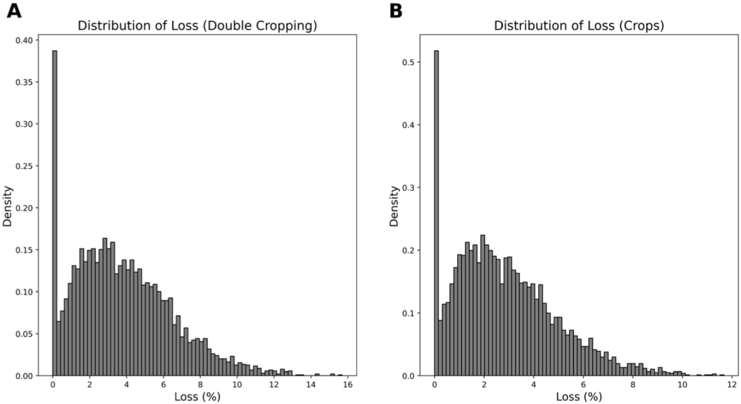


Figure: Distribution of loss (%) using year-to-year variation in the atmospheric trajectory data for double cropping (A) and crops in general (B).

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