A Model of Deforestation for Agricultural Land Clearance in the Brazilian Rainforest

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Introduction

Deforestation, and in particular, illegal logging and land clearance have some of the most damaging effects on the world's forest. Identified in a paper by Slough and Urpelainen (2018), are two significant types of deforestation, land clearance for agriculture and the illegal logging of timber [1]. In this project, we describe how we model the first phenomenon, deforestation for agricultural land clearance in the Brazilian rainforest.

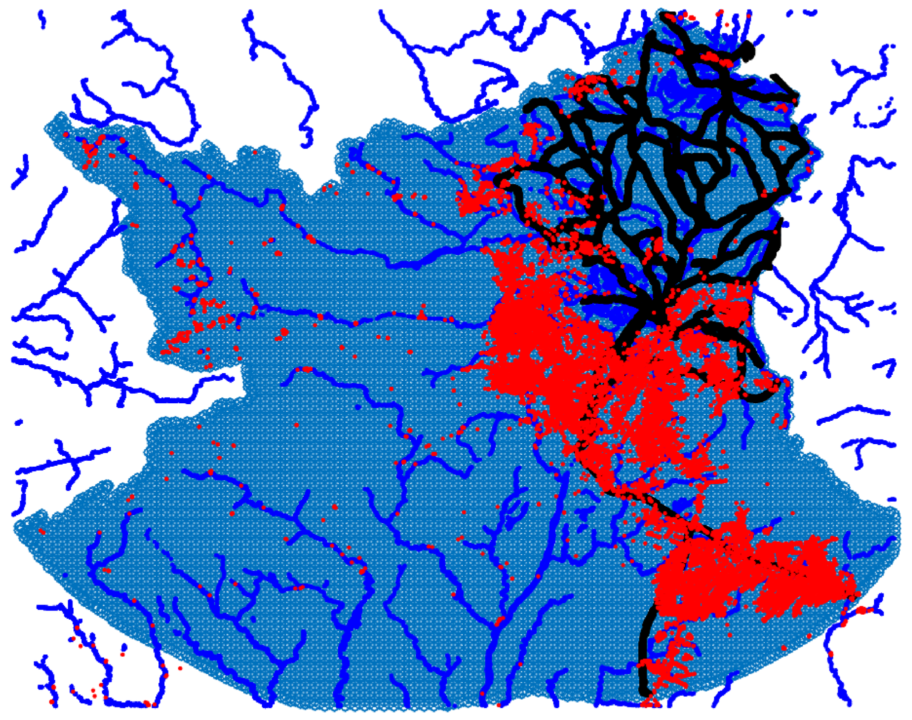


Figure 1: Dark blue is rivers, black is a subset of roads, red dots are deforestation events. Most events happened along the roads, those far from roads are mainly along rivers.

Farming Model Overview

Assumptions:
Farmers have perfect information regarding patrol & choose locations for farms to gain the highest expected profit.

Cost Per Month:

$$C(x,y) = \frac{c_1 \cdot d_r(x,y) + c_2 \cdot d_c(x,y) + c_4}{1 + c_3 \cdot A(x,y)},$$

Benefit Per Square Meter Per Month:

$$B(x,y) := \xi \chi_{\text{trees}}(x,y) \frac{1}{1 + ||\nabla E(x,y)||^{\gamma}}$$

The probability of **not being captured by the end of the i^{th} month** at location (x,y) is

$$\beta_i(x,y) = \prod_{j=1}^{i} (1 - \psi(x,y) S_j),$$

- d_r - distance to roads, d_c - distance to cities
- A - accessibility, E - elevation
- χ_{trees} - the indicator function of trees
- ψ - capture prob., $S_j = S_0 + jdS$ - farm area

Thus, the **expected benefit a farmer will receive in month** i is $\mathbb{E}(\text{Benefit}_i(x,y)) = B_i(x,y) \cdot S_i \cdot \beta_i(x,y) - \alpha \cdot B_i(x,y) \cdot S_i \cdot (1 - \beta_i(x,y))$

And the expected benefit a farmer will receive by the end of month i is $\sum_{j=1}^{i} \mathbb{E}(\text{Benefit}_j(x,y))$

The farmer's expected profit is $\mathbb{E}(P(x,y)) :=$

$$\left(\max_{i=1,\dots,K_{\max}} \sum_{j=1}^{i} \left(\mathbb{E}(\text{Benefit}_j(x,y)) - C_j(x,y) \right) \right)_+$$

Then we normalize $\mathbb{E}(P(x,y))$ to make it into a probability density function.

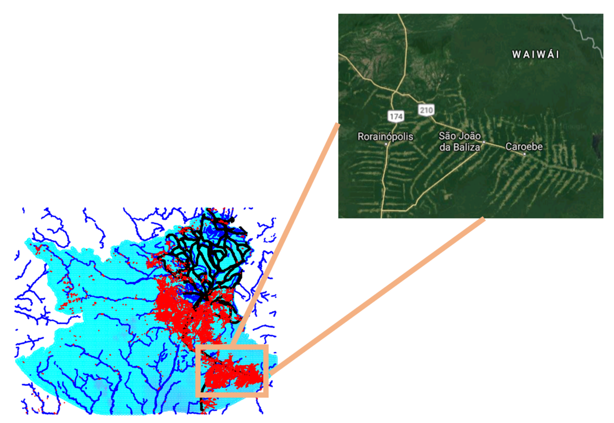
Time Series Simulation

Simulation in a Month (Iterate Month)

- Obtain $\mathbb{E}P$ with expected profit algorithm.
- Sample N points from $\mathbb{E}P$, where N is based on average proportion of events in month i.
- Start a farm at every point chosen with area S_0, profit $P = 0$ and age $t = 1$.
- Update Benefit (for farmers in growing farms) for every growing farm $\bar{B} \leftarrow (1 - \frac{t}{K_{\max}})B$.
- Calculate marginal expected profit for each farm by $P_m = \bar{B} \cdot (S + dS) - C$.
- Stop growing farms where no more expected profit can be gained.
- Update farm area and profit for every growing farm $S \leftarrow S + dS, P \leftarrow P + P_m$.
- Update Benefit (for new farmers) for every point in growing farms $$B(x,y) \leftarrow (1-\lambda)B(x,y), \lambda \in (0,1).$$
- Update Accessibility by centers of growing farms $A(x,y) \leftarrow$ $$A(x,y) + (\frac{1}{2})^{t_i} \frac{1}{2\pi h} \exp\left(-\frac{(x-x_i)^2 + (y-y_i)^2}{h^2} \right),$$ where t_i is the age of the farm centered at (x_i, y_i). Then normalize A.
- Run a Bernoulli trial with $p = \psi \cdot S_i$. Stop captured farms from growing and decrease the profit by $\alpha \bar{B} S$.
- Update farm age for every growing farm $t \leftarrow t + 1$.
- Update patrol to be a multiple of $\mathbb{E}P$. (or other patrol strategies, e.g. update when capturing, $\sim$ update accessibility)
- Update distance to roads after adding optimal paths from new farms.

Experimental Setup

We focus on the bottom right region of the Roraima, form a 500×500 grid with grid size $300\text{m} \times 300\text{m}$. For farming, we only consider events within 10km from roads.



Evaluation Metrics

1. F1 score: To evaluate the performance of our simulation model we compare the results with real events in the PRODES data set.
Due to sparsity of events, we give some tolerance for the prediction. Let T_n, R_n denote the predicted and real event matrix for year n respectively. Each entry of the event matrices count the number of events happen in year n that are closest to the location that the entry represents.

Then we classify a real event at location (x,y) as being accurately predicted if the sum of entries in T_n in a neighborhood of (x,y) is no less than $R_n(x,y)$. And we classify a point (x,y) to be false positive only if the sum of entries in R_n in a neighborhood of (x,y) is less than $T_n(x,y)$.

2. av. capture rate: $\frac{1}{11}\sum_{n=2005}^{2015} \frac{\#\text{captured}}{N_n}$

3. av. grwoing farm rate: $\frac{1}{11}\sum_{n=2005}^{2015} \frac{\sum_f f.g}{N_n}$

4. av. farm growing time: $\frac{1}{11}\sum_{n=2005}^{2015} \frac{\sum_f f.t}{N_n}$

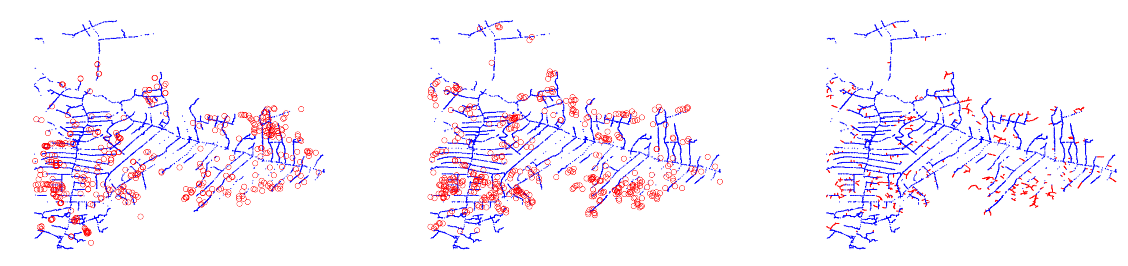
5. av. profit: $\frac{1}{11}\sum_{n=2005}^{2015} \frac{\sum_f f.P}{N_n}$

Results

	av. profit	av. capture rate
Expected Profit Patrol	0.008	0.238
Capture Patrol	0.012	0.018

Table 1: Comparison between patrol strategies. Expected Profit Patrol (we currently use) has better scores.

Our model yields an av. recall of 0.64, precision of 0.57, and F1 score of 0.61. Av. capture rate is 24%, av. growing farm rate by Dec. is 49%, av. farm growing time is 5 months.



(a) Real Events in 2015 (b) Simulation Results in 2015 (c) Road Change in 2015

References

[1] T. Slough, J. Urpelainen, and Johns Hopkins SAIS., *Public policy under limited state capacity: Evidence from deforestation control in the Brazilian Amazon.* Technical report, mimeo, 2018

Acknowledgements

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