Synthetic Control with Multiple Outcomes for Conservation Evaluation

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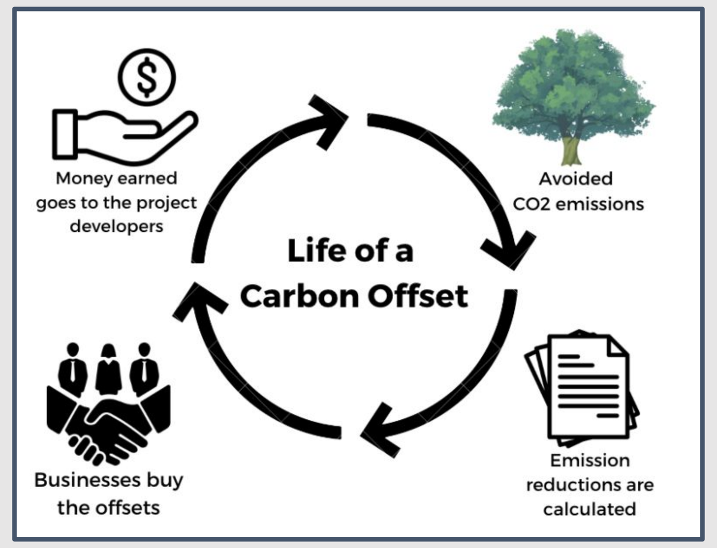
SPIRES
Study of Politics and Institutions with Remote Environmental Sensing

Abstract

This study applies the Synthetic Control Method with Multiple Outcomes (SCMO) to evaluate the carbon impact of REDD+ projects using remote sensing data. Addressing challenges like spatial autocorrelation and low pre-treatment variation, SCMO provides robust counterfactuals. Using the Maísa project in Pará, Brazil as a case study, we construct a 2000–2020 panel from Landsat and Hansen datasets. Preliminary results highlight SCMO's potential for improving the credibility and transparency of REDD+ impact evaluations.

Introduction

REDD+ (Reducing Emissions from Deforestation and Forest Degradation) projects aim to protect forests and prevent the release of stored carbon into the atmosphere (1). Although demand for REDD+ has increased, persistent concerns about carbon credit quality have undermined trust and discouraged corporate investment (2). While local REDD+ interventions are increasingly studied, few evaluations use rigorous, counterfactual-based methods to assess their true impact on carbon emissions (3). This study addresses that gap using a novel causal inference approach.



Goal

To apply the Synthetic Control Method with Multiple Outcomes (4) to estimate carbon emission reductions in REDD+ projects using remote sensing data.

Figure 1: State of Pará, Brazil

Background

Conventional methods often struggle with spatial autocorrelation and unobserved confounders (5). SCMO offers a promising alternative by constructing a counterfactual scenario from untreated areas. It estimates a common set of weights across outcomes in the pre-treatment period that (4).

Data

Case study: Maísa REDD+ project

Remote Sensing Sources:

- Landsat 7 Reflectance Data (6)
- Hansen et al. Deforestation Dataset (7)

Panel Construction:

- Annual panel (2000–2020)
- 1 treated unit (Maísa project)
- 100 donor units randomly drawn

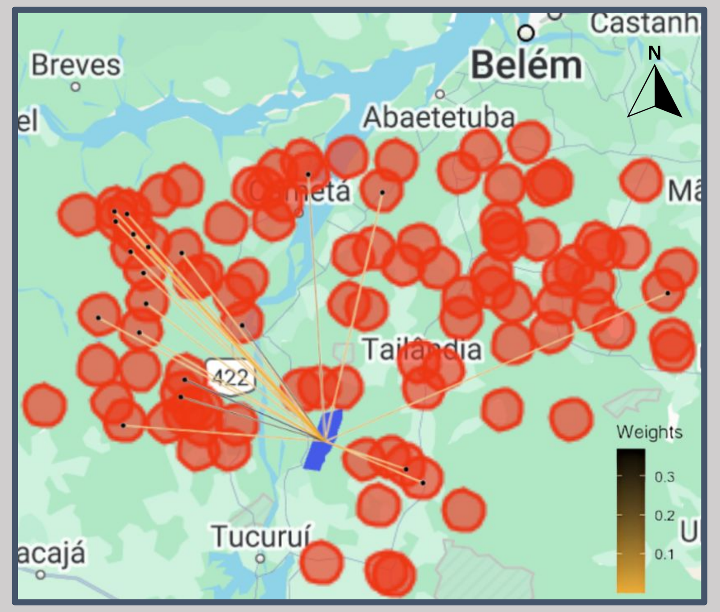


Figure 2: Project zone, donor areas, and associated weights

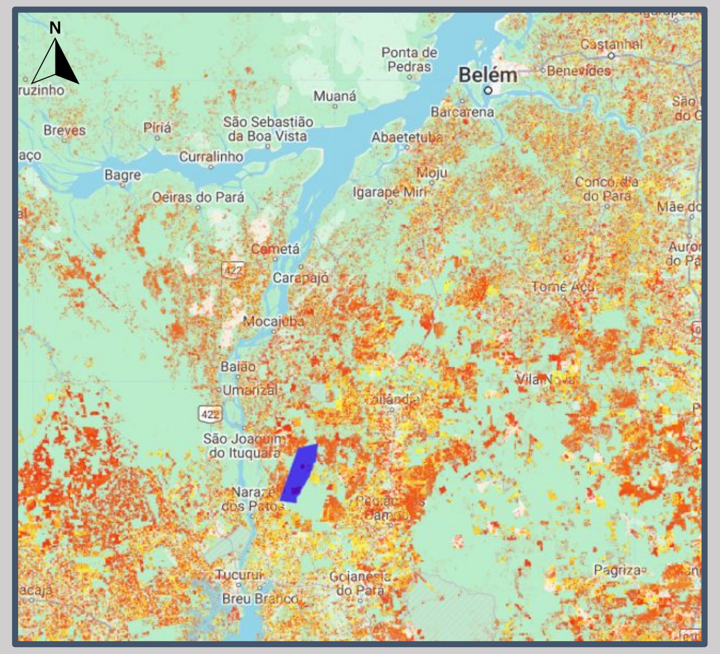


Figure 3: Hansen 2023 Deforestation data

Results

Balance measure:

$$q^{avg}(\gamma) \equiv \sqrt{\frac{1}{T_0}\sum_{t=1}^{T_0}\left(\frac{1}{K}\sum_{k=1}^{K}\dot{Y}_{1tk} - \sum_{W_i=0}\gamma_i \dot{Y}_{itk}\right)^2}$$

Corresponding weights:

$$\hat{\gamma}^{avg} \equiv \underset{\gamma \in \mathcal{C}}{\operatorname{argmin}}\ q^{avg}(\gamma)^2$$

Constructed control 'forest'

$$Y_{control} = \sum_{W_i=0} \hat{\gamma}_i Y_i$$

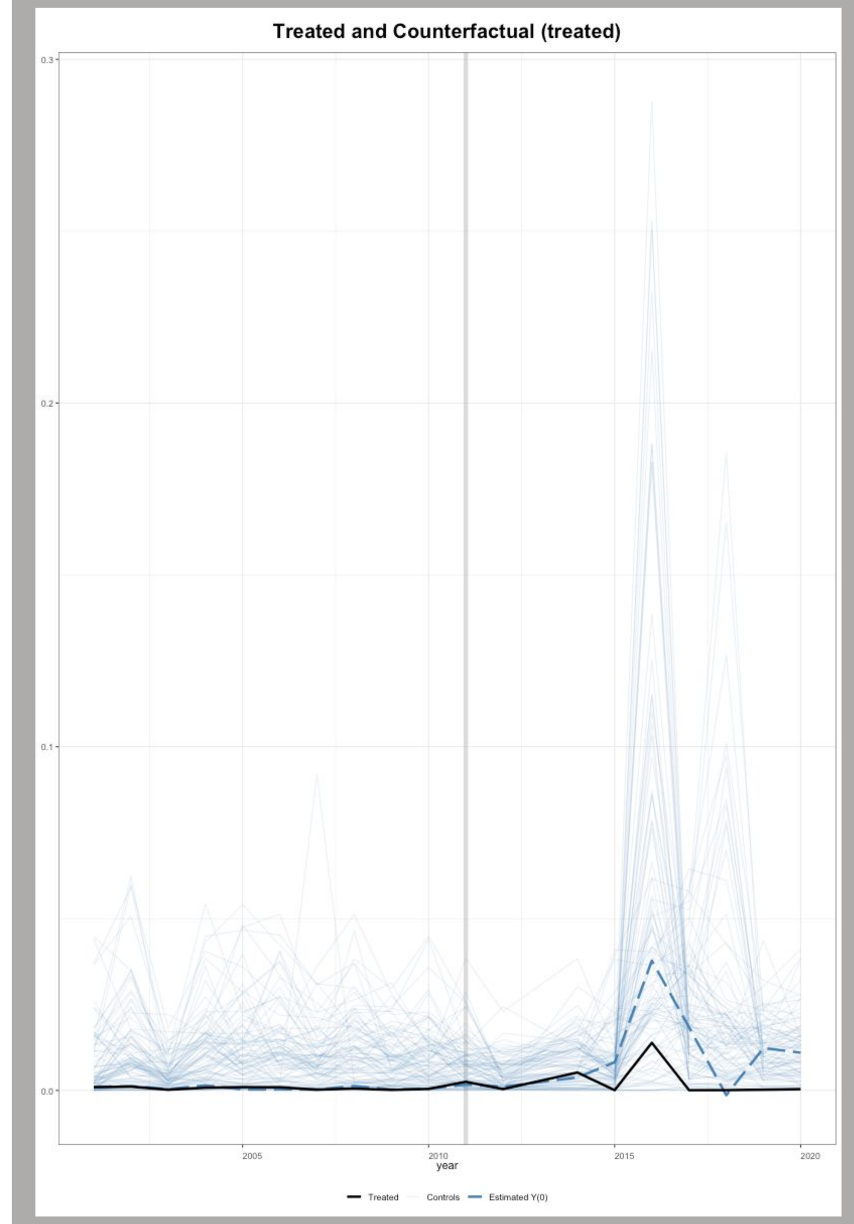


Figure 4: Single outcome synthetic control method: deforestation ~ treatment

- SCMO performs well and addresses limitations of traditional synthetic control when deforestation near-zero in the pre-treatment period.

- Remote sensing data supports the inclusion of multiple outcome variables, improving robustness of impact estimates.

Table 1: Average Treatment on Treated (ATT)

Results		
Outcome Variable	Estimate	p value
Deforestation	-0.001302587	0.067
Blue band	-0.005824967	0.067
Green band	-0.007126615	0.067
Red band	-0.008577518	0.067

Software:
Google Earth Engine + R

Scan for GitHub

LinkedIn

Conclusion

This study demonstrates the potential of the Synthetic Control Method with Multiple Outcomes for evaluating the effectiveness of REDD+ projects using remote sensing data. By addressing key methodological challenges—such as spatial dependencies and lack of variation in pre-treatment deforestation—SCMO provides estimates of carbon emission reductions with lower p-values. The approach offers a scalable and transparent framework for improving accountability and impact assessment in forest conservation efforts.

Next steps:

- Conduct pixel-level analysis
- Compare performance across different deforestation datasets
- Introduce training/test data split for model validation
- Scale methodology to additional REDD+ project sites

Author

Mariam Gedenidze, Her interests include Environmental Data Science, Economics, and policy evaluation.

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