Mapping sugarcane yield in São Paulo State: applying panel data analysis and machine learning

Nélida E. Q. Silvero João Vitor Matos Gonçalves

## Agenda

- Introduction
- Material and methods
- Results
- Final considerations



## INTRODUCTION

#### Introduction

- Brazil is one of the most important producers
- Sugarcane production occupies the third position, representing approximately 8 M ha and a total production of 654.8 Mt
- São Paulo State → Highest producer with 51% of the area and 54% of the total production
- Average yield 76 Mg ha<sup>-1</sup>





## Why is important to forecast sugarcane yield?

- Essential tool to support decision making processes regarding harvesting, marketing, milling, and selling strategies
- To evaluate strategies to select new cultivars that may better adapt in an area, climate risks and need for irrigation





How sugarcane yields are predicted/forecasted?

Agrometeorological models

Process-based models

Machine learning



### Objective and hypothesis

This research will focus on estimating sugarcane yield for the upcoming years at the county level using panel data analysis and machine learning, specifically Random Forest and Gradient Boosting.

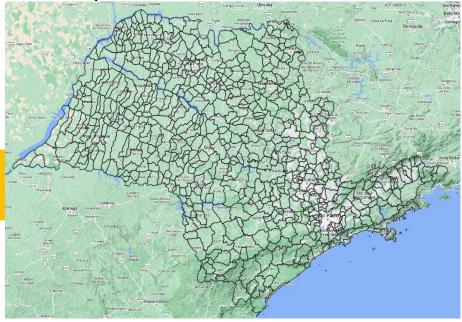
The hypothesis is that sugarcane yield is affected by several soil, climatic and vegetation historical variables and that future yield can be accurately estimated from these variables using panel data analysis and machine learning



## Material and methods

### Study area and datasets

#### Municipalities of the State of São Paulo



Variable Y: Sugarcane yield (kg/ha)

From Table 1612 of the SIDRA Platform Years 2000-2020

#### **Variables X (Years 2000-2020):**

- Harvested area (AC, ha)
- Total production (QP, tn)
- Production values (VP, R\$)



- Precipitation (pr)
- Soil moisture (soil)
- Evapotranspiration (aet)
- Minimum temperature(tmin)
- Maximum temperature (tmmx)
- **FROM MODIS** 
  - NDVI, NPP, LST







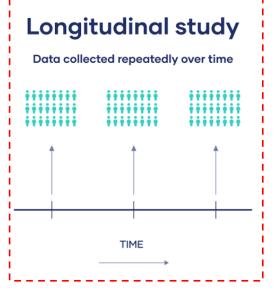




## Statistical analysis



Mean and standard deviation for all years and municipalities and over time.



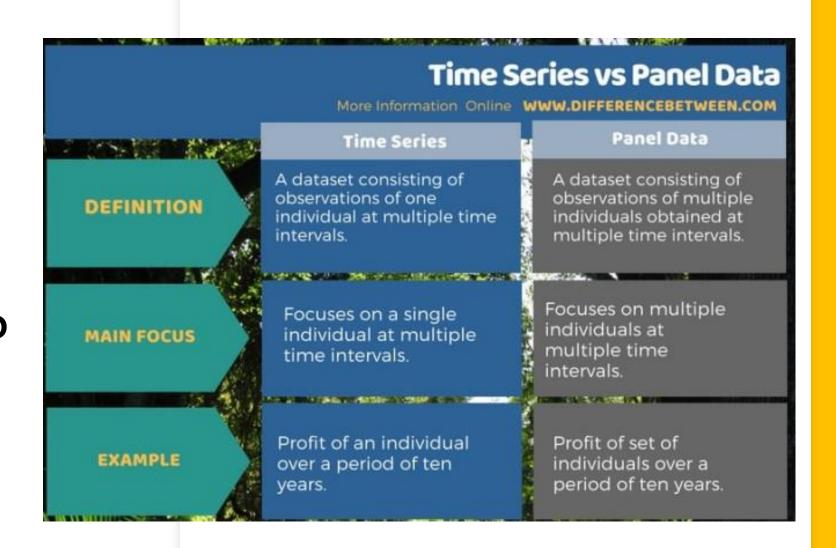
Panel Data Analysis



**Gradient Boosting** 

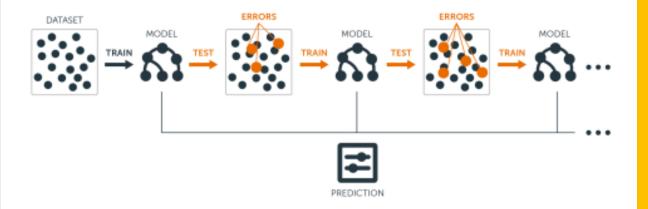


# Why Panel Data Analysis?





## **Gradient Boosting**



Weak learners used sequentially to reduce errors

Usually used with decision trees



## Modeling strategies

#### **Panel Data Analysis and Gradient Boosting**

Training set: Sugarcane yield and variables from years 2000 to 2014

Test set: Sugarcane yield and variables from years 2015-2020

Validation set: Sugarcane yield from year 2021

Metrics: R<sup>2</sup> and RMSE

#### **Only Gradient Boosting**

Hyperparameterization: Yes

#### **Only Panel Data Analysis**

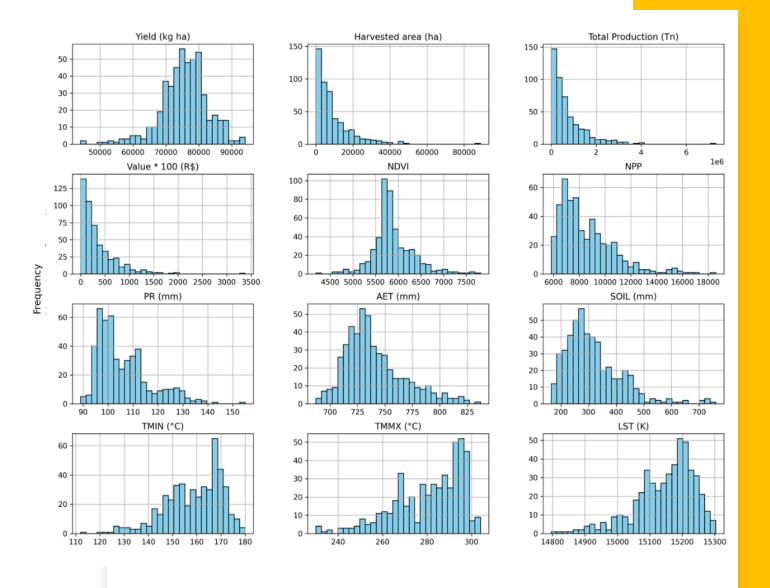
Groupings by quantiles



## RESULTS

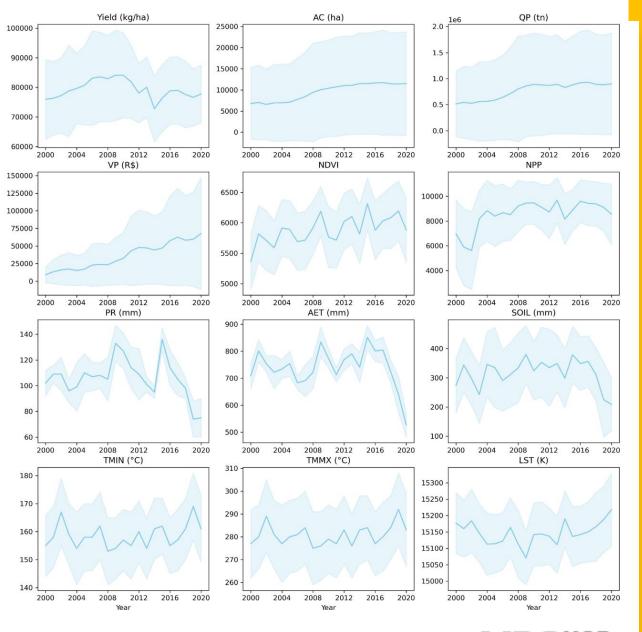
### Descriptive statistics

# Average of all variables



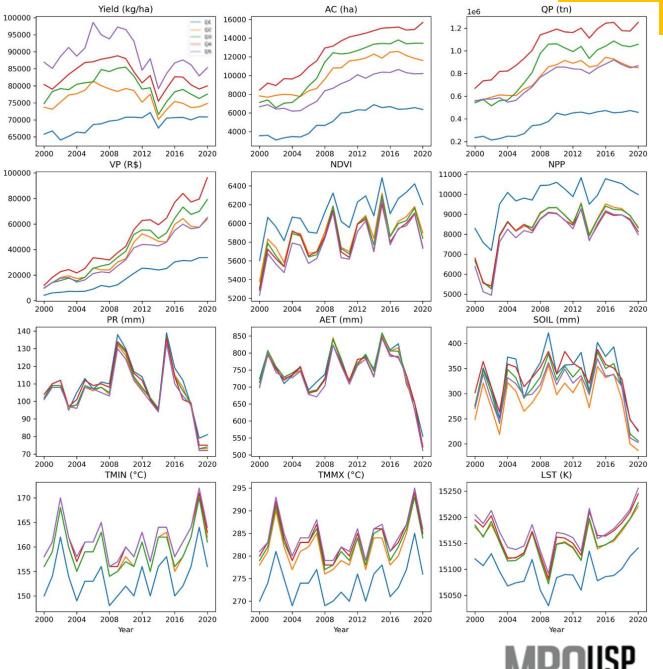


## All variables by year





# Grouping by quantiles





## Panel Data Analysis

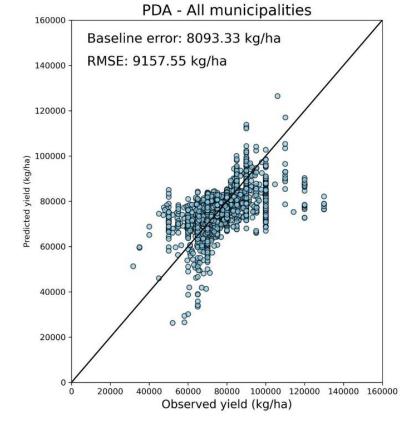
R<sup>2</sup><sub>traininig</sub>: 0.4

R<sup>2</sup><sub>test</sub>: 0.3

Significance: Yes (5%)

All variables were significant except soil moisture

PDA with quartiles had the worst performance



2012

100000

95000

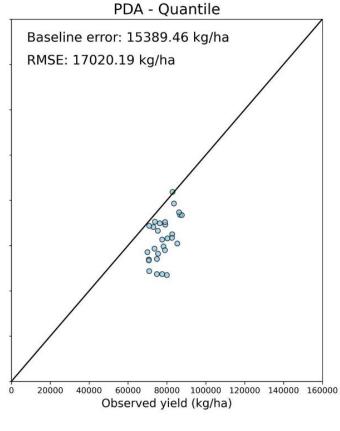
90000

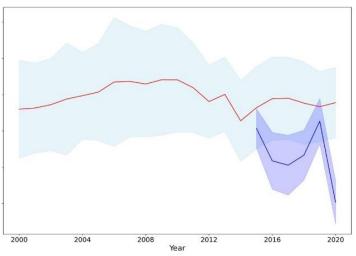
75000

65000

Yield (kg/ha)







### **Gradient Boosting**

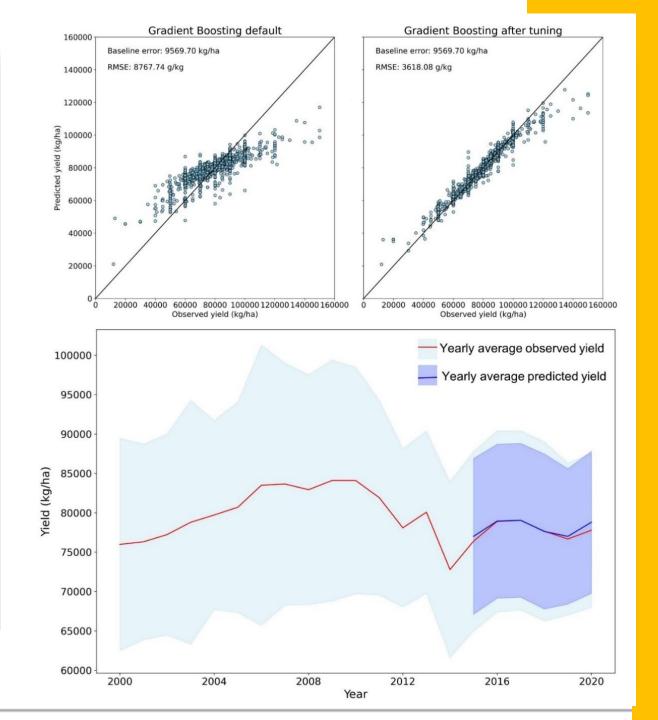
Default With hyperparameterization

 $R^2_{traininig}$ : 0.70  $R^2_{traininig}$ : 0.92

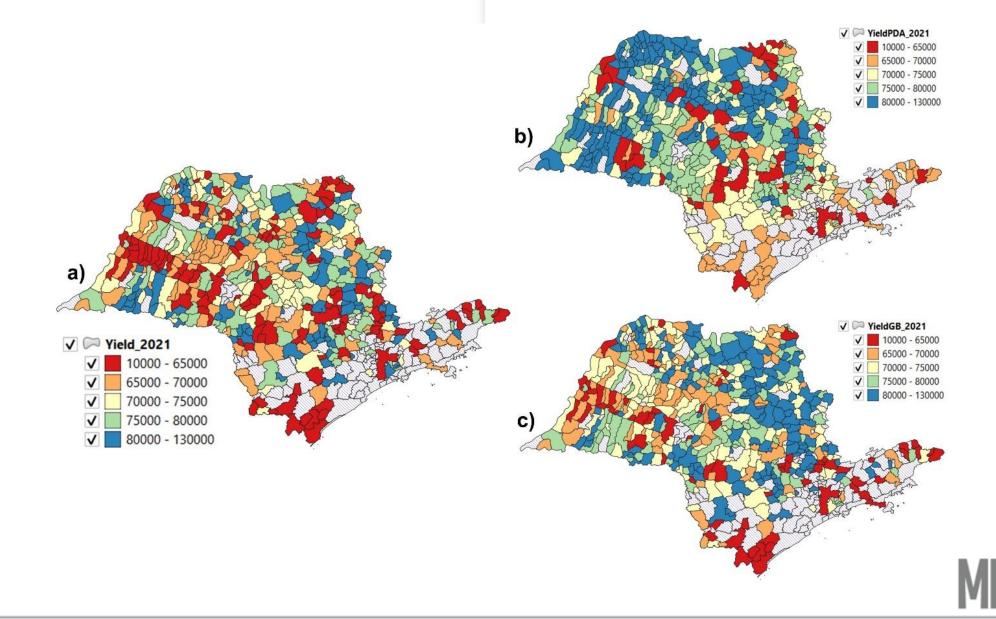
 $R_{\text{test}}^2$ : 0.60  $R_{\text{test}}^2$ : 0.87

Most important variable: QP

GB with hyperparameterization was the best



### Spatial distribution of sugarcane yield



## FINAL CONSIDERATIONS



- The importance of crop yield prediction for different stakeholders
- Gradient Boosting better than Panel Data Analysis after a set of hyperparameterization runs
- More research is needed to explore other environmental covariates and specifically management practices that were not available at the municipality level





https://neli12.github.io/



nelida.silvero@rothamsted.ac.uk



https://github.com/neli12



linkedin.com/in/nsilvero

## Obrigada!