

The Data Mine

# Development of Google Earth Engine-Based App for National Forest Inventory Plot Data Exploration

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## Introduction

Efficient land use starts with understanding the available resources. Our team is focused on developing a comprehensive approach to land resource monitoring, leveraging both in-house and geostationary data to create an algorithm that displays the land's different use cases. Our objective is to provide land resource information and usage trends to those who depend on the forests. In this poster, Costa Rican land data is used.

#### 1. Nature of the Data

- Nine land use classifications data points are determined and grouped per hectare. (Fig 1)
- These groups are called plots and are obtained for every hectare across the country (Fig 2)
- This totals to 101160 individual data points from 11240 plots, with additional information for vegetation, water, and ground types.





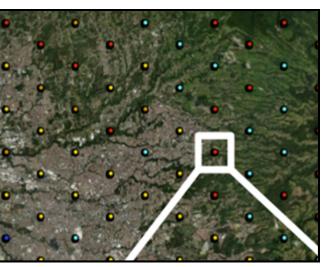


Fig 2. Land Use Plots

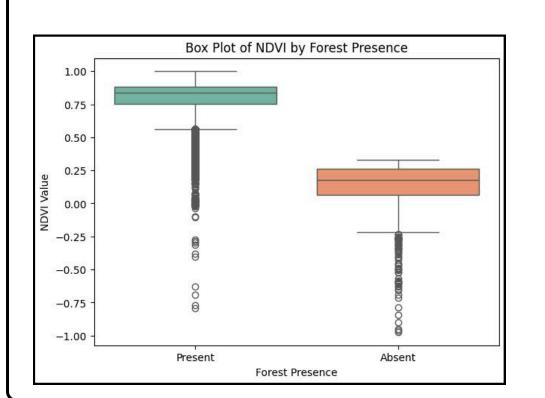
# 2. Exploratory Data Analysis (EDA)

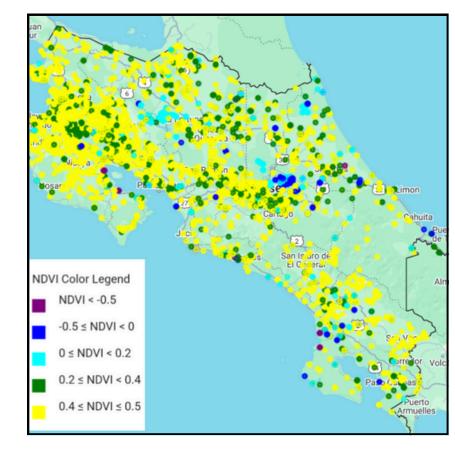
#### Cleaning the Data

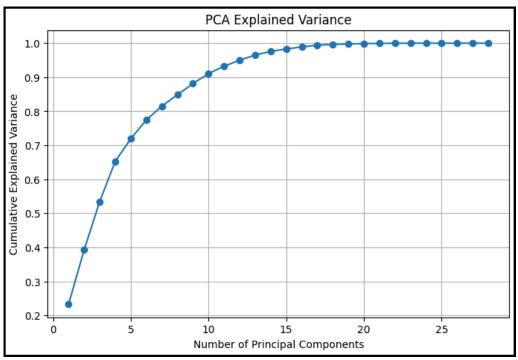
- Raw data had to be preprocessed and cleaned due to duplicate instances of data:
  - Concluded the duplicates were for quality assurance reasons
  - Compared QA and initial entries and removed extras

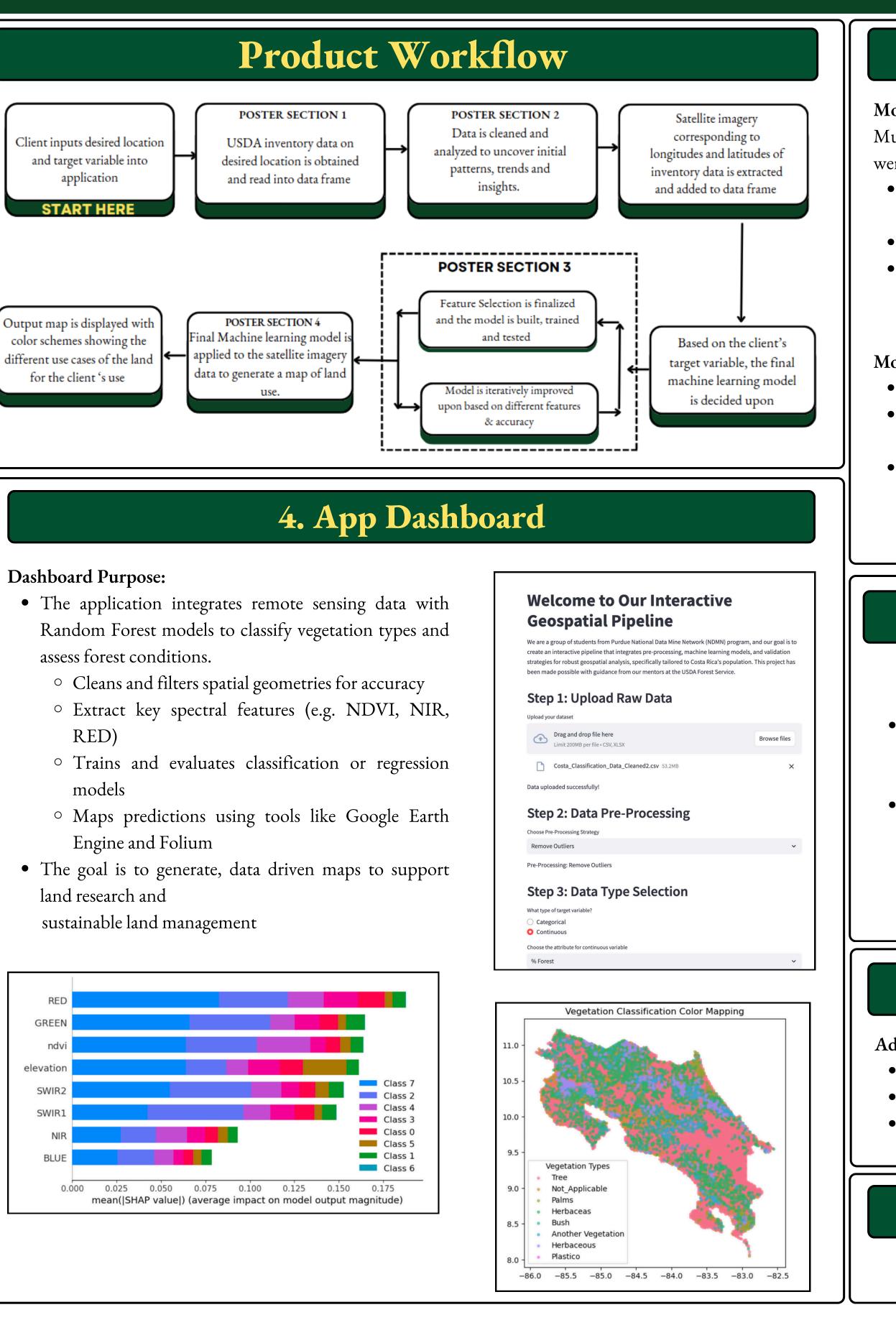
#### **Outlier** Detection

- Using box-and-whisker plots and other graphical analysis tools:
  - Identified and removed outlier points in dataset









# The Data Mine Corporate Partners Symposium 2025



#### **USDA** Forest Service

## 3. Machine Learning & Methodologies

#### Model & Feature Selection

Multiple Machine Learning (ML) classification models were trained

- Logistic regression, Random Forest, Support Vector Machine
- Predictor variable is land use
- 80-20 split was used to partition the dataset into
- training and testing sets

Agriculture 1408 64 0 64 0 0 8 1 -100   Forest 14 10323 0 168 0 0 5 2 -800   Forest plantation 0 17 137 8 0 0 13 3 -600   Grasslands 12 256 0 4139 0 0 13 3 -600   No information 0 5 0 2 33 0 2 1 -400   Not_Applicable 0 3 0 2 0 31 0 0 -200   Wetlands 6 28 0 18 0 0 33 659 -0			Predicted								
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Agriculture - 1408 64 0 64 0 0 8 1   Forest - 14 10323 0 168 0 0 5 2 -800   Forest plantation - 0 17 137 8 0 0 0 0 0 0 -800   Grasslands - 12 256 0 4139 0 0 13 3 -600   No information - 0 5 0 2 33 0 2 1		Other classes -	4	38	0	69	0	0	837	1	- 200
Agriculture - 1408 64 0 64 0 0 8 1   Forest - 14 10323 0 168 0 0 5 2 -800   Forest plantation - 0 17 137 8 0 0 0 0 0 600   Grasslands - 12 256 0 4139 0 0 13 3 -600   No information - 0 5 0 2 33 0 2 1		Not_Applicable -	0	3	0	2	0	31	0	0	
Agriculture - 1408 64 0 64 0 0 8 1   Forest - 14 10323 0 168 0 5 2 -800   Forest plantation - 0 17 137 8 0 0 0 0 600		No information -	0	5	0	2	33	0	2	1	- 400
Agriculture - 1408 64 0 64 0 0 8 1 Forest - 14 10323 0 168 0 0 5 2 -800		Grasslands -	12	256	0	4139	0	0	13	3	- 600
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Agriculture - 1408 64 0 64 0 0 8 1		Forest -	14	10323	0	168	0	0	5	2	- 800
		Agriculture -	1408	64	0	64	0	0	8	1	- 100

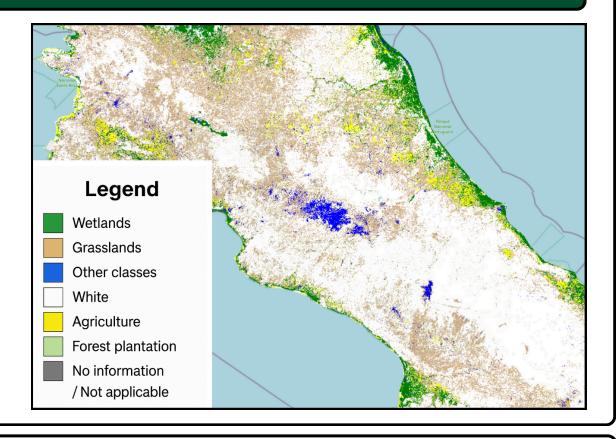
#### Model Results

- Models were evaluated by ccuracy, precision, recall, F-1 score, and confusion matrix • Random forest performed the best at 96% accuracy,
- It may be overfitting, as accuracy scores varied across test samples
- Dettermined that some of the most improtant features across models include elevation,
- NDVI, and other remote senssing variables such as red, green bands nad shortwave infrared

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#### 5. Conclusion & Results

• Obtained a map of Costa Rica based on the different land use cases using our Machine Learning Model. • Built an interactive application dashboard for potential external use



#### 6. Future Work

Adjustments & Future Projection:

- Collect feedback from Costa Rican scientists and authorities on project results and dashboard • Update the project's pipeline and dashboard as necessary and as requested
- Enable the software and application to be available for external companies and countries

# Acknowledgements

Thank you to our Corporate Partners, our professional mentors Andy Lister, John Hogland, and Rachel Riemann, as well as our peer mentor Wendy Jiang.