São Paulo 2025

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INSTITUTO BRASILEIRO DE ATUÁRIA

# Crop Classification with SAR Data and Deep Learning Algorithms: A Method for Areas with Limited Labels and High Cloud Cover

IRB(P&D)


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Research Data Scientist | IRB(P&D)

# Motivation – Crop Insurance Context

- Importance of agriculture

2024 TRADE BALANCE

## Brazilian agribusiness reaches historic milestone in global food security

Growth in strategic sectors and market diversification strengthen Brazil's position as a global supplier of food, fiber, and energy

Published in Feb 03, 2025 05:13 PM

Share:

Brazilian agribusiness exports totaled USD 164.4 billion in 2024, marking the second-highest value on record. The sector accounted for 49 percent of the country's total exports, demonstrating its resilience despite declining international prices for some major commodities.

# Motivation – Crop Insurance Context

- Importance of agriculture
- High volatility
- High climate sensitivity
- Difficulty in risk assessment

2024 TRADE BALANCE

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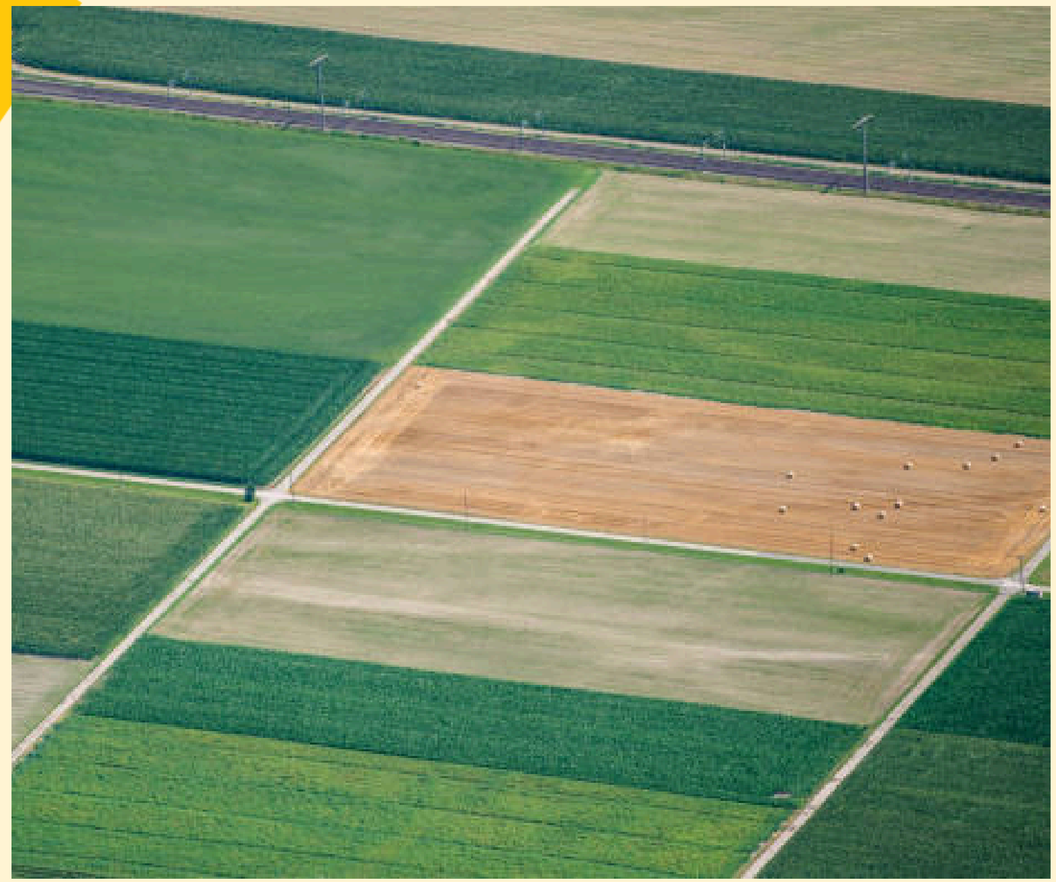
## Extreme weather events impose billions in losses on agribusiness

After strong El Niño, signs emerge of La Niña formation, which caused droughts in the South

Por Rafael Walendorff, Raphael Salomão, Marcelo Beledeli — São Paulo

14/11/2023 08h45 - Atualizado há um ano

# Motivation – Crop Insurance Context



- With crop information at the field plot level, we can achieve:
  - Regional market insights
  - Analysis of planting methods
  - Crop rotation analysis
  - Performance comparison among neighboring plots
  - Improved yield predictions

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- With crop information at the field plot level, we can achieve:
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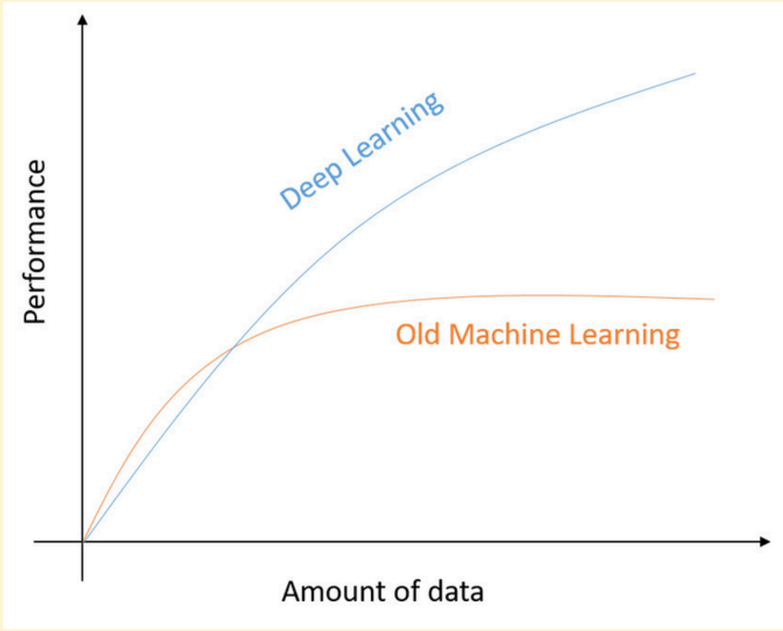
  - Crop rotation analysis
  - Performance comparison among neighboring plots
  - Improved yield predictions

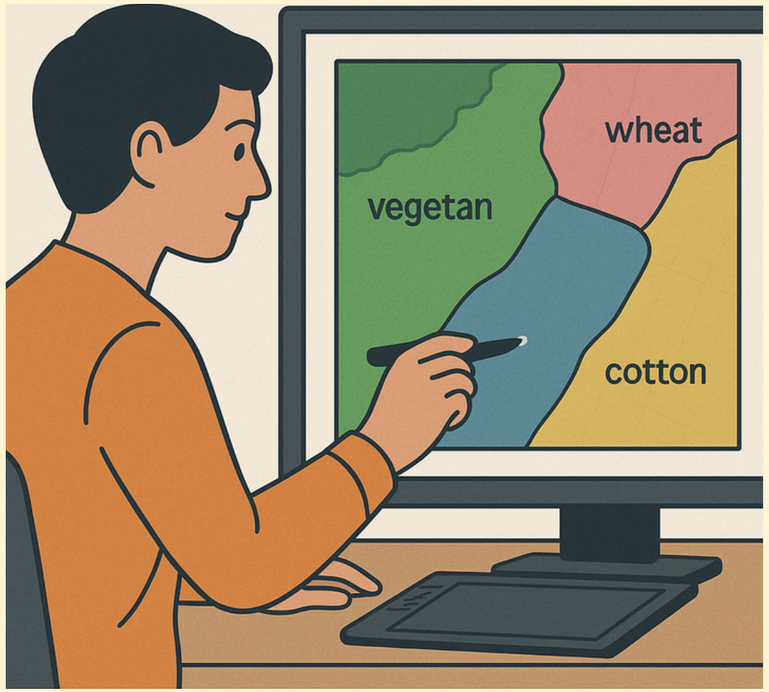
# Motivation - Theoretical

- Deep Learning (DL) Models
  - State-of-the-art in Earth Observation (EO) image analysis
  - High predictive performance
  - Strong generalization capabilities
  - Require large volumes of training data



# Motivation – Theoretical

- Annotating EO images at the pixel level is very costly.
- There is room for research on how to optimize the performance of models trained with limited data.

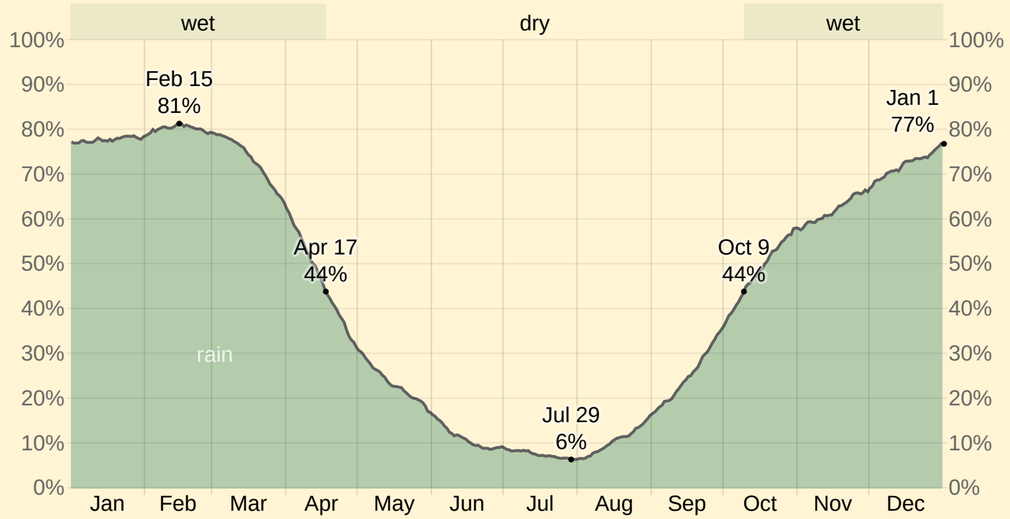


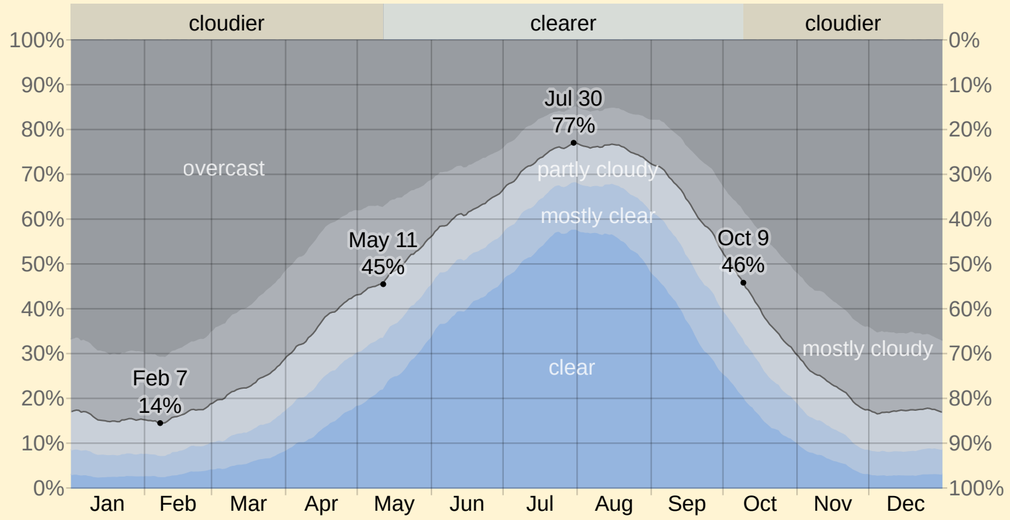
# Challenges

- Few data on field plot geometries in Brazil.
- Limited data on field plots with crop type labels in Brazil.
- Significant differences in field plot patterns and crop types between Brazil and other countries.

# Challenges

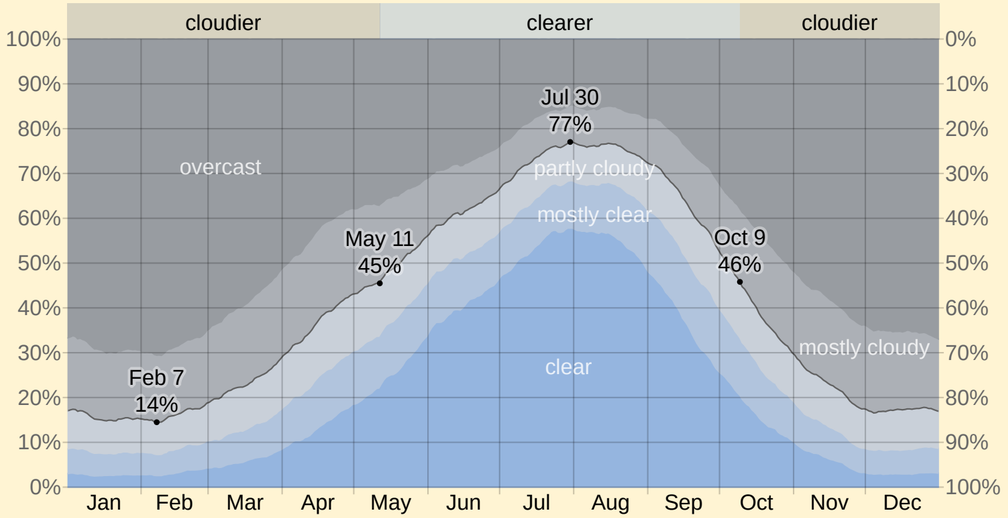
- During periods when crops are most visible (harvest seasons), the sky has significant cloud coverage.

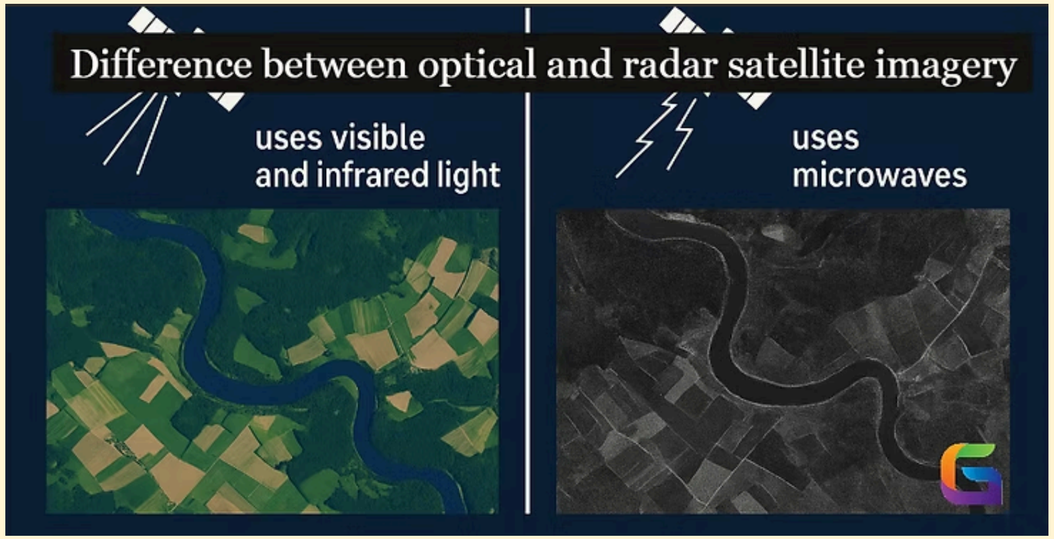


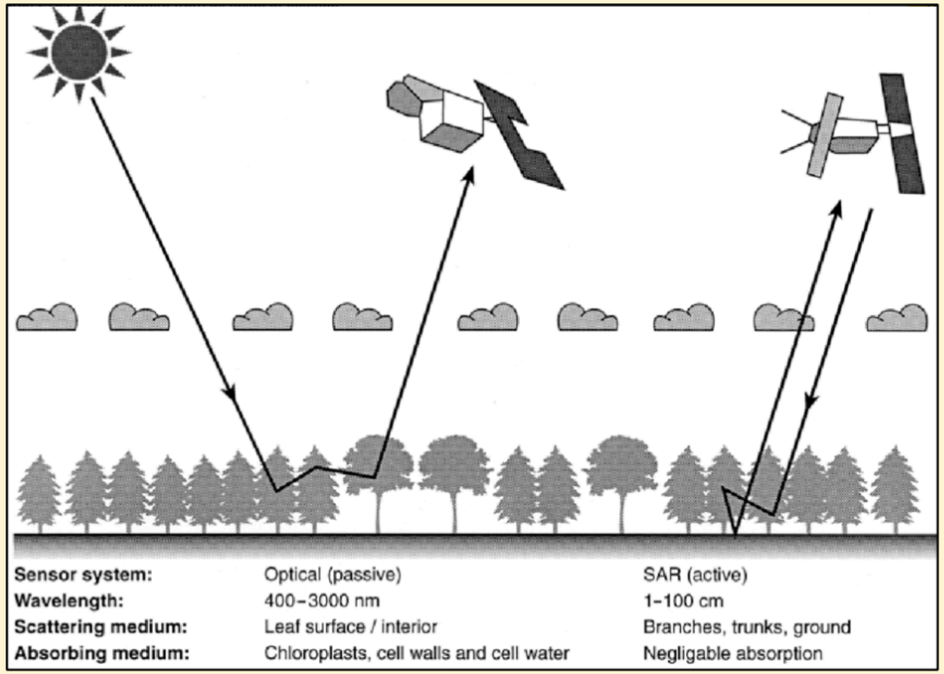



# Challenges

- During periods when crops are most visible (harvest seasons), the sky has significant cloud coverage.
- Optical satellites provide rich information but don't work well with clouds.



# Proposal

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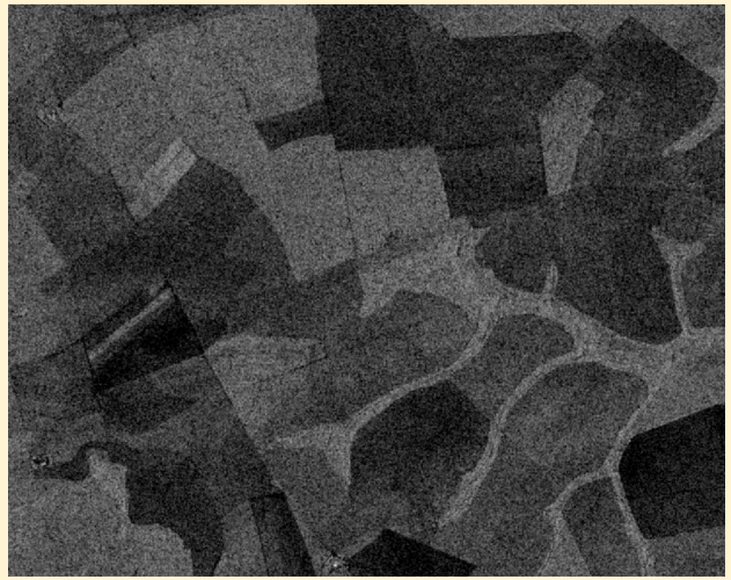

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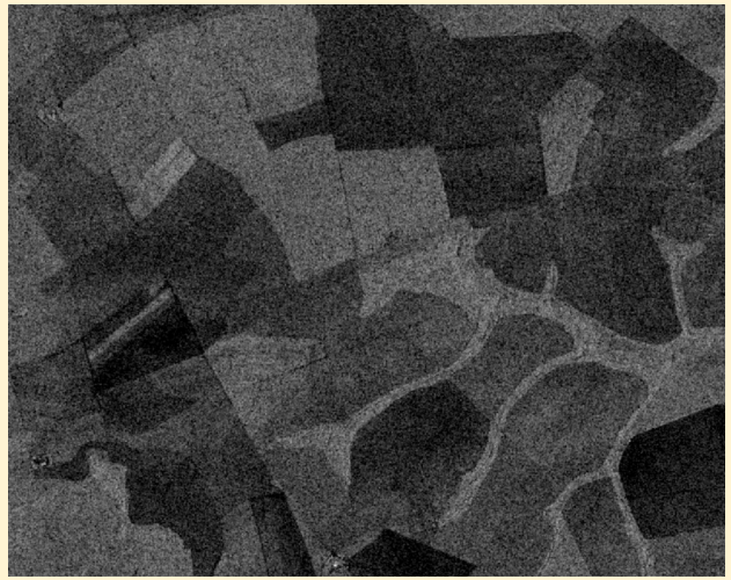
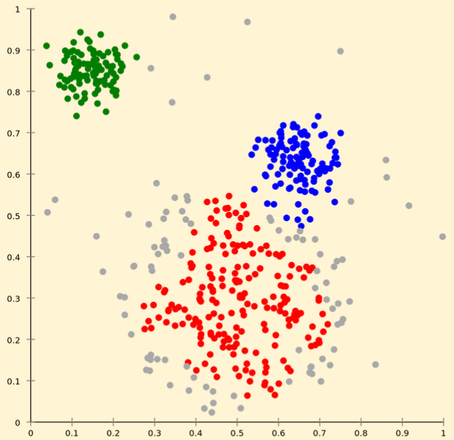
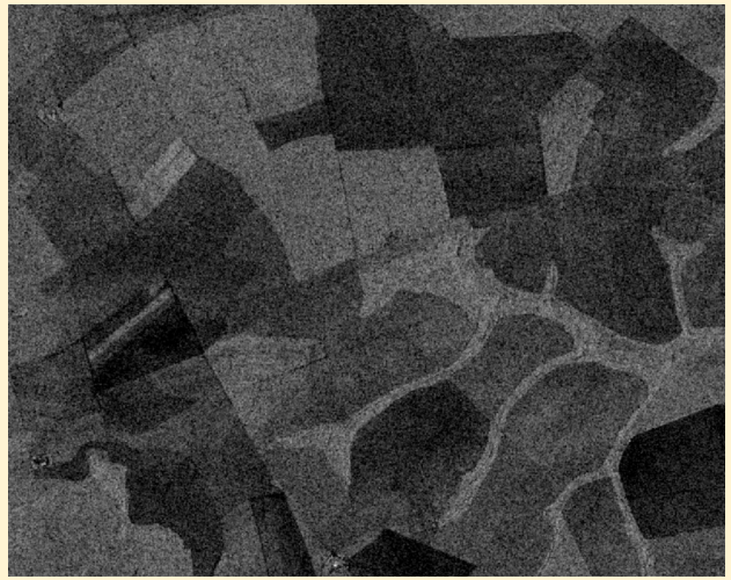
- Use radar (SAR) images to obtain information about field plots.
- Use clustering models to semantically group crops.

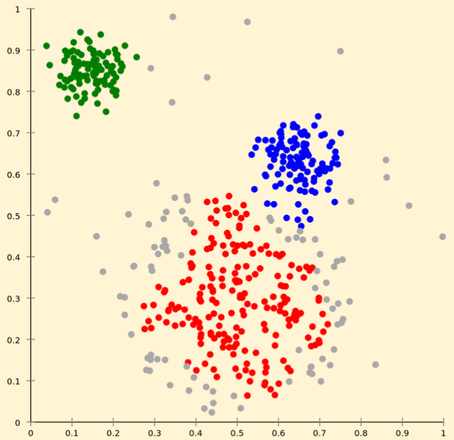




# Proposal

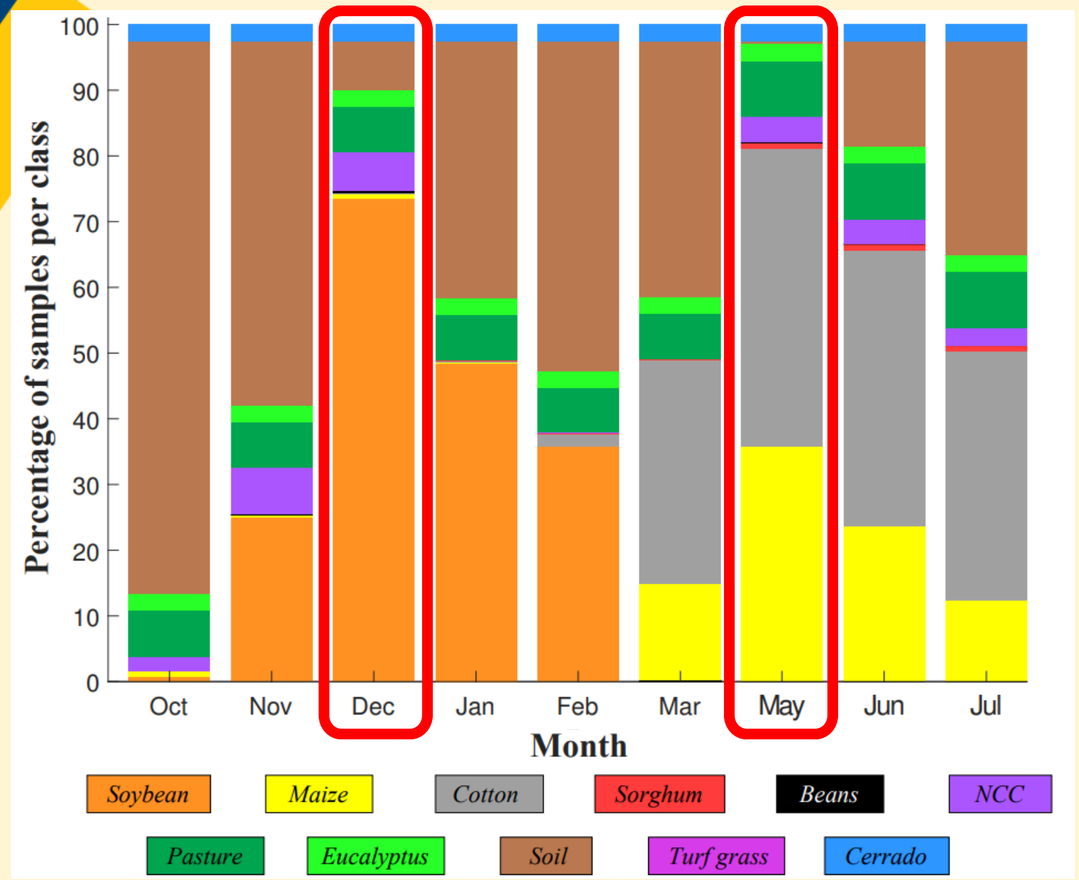
- Efficiently segment crop field plots.
- Use radar (SAR) images to obtain information about field plots.
- Use clustering models to semantically group crops.
- Classify the entire municipality of Campo Verde with only 23.76% of it labeled.

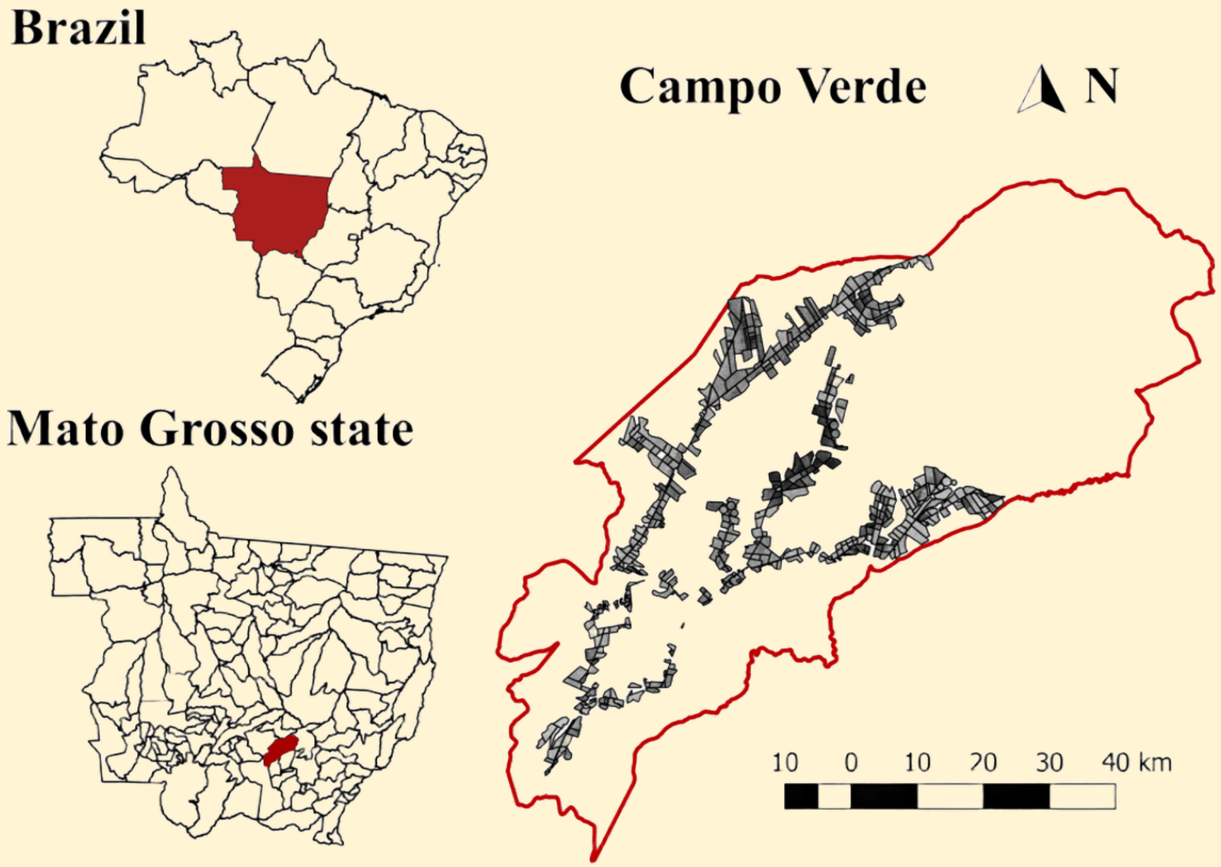




# Dataset

# Dataset



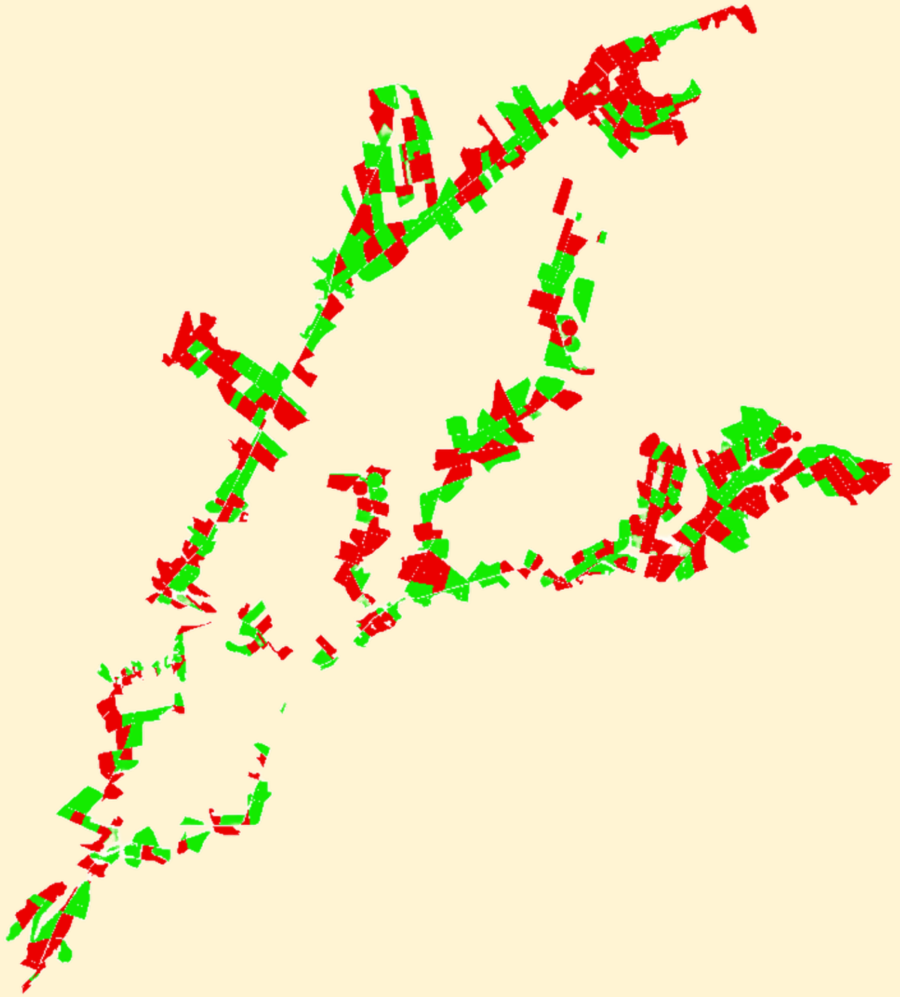




- 520.29 km²
- 513 labeled field plots

# Dataset

| Crop | N# | Percentage |
|---|---|---|
| **Soybean** | 4288 | 37,09 |
| **Maize** | 2076 | 17,96 |
| **Cotton** | 2694 | 23,30 |
| **Sorghum** | 47 | 0,41 |
| **Beans** | 10 | 0,09 |
| **NCC*** | 583 | 5,04 |
| **Pasture** | 854 | 7,39 |
| **Eucalyptus** | 284 | 2,46 |
| **Soil** | 442 | 3,82 |
| **Cerrado** | 284 | 2,46 |
| **Total** | 11562 | 100,00 |

*NCC refers to Non-Commercial Crops.



Red Train - Green Test

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**78.35%**

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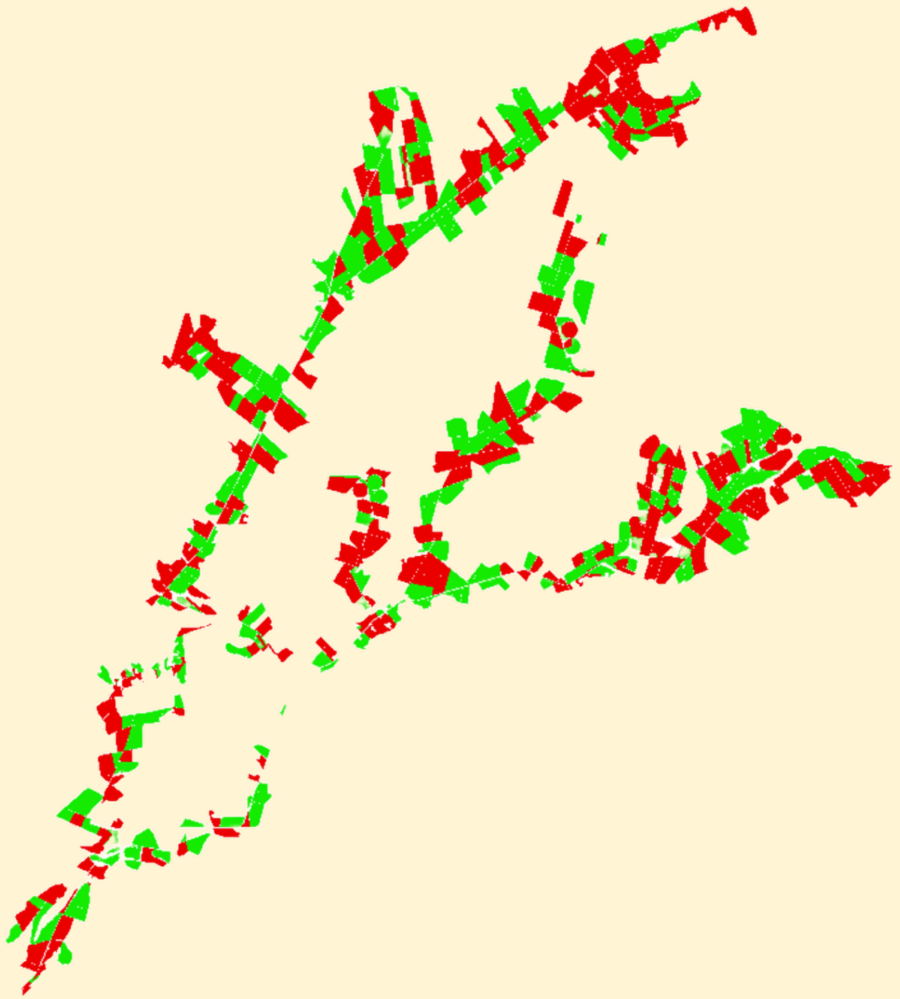

Red Train - Green Test

# Methodology

# Automatic Field Plot Mask Generator

- Sentinel-2
- Level 1C
- 10m per pixel
- Composition of 4 months per image
- Cloud Score+
- Patches 1024×1024
- Overlap 256 pixels

# Automatic Field Plot Mask Generator

Segment Anything Model 2

SAM2

Raw Masks

- Sentinel-2
- Level 1C
- 10m per pixel
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# Automatic Field Plot Mask Generator

Segment Anything Model 2

SAM2

Raw Masks

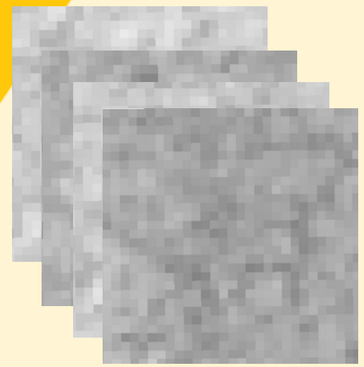
Filters

Final Masks

- Sentinel-2
- Level 1C
- 10m per pixel
- Composition of 4 months per image
- Cloud Score+
- Patches 1024×1024
- Overlap 256 pixels

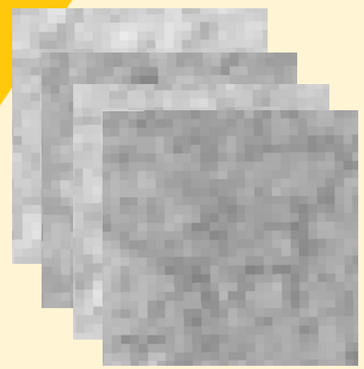
- Size
- Overlap
- Cultivation area
  - MapBiomas

# Crop Clustering and Classification



- Sentinel-1
- SAR images
- 10m per pixel
- 2 channels per image
- Concatenates 5 images
- Oct-Feb = 1st harvest
- Mar-Jul = 2nd harvest
- Patches 30×30

# Crop Clustering and Classification



Masked Siamese Networks

**MSN**

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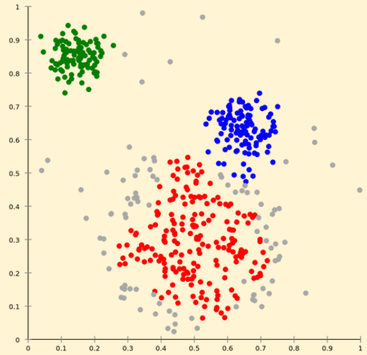

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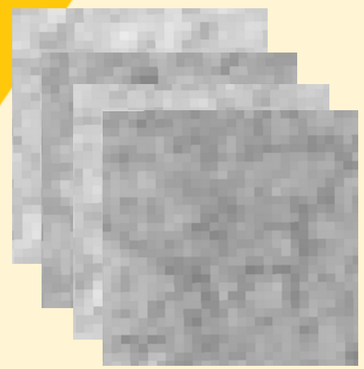

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Multi-layer perceptron

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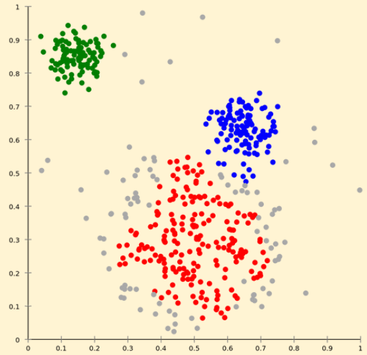

- 2 hidden layers
- 128x64
- Batch Normalization
- ReLU

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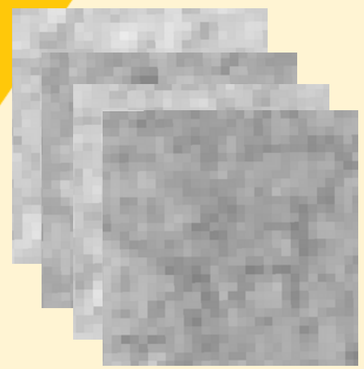

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**Fine-tuning**

**Frozen**

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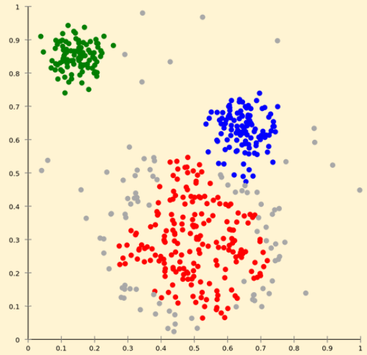

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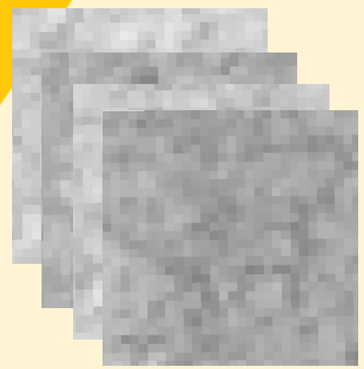

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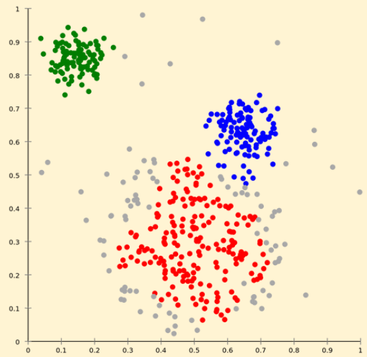

Multi-layer perceptron

**MLP**

- 2 hidden layers
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**Fine-tuning**

- **10 Classes**
- **4 Classes**

**Frozen**

- **10 Classes**
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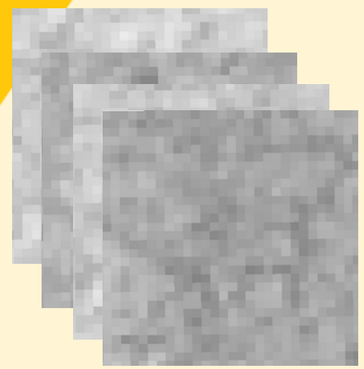

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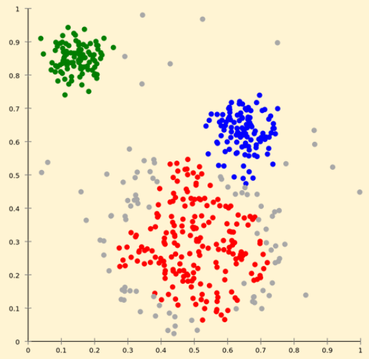

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**Frozen**

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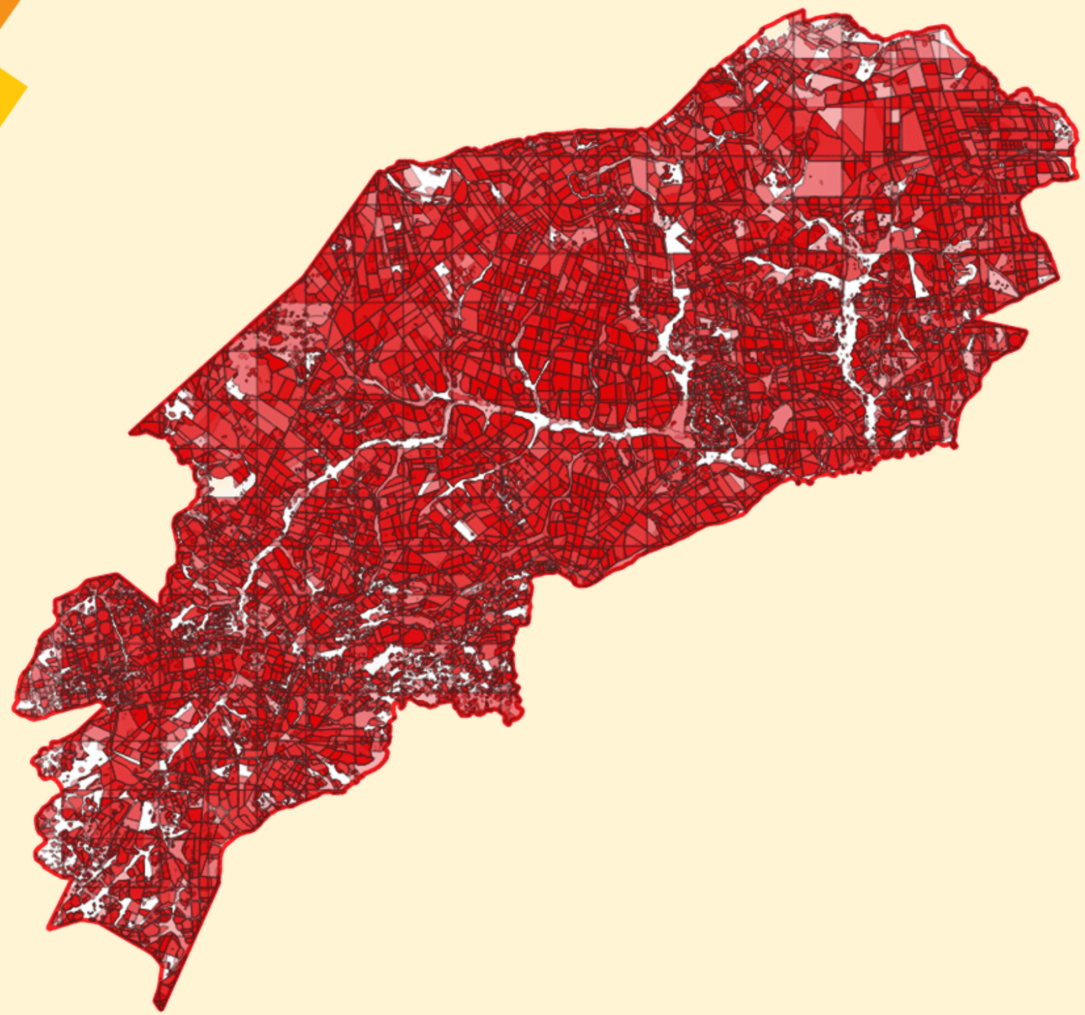
- **4 Classes**

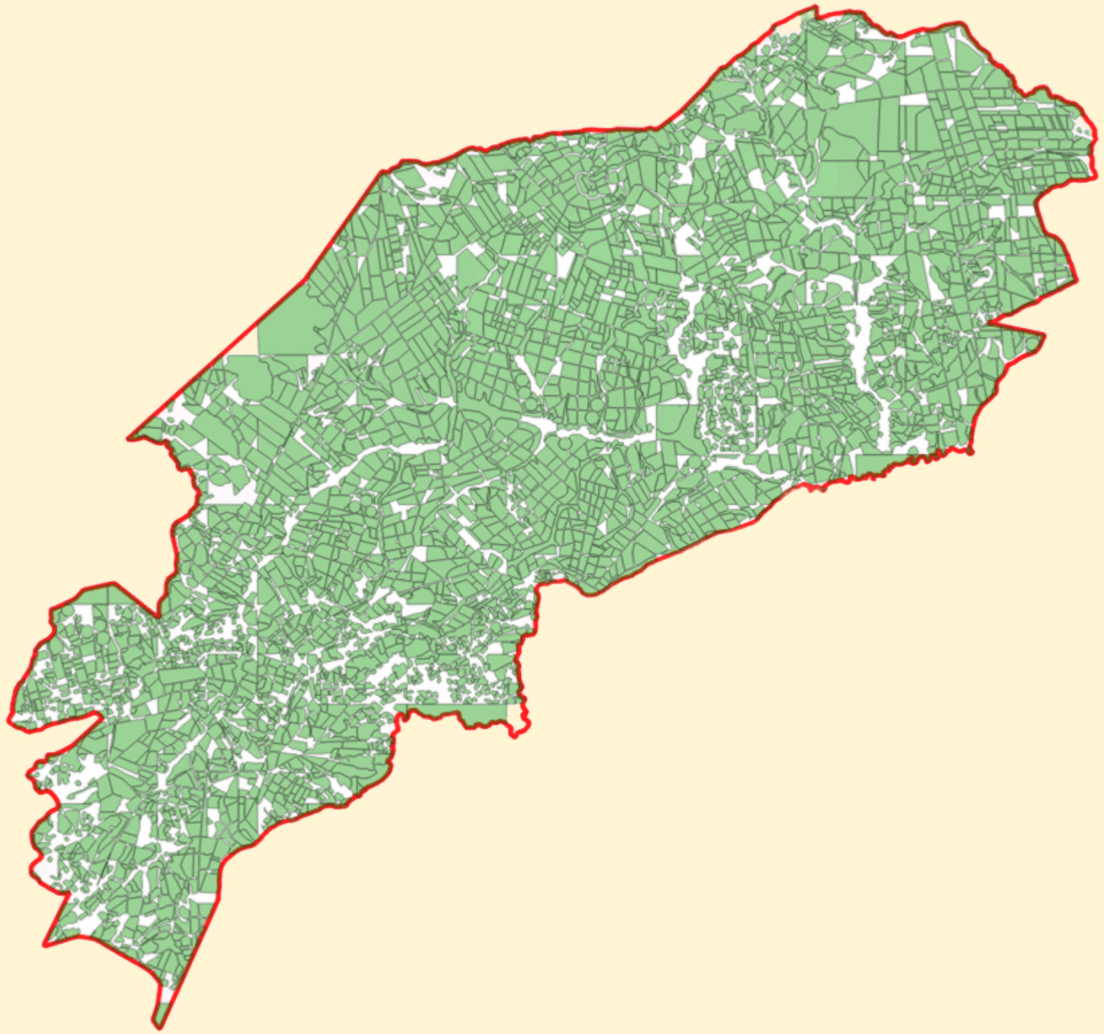
- Soybean
- Maize
- Cotton
- Others

# Application and Results

# Segmentation



Raw Masks



Filtro size e overlap

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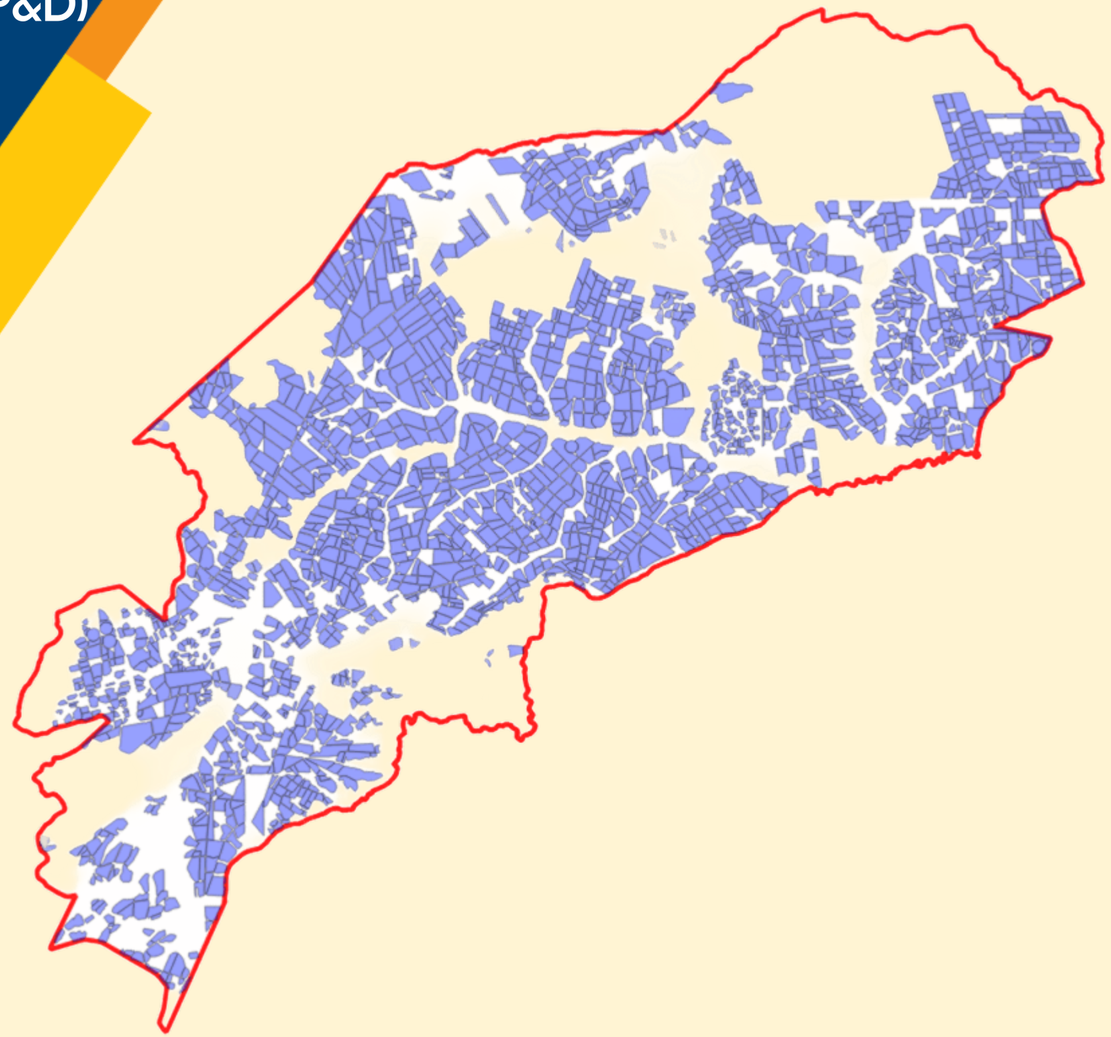
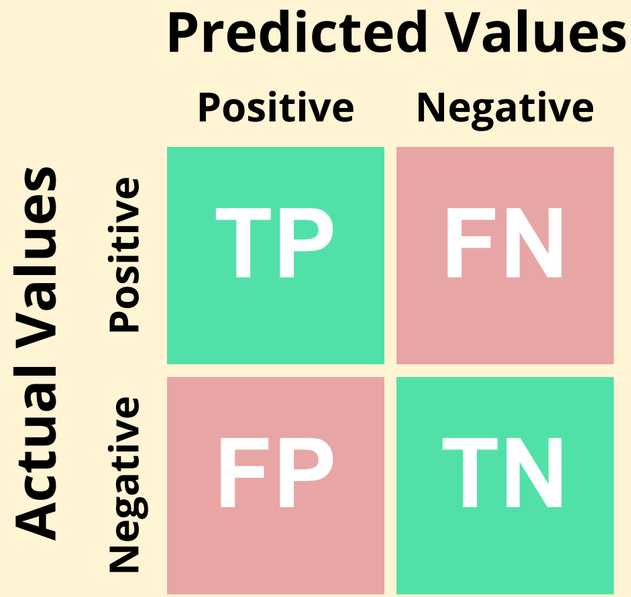


MapBiomas Filter

- 2189.73 km²
- 4014 labeled field plots

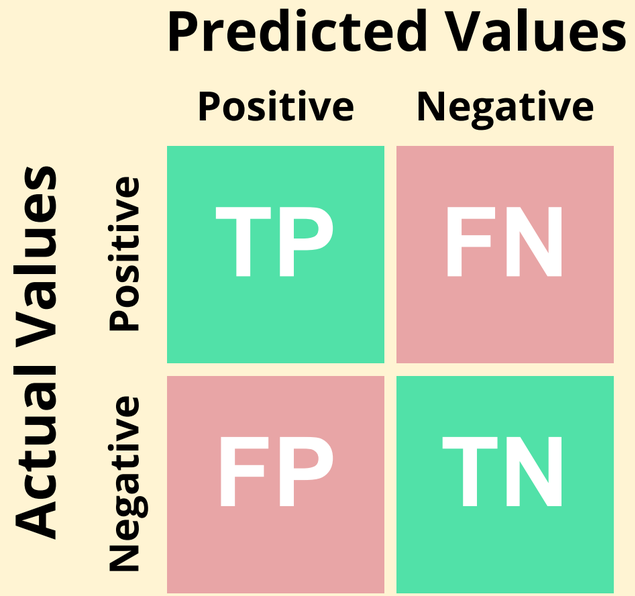
Zoom

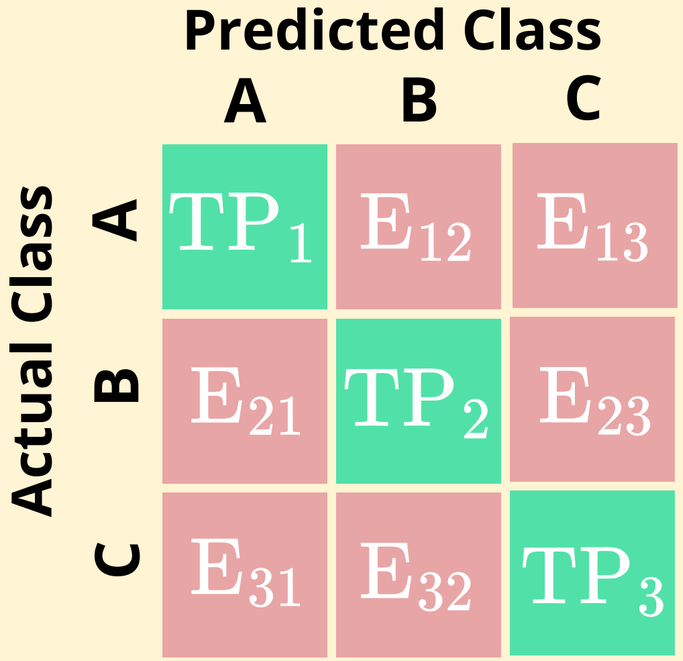
# Confusion Matrix




$$\text{Accuracy} = \text{acc} = \frac{TP + TN}{TP + TN + FP + FN}$$

# Confusion Matrix




$$\text{acc} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{total acc} = \frac{\sum_i^N TP_i}{\sum_i^N (TP_i + \sum_j^N E_{ij})}$$

$$\text{acc}_i = \frac{TP_i}{TP_i + \sum_j^N E_{ij}}$$

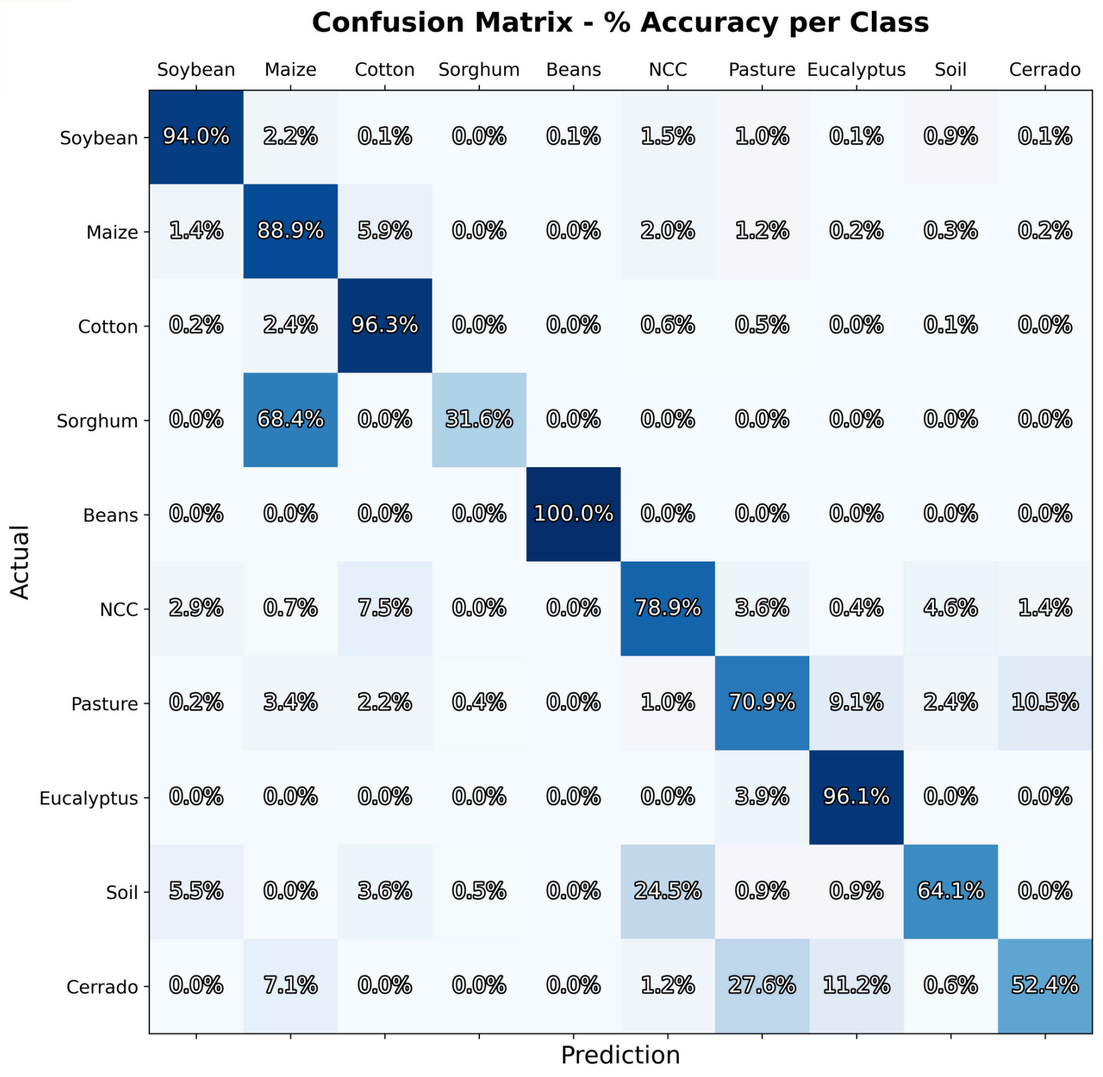
$$\text{mean acc} = \frac{\sum_i^N acc_i}{N}$$

# Classification - 10 classes

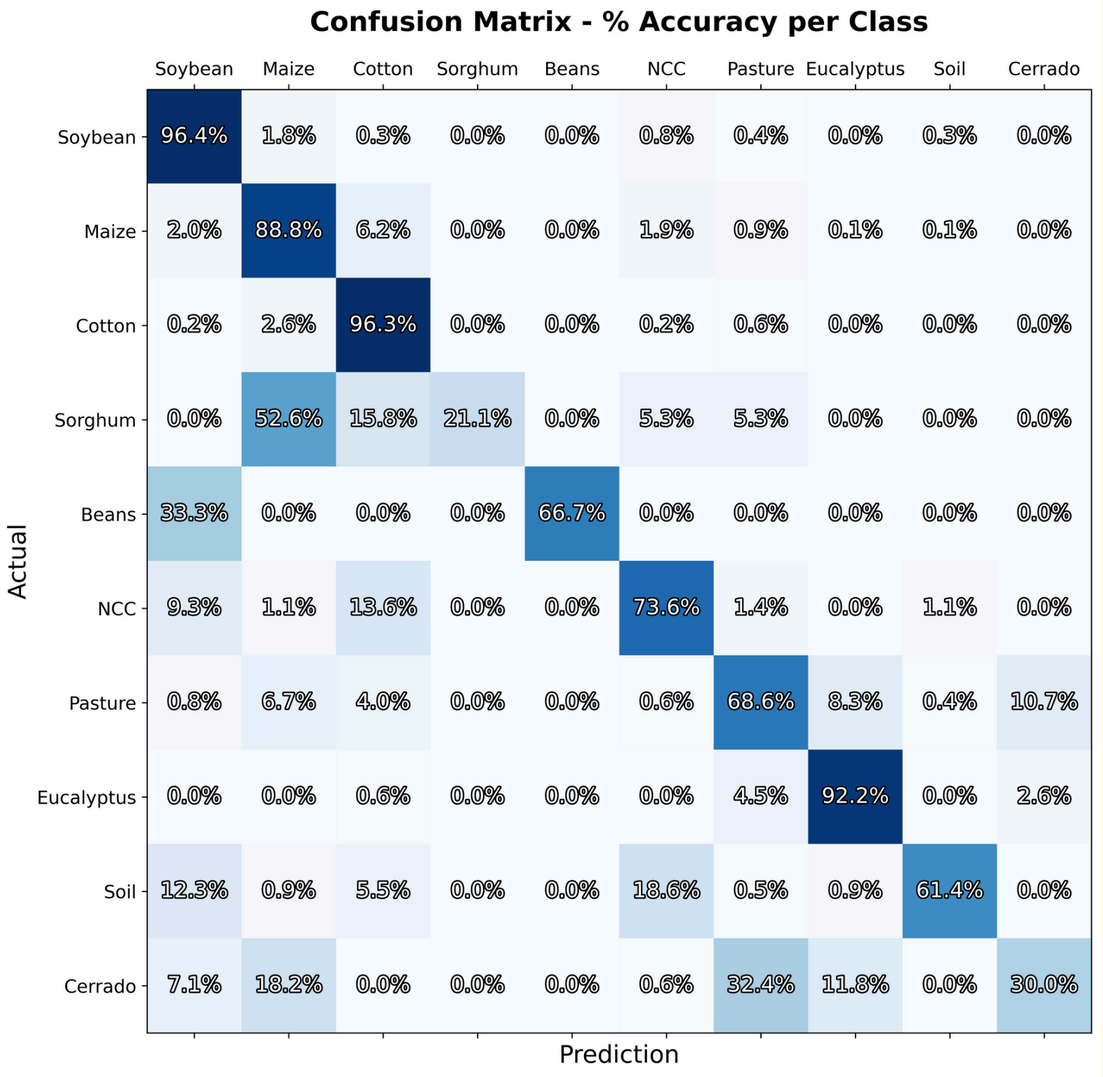
| Model | Fine-tuning | Frozen |
|---|---|---|
| **N# de classes** | 10 | 10 |
| **Total Acc** | 88.05 | 87.41 |
| **Mean Acc** | 77.32 | 69.49 |
| **Epochs** | 7341 | 40000 |
| **Patience** | 200 | 200 |
| **Learning Rate** | 5,00E-07 | 5,00E-07 |

| Crop | Train | | Test | |
|---|---|---|---|---|
| | N# | % | N# | % |
| **Soybean** | 2357 | 38,55 | 1931 | 35,44 |
| **Maize** | 1124 | 18,38 | 952 | 17,47 |
| **Cotton** | 1481 | 24,22 | 1213 | 22,27 |
| **Sorghum** | 28 | 0,46 | 19 | 0,35 |
| **Beans** | 7 | 0,11 | 3 | 0,06 |
| **NCC** | 303 | 4,96 | 280 | 5,14 |
| **Pasture** | 348 | 5,69 | 506 | 9,29 |
| **Eucalyptus** | 130 | 2,13 | 154 | 2,83 |
| **Soil** | 222 | 3,63 | 220 | 4,04 |
| **Cerrado** | 114 | 1,86 | 170 | 3,12 |
| **Total** | 6114 | 100,00 | 5448 | 100,00 |

# Classification - 10 classes

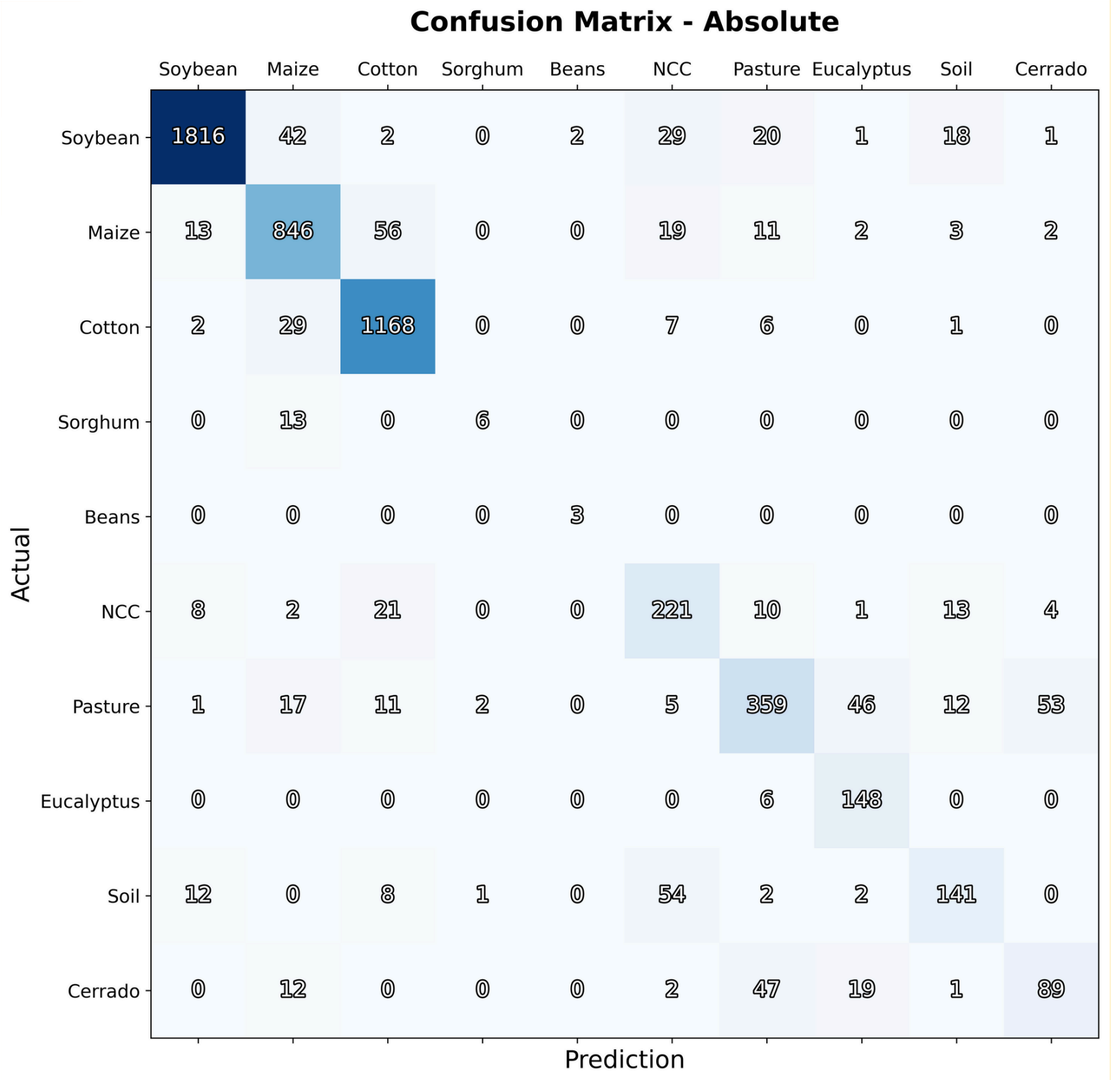



Fine-Tuning Model




Frozen Model

# Classification - 10 classes

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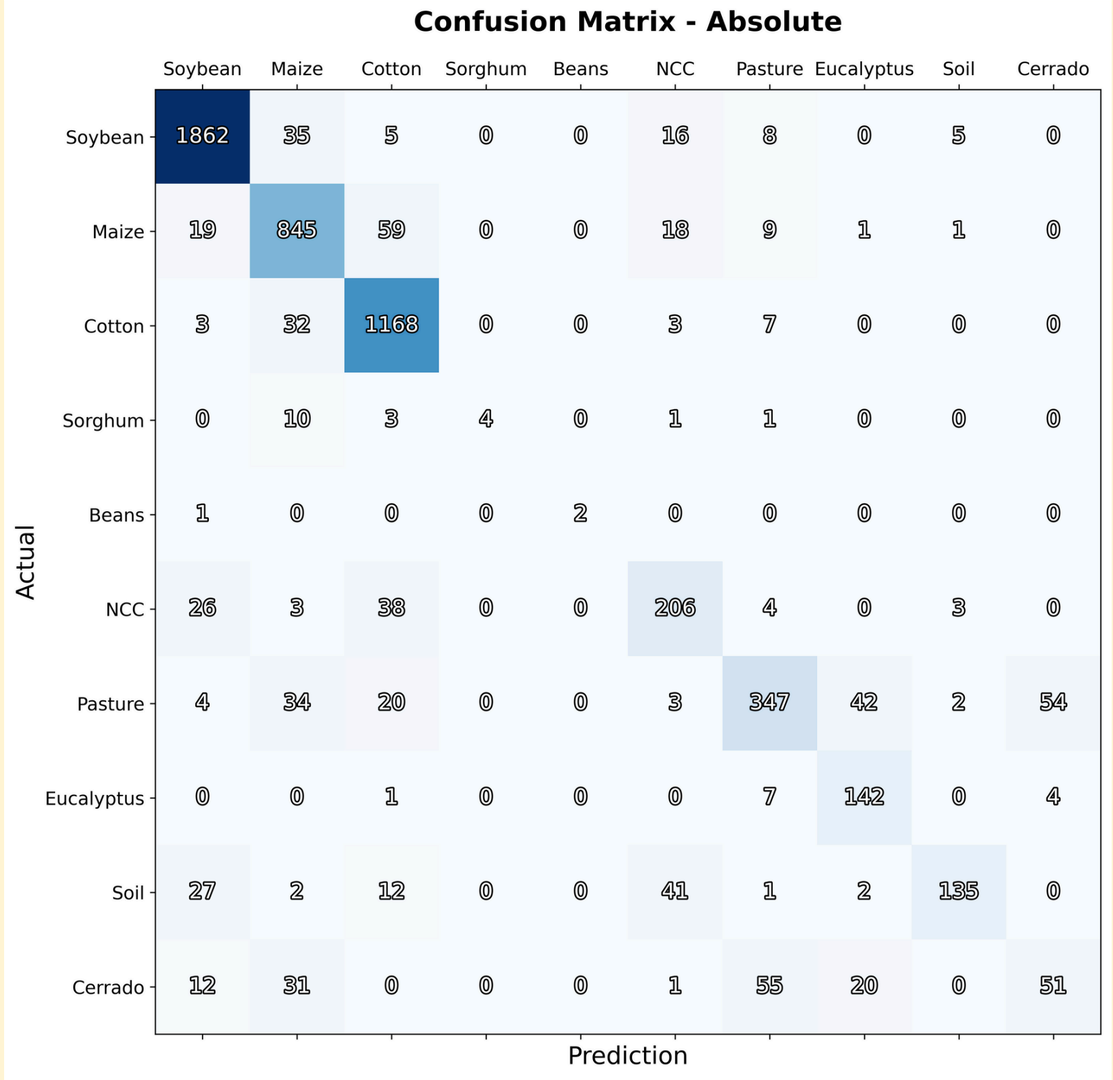
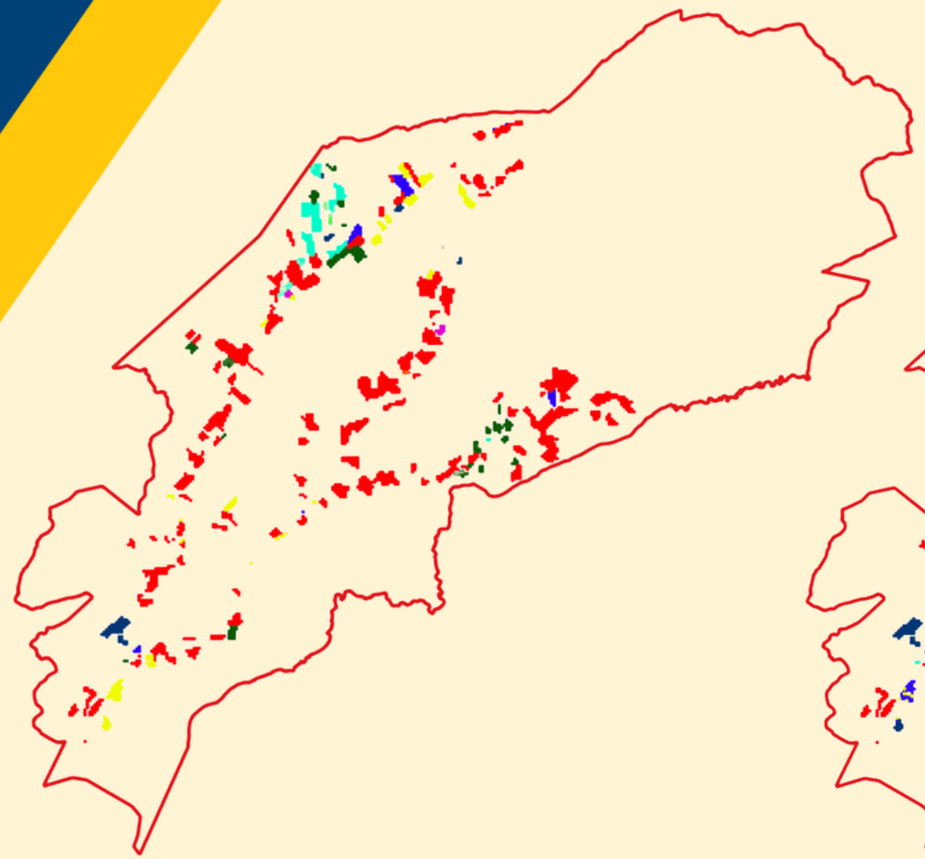



Frozen Model

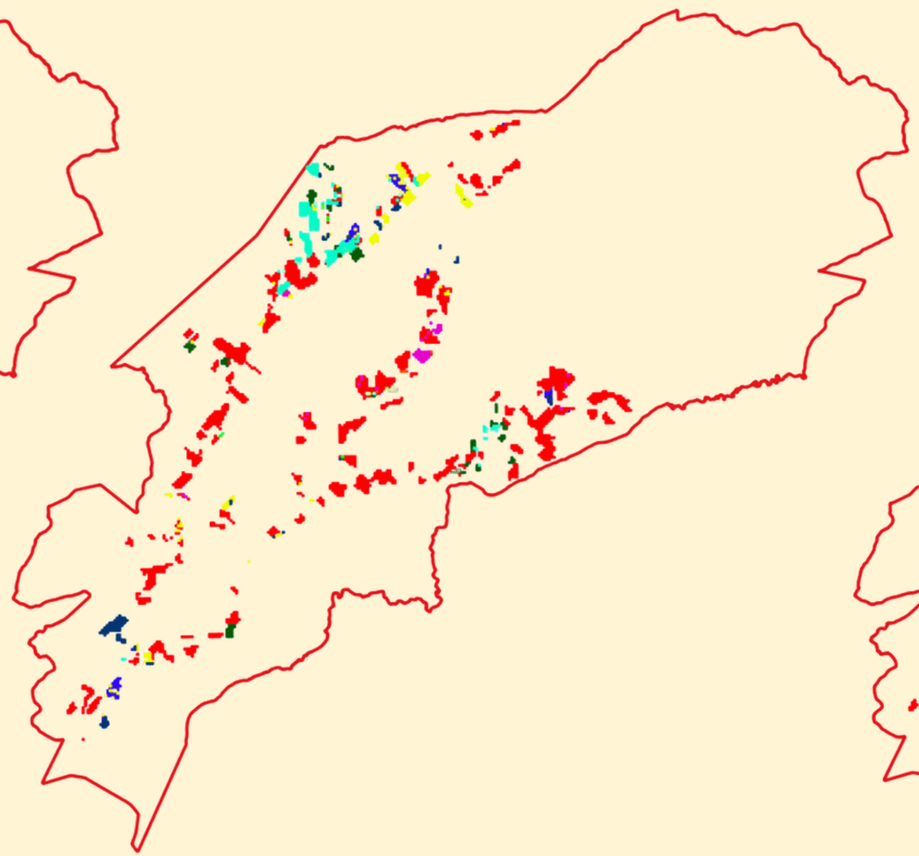
# Classification - 10 classes

## December - Test Dataset

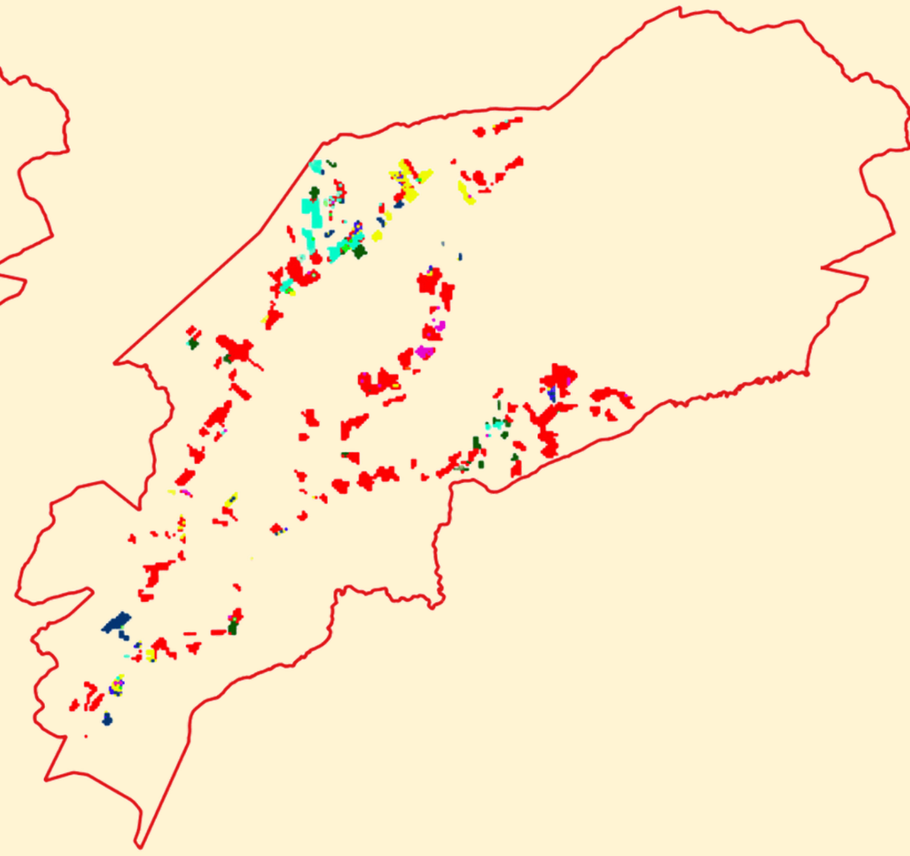
Soybean
Cotton
Beans
Pasture
Soil
Maize
Sorghum
NCC
Eucalyptus
Cerrado



Labeled Data



Fine-Tuning Model

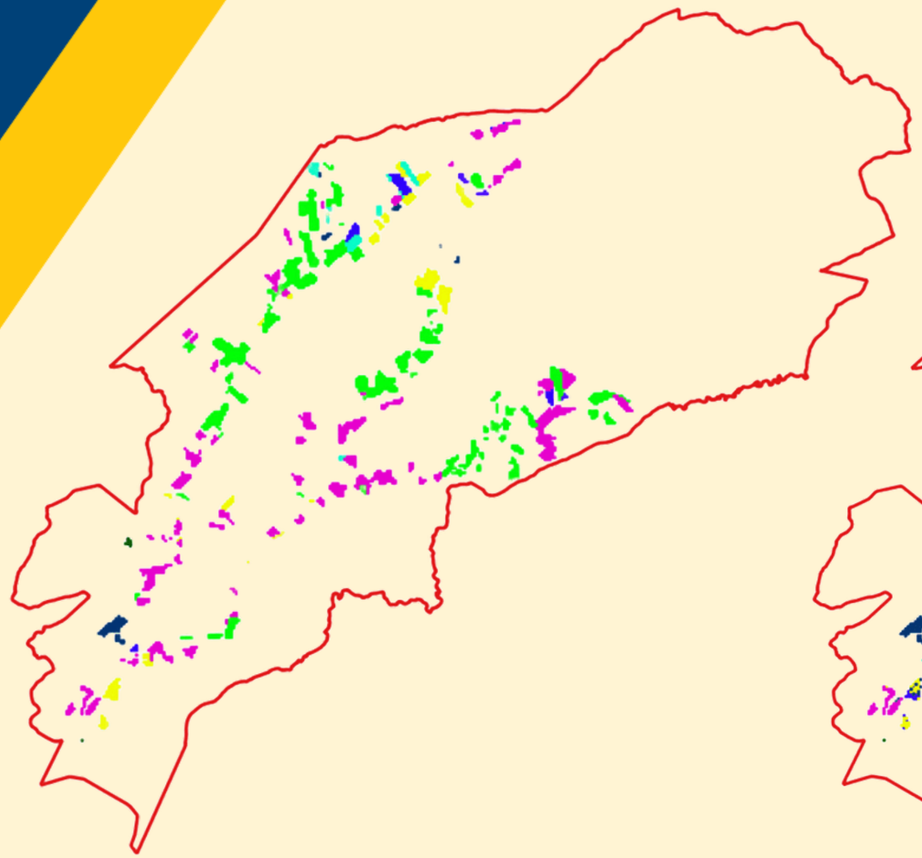


Frozen Model

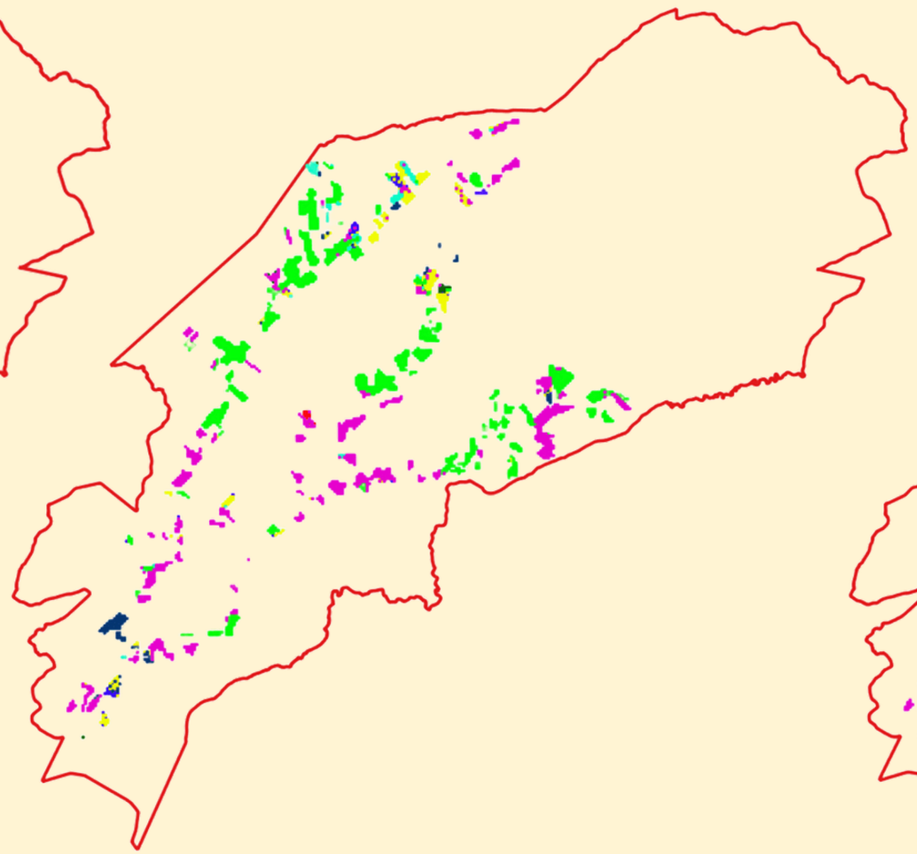
# Classification - 10 classes

## May - Test Dataset

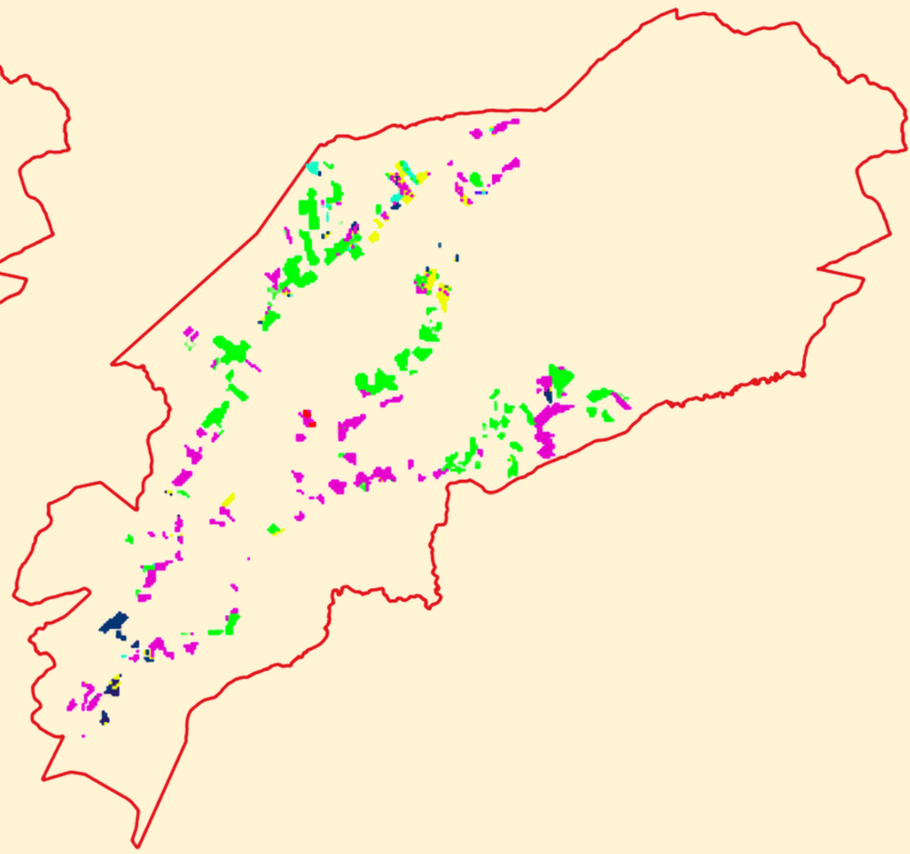
Soybean
Cotton
Beans
Pasture
Soil
Maize
Sorghum
NCC
Eucalyptus
Cerrado



Labeled Data



Fine-Tuning Model

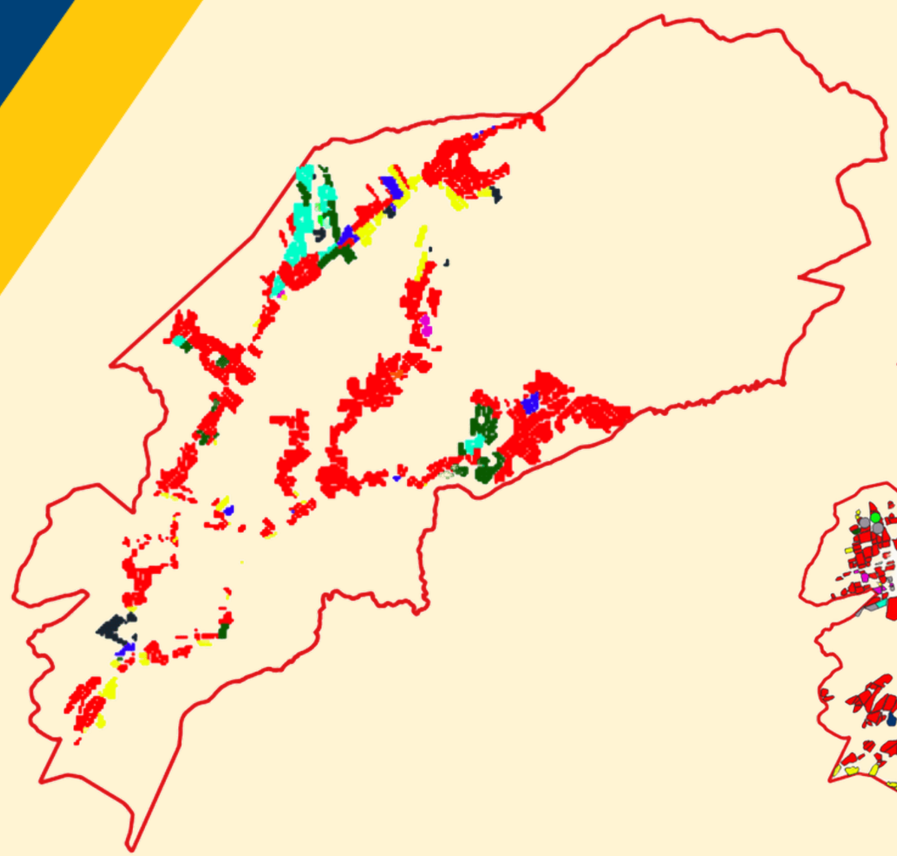


Frozen Model

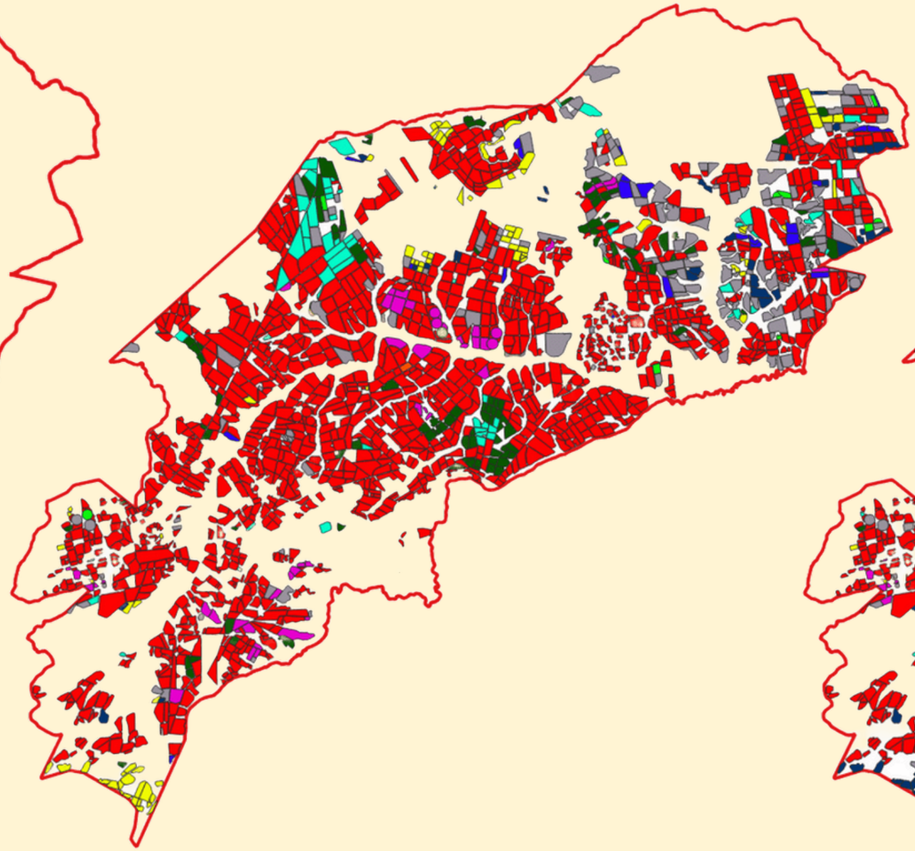
# Classification - 10 classes

## December - Generated Masks

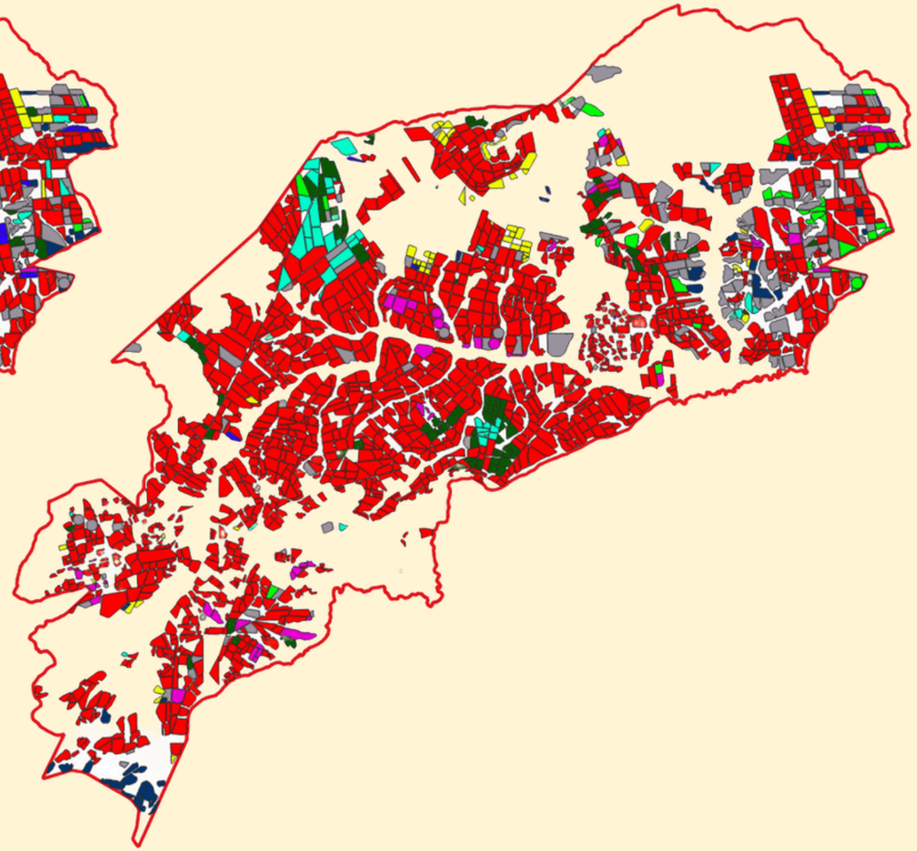
Soybean
Cotton
Beans
Pasture
Soil
Maize
Sorghum
NCC
Eucalyptus
Cerrado
Not Classified



Labeled Data



Fine-Tuning Model

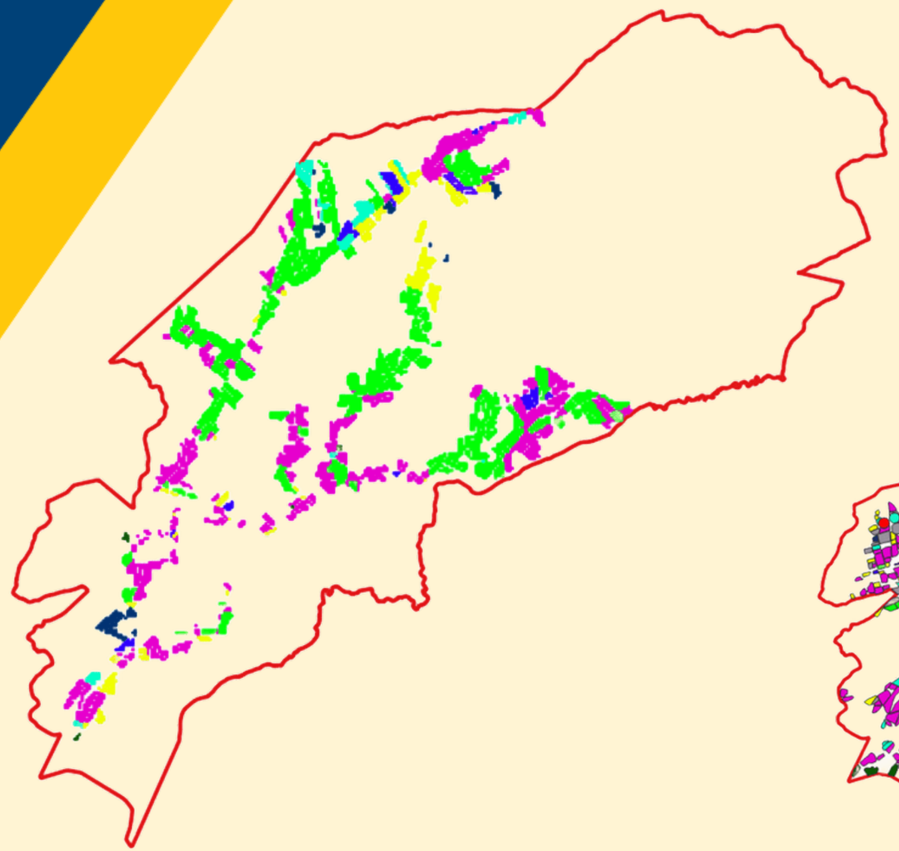


Frozen Model

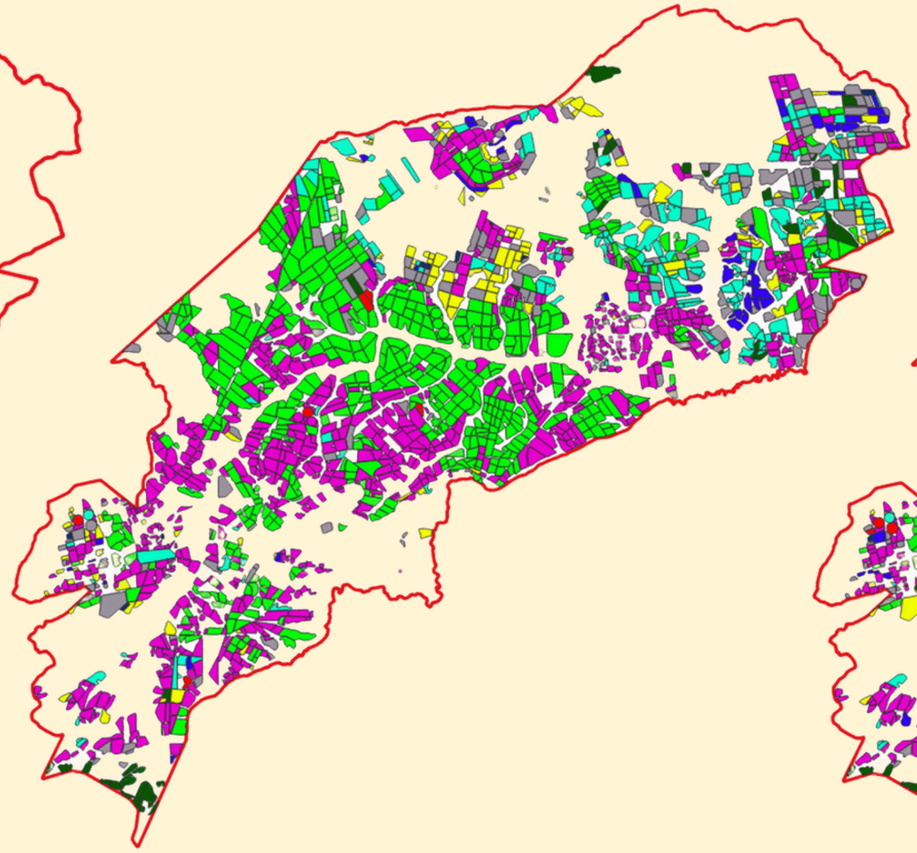
# Classification - 10 classes

## May - Generated Masks

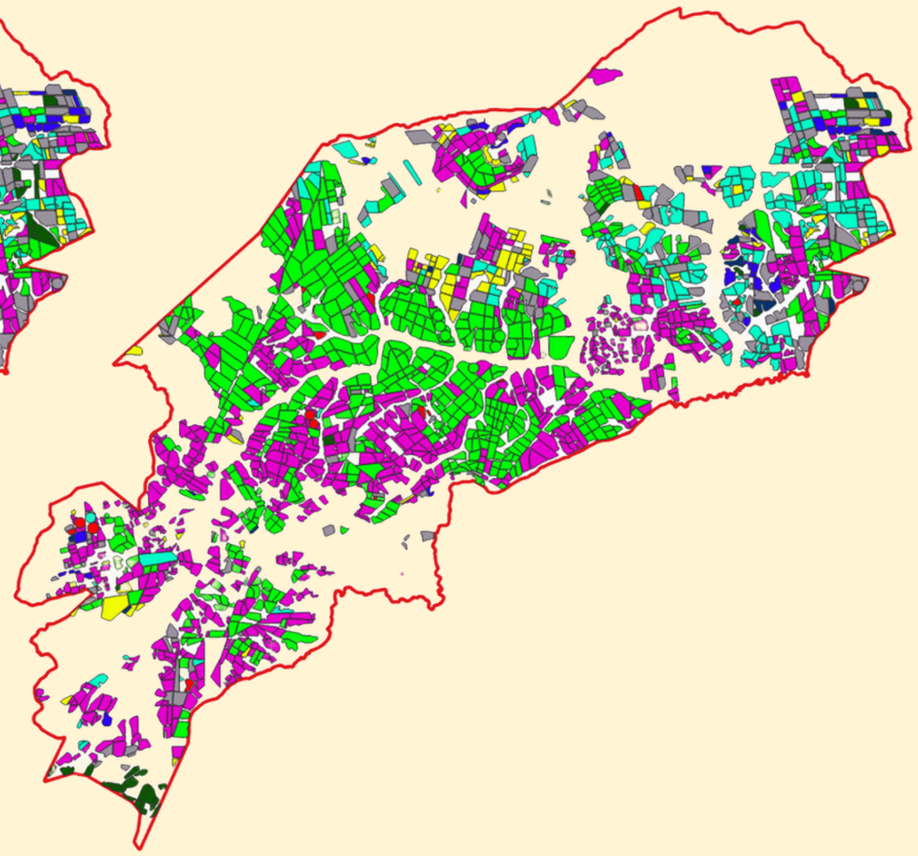
Soybean
Cotton
Beans
Pasture
Soil
Maize
Sorghum
NCC
Eucalyptus
Cerrado
Not Classified



Labeled Data



Fine-Tuning Model



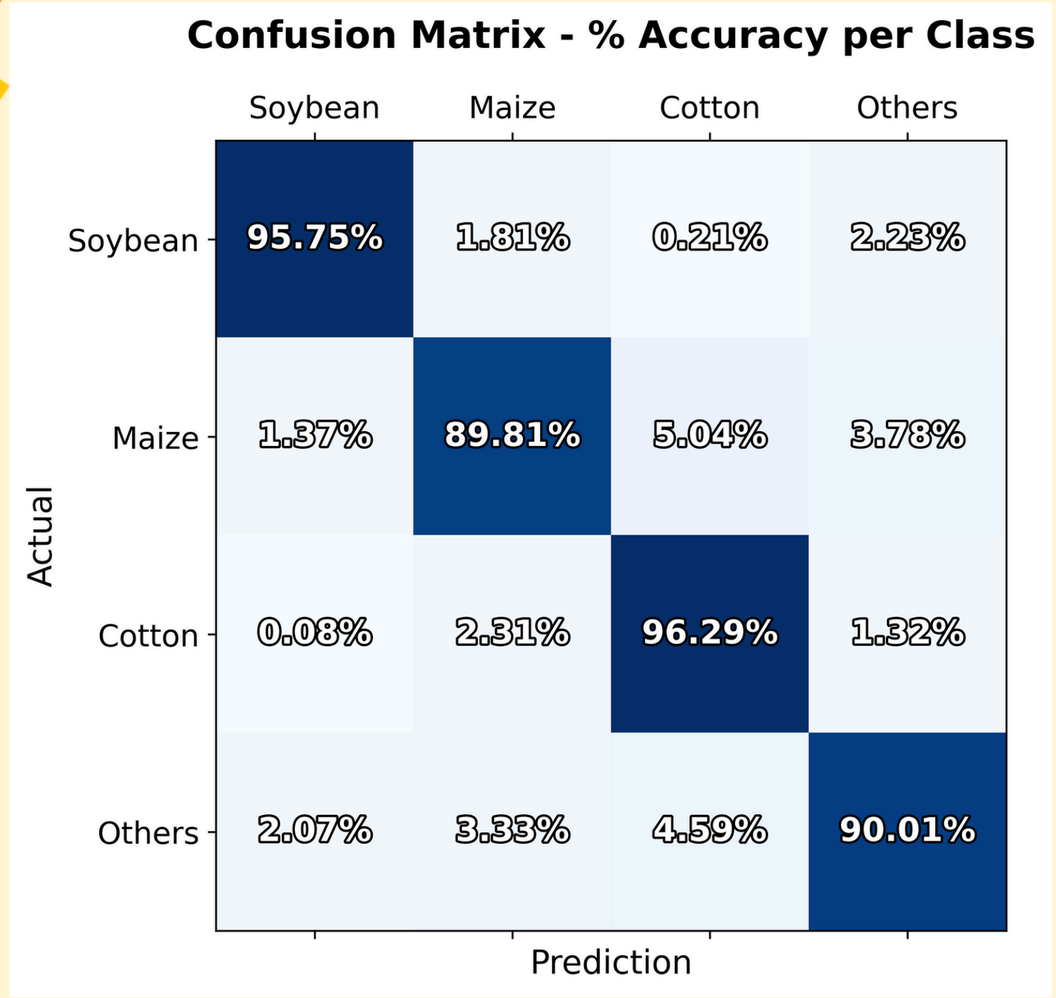
Frozen Model

# Classification - 4 classes

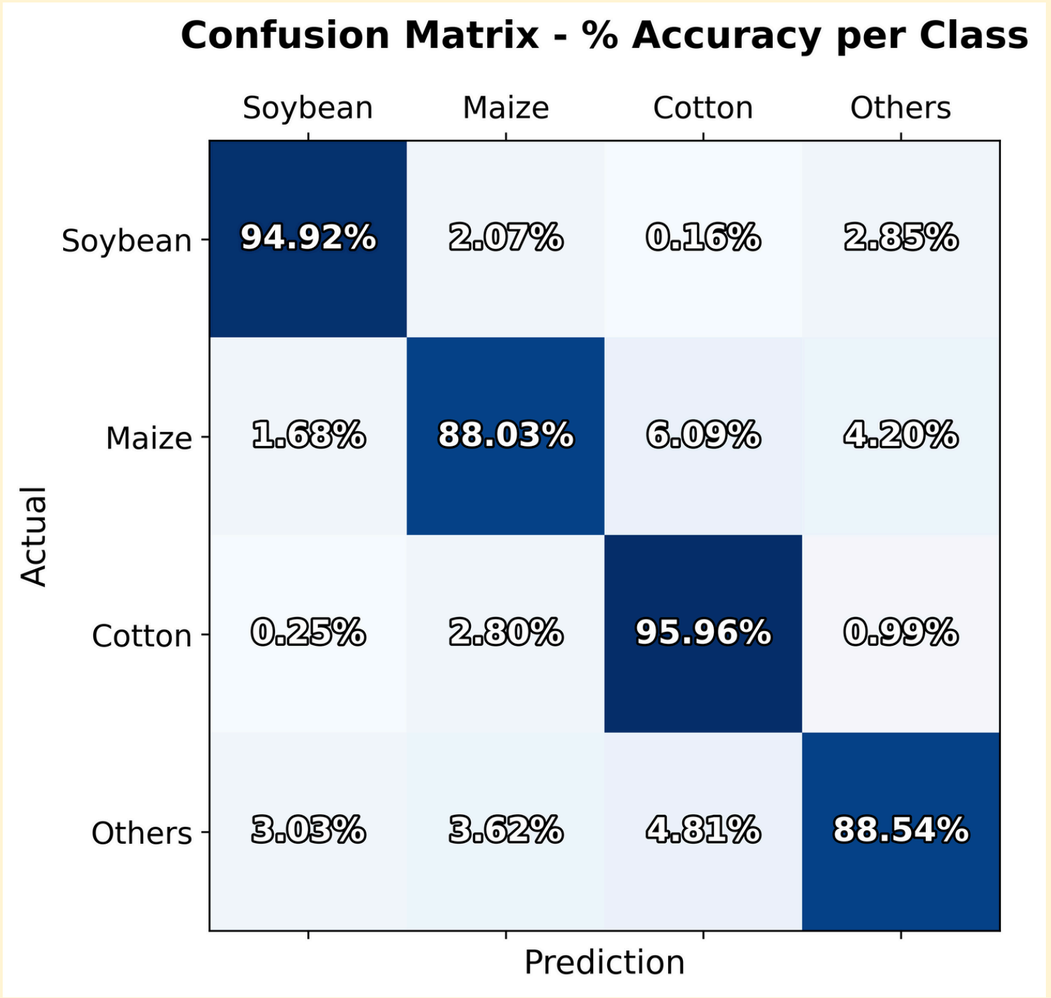
| Model | Fine-tuning | Frozen |
|---|---|---|
| **N# de classes** | 4 | 4 |
| **Total Acc** | 93.41 | 92.36 |
| **Mean Acc** | 92.97 | 91.86 |
| **Epochs** | 5080 | 40000 |
| **Patience** | 200 | 200 |
| **Learning Rate** | 5,00E-07 | 5,00E-07 |

| Crop | Train | | Test | |
|---|---|---|---|---|
| | N# | % | N# | % |
| **Soybean** | 2357 | 38,55 | 1931 | 35,44 |
| **Maize** | 1124 | 18,38 | 952 | 17,47 |
| **Cotton** | 1481 | 24,22 | 1213 | 22,27 |
| **Others** | 1152 | 18,84 | 1352 | 24,82 |
| **Total** | 6114 | 100,00 | 5448 | 100,00 |

# Classification - 4 classes

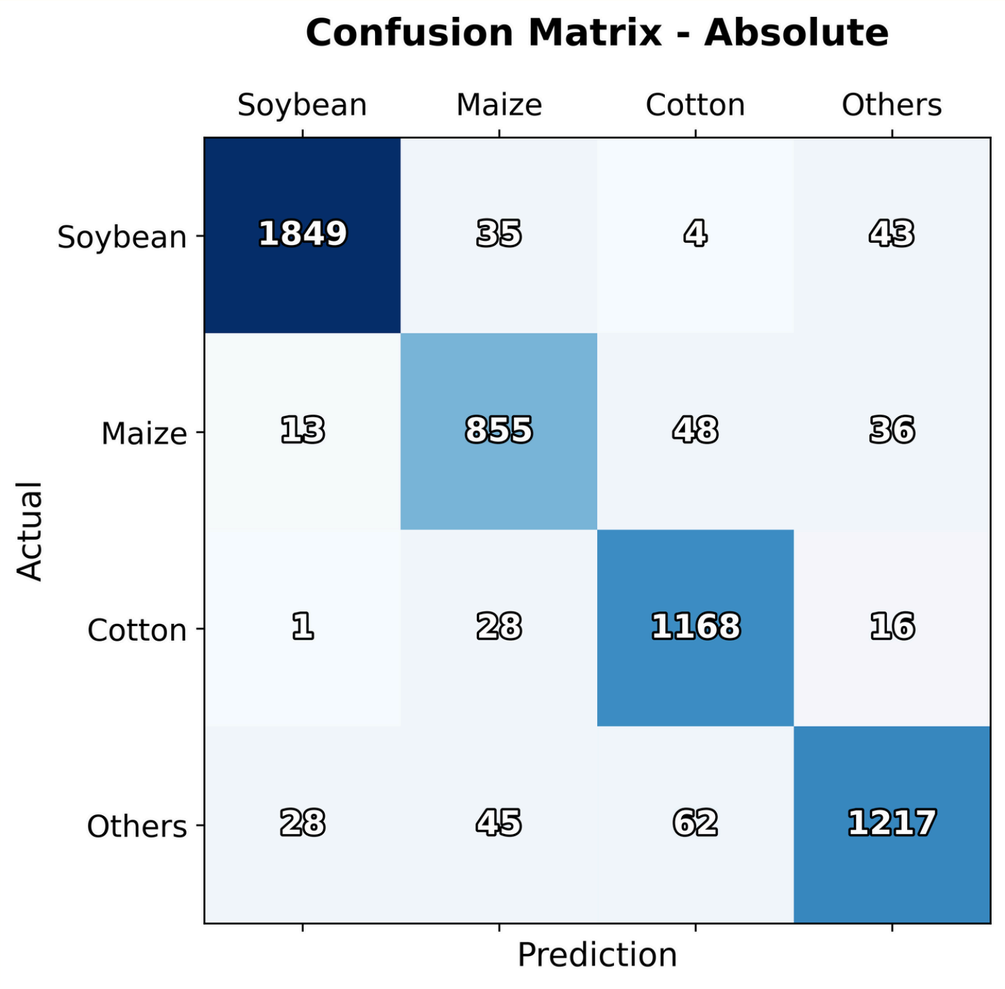



Fine-Tuning Model

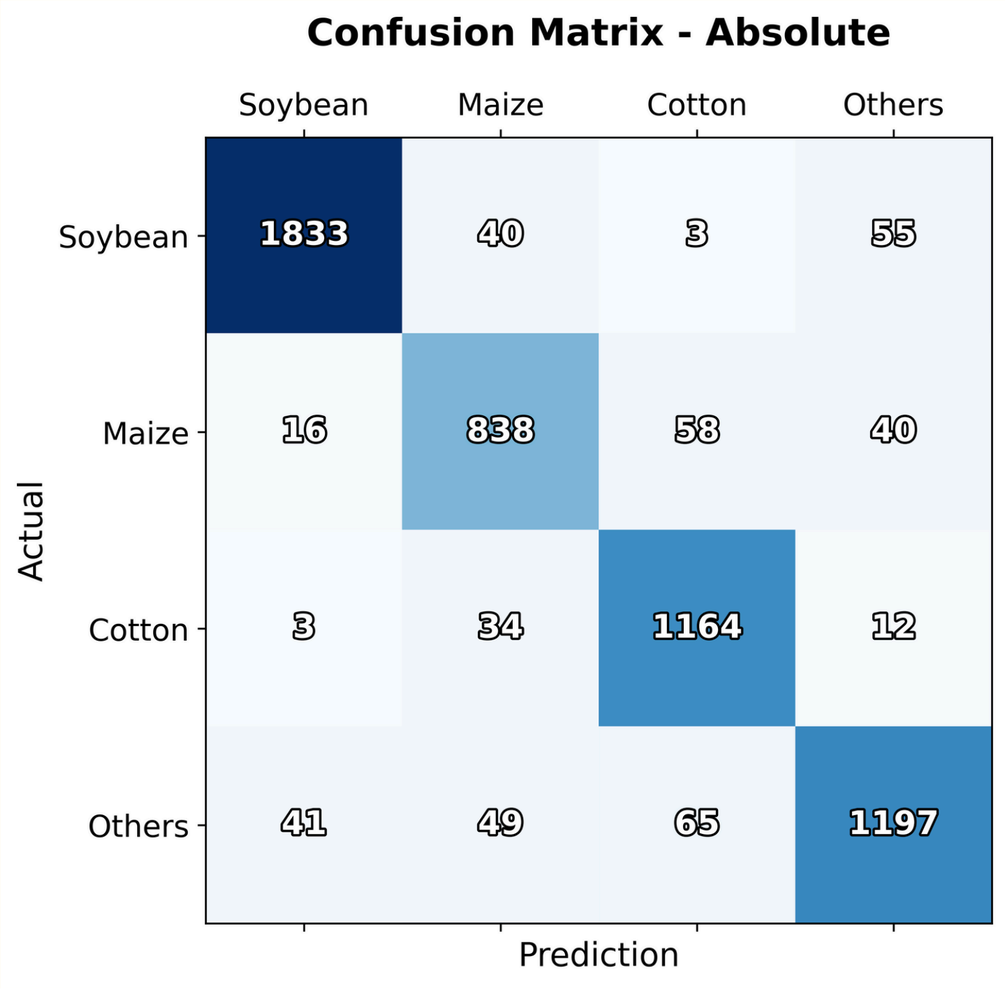



Frozen Model

# Classification - 4 classes




Fine-Tuning Model

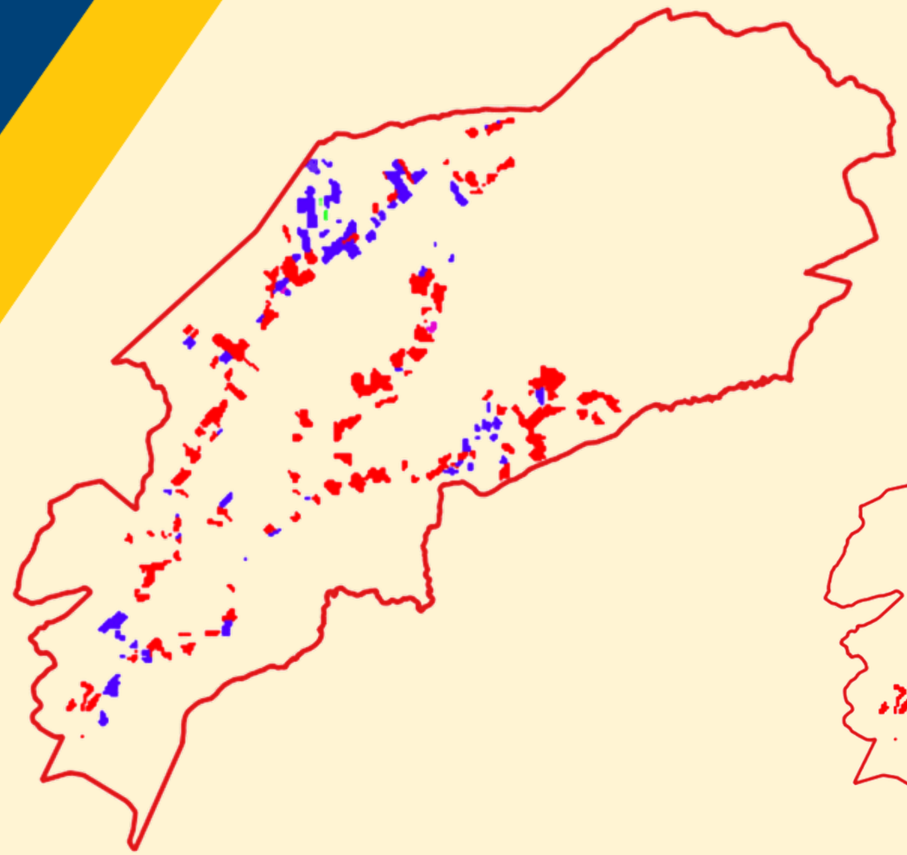



Frozen Model

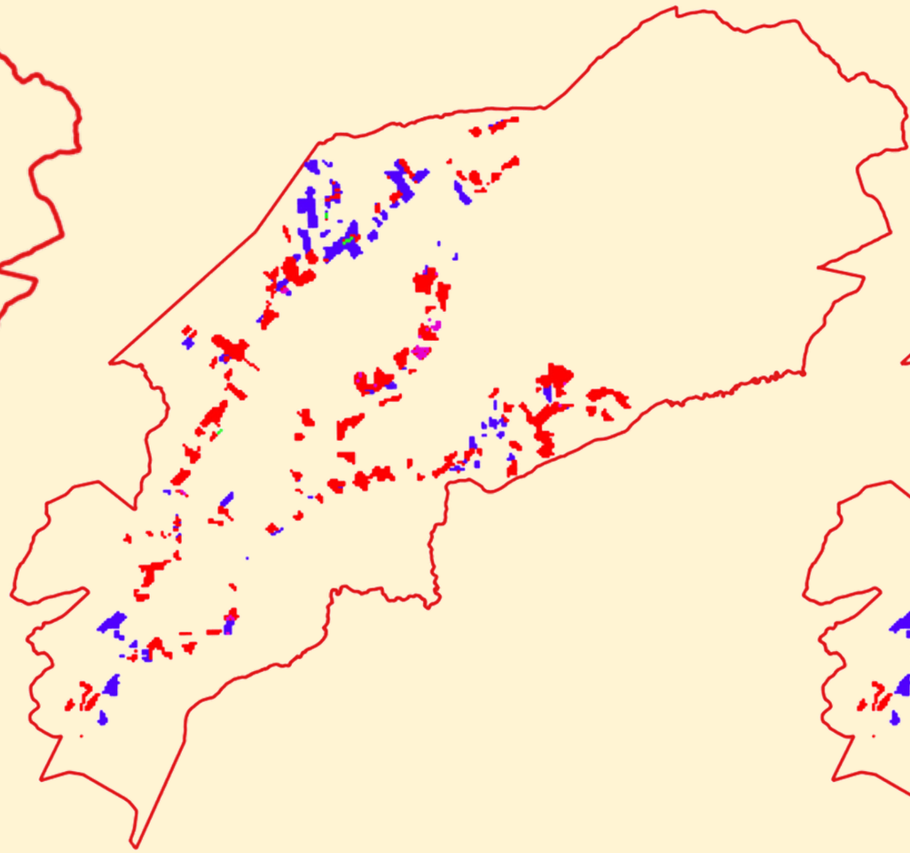
# Classification - 4 classes

## December - Test Dataset

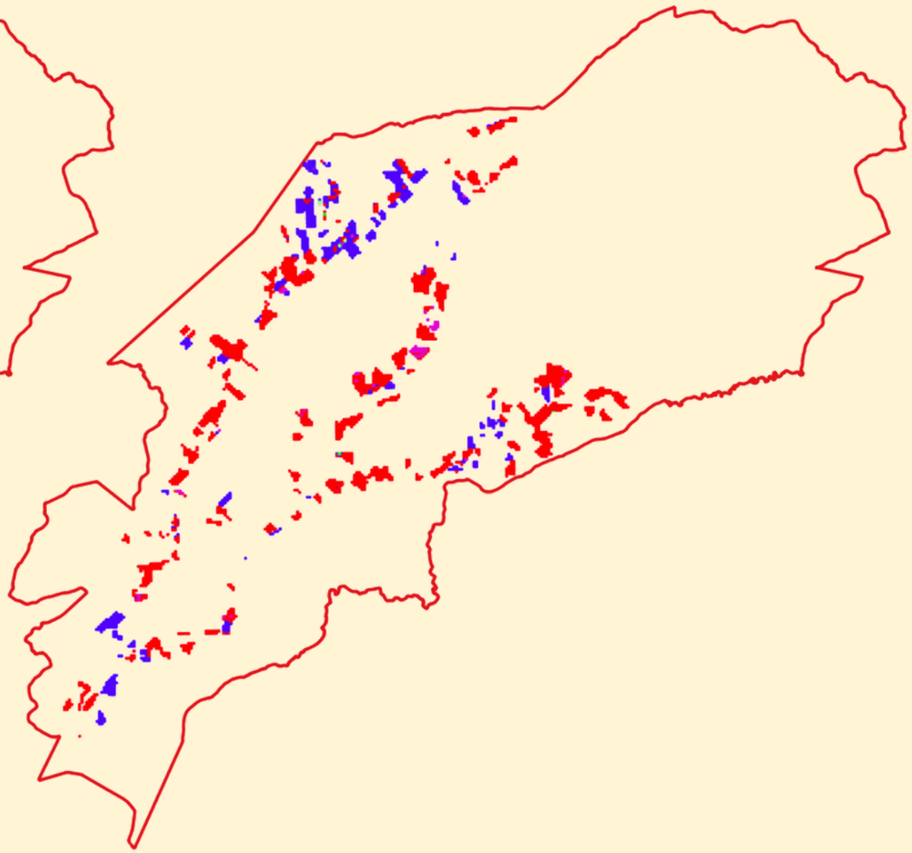
Soybean
Cotton
Maize
Others



Labeled Data



Fine-Tuning Model

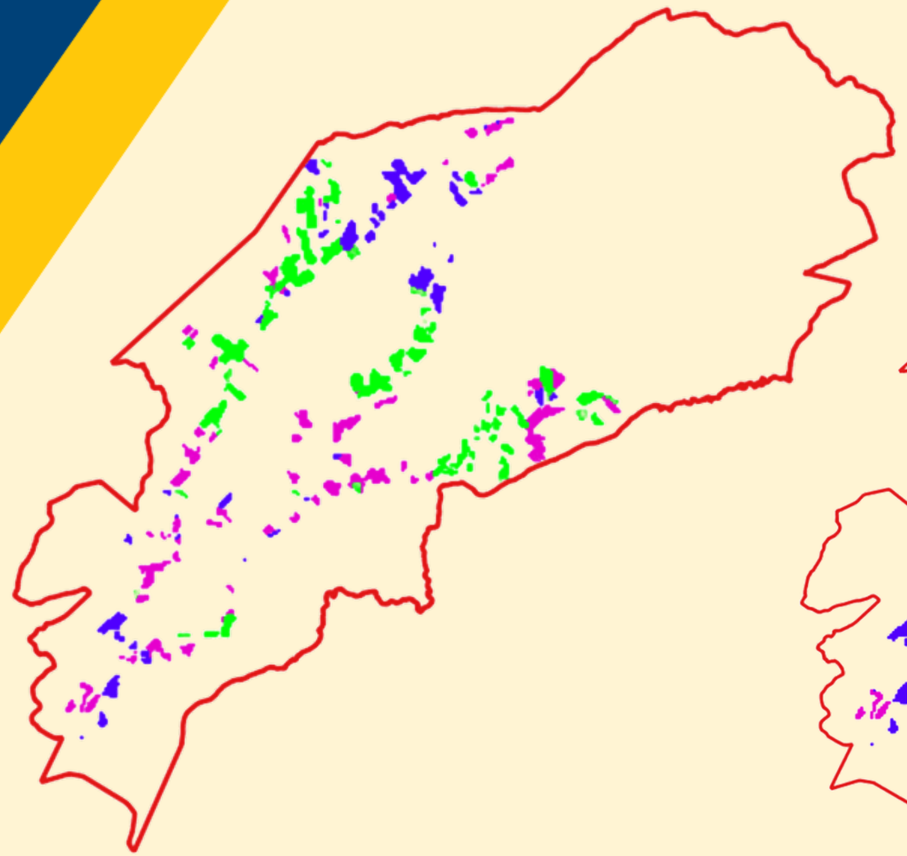


Frozen Model

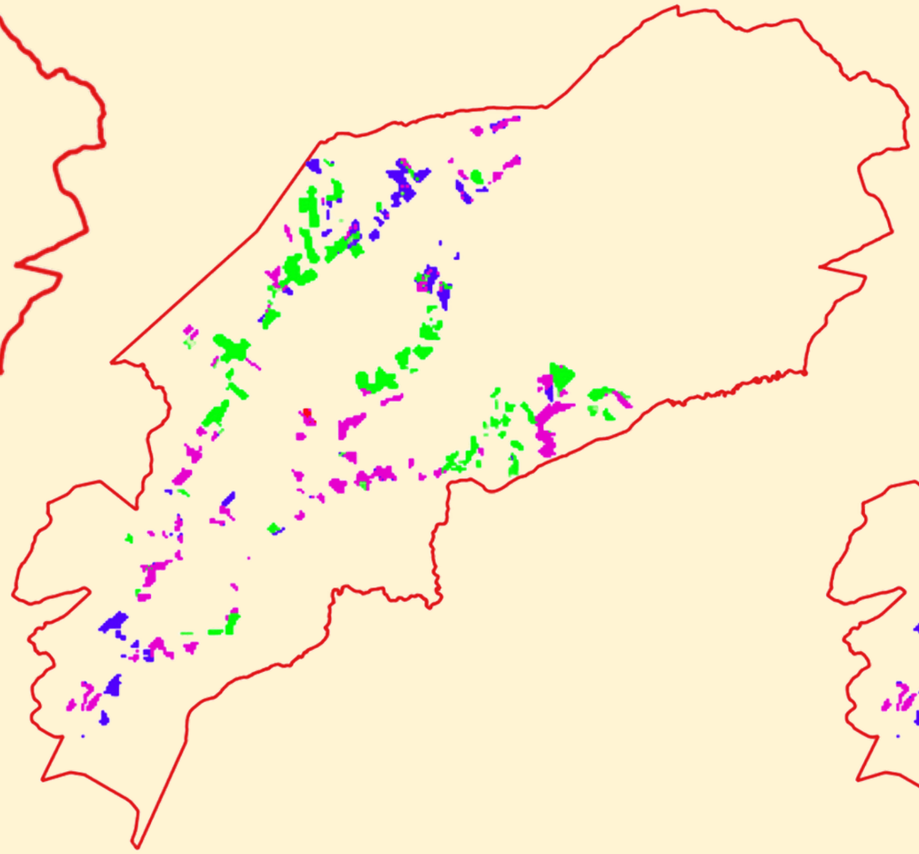
# Classification - 4 classes

## May - Test Dataset

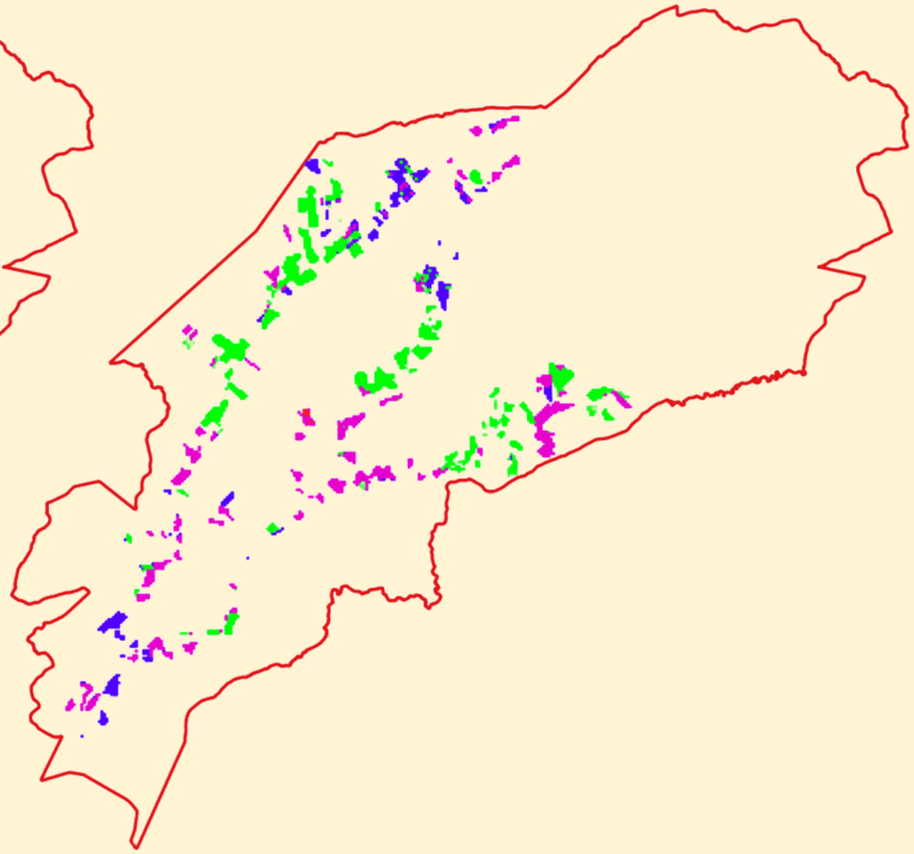
Soybean
Cotton
Maize
Others



Labeled Data



Fine-Tuning Model

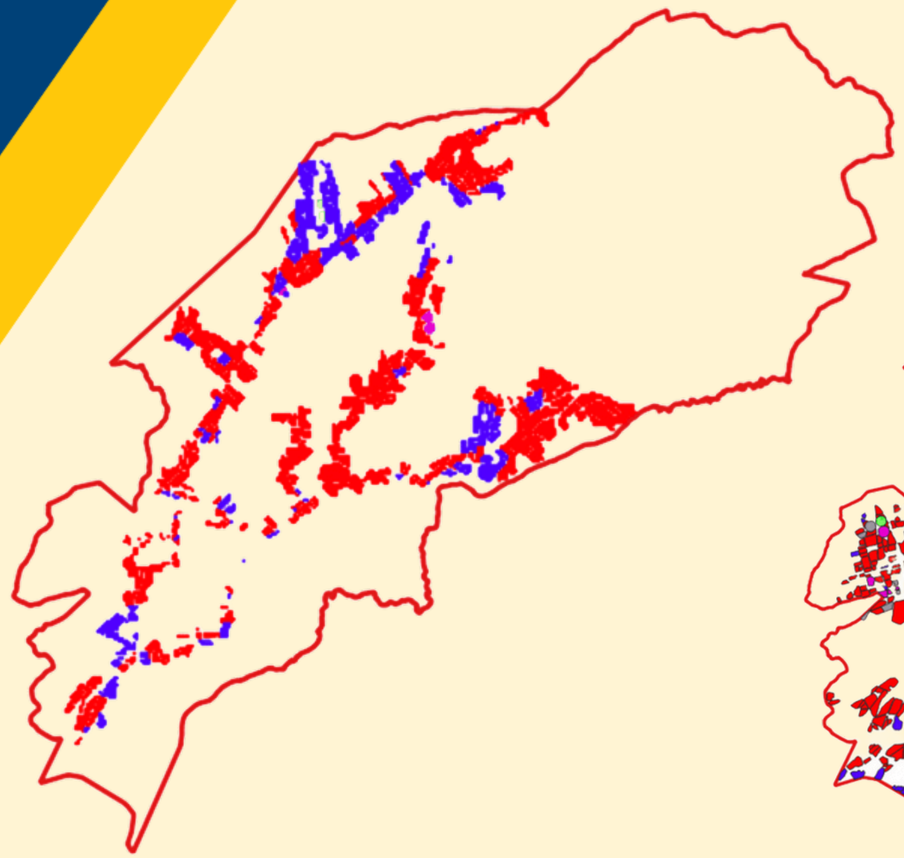


Frozen Model

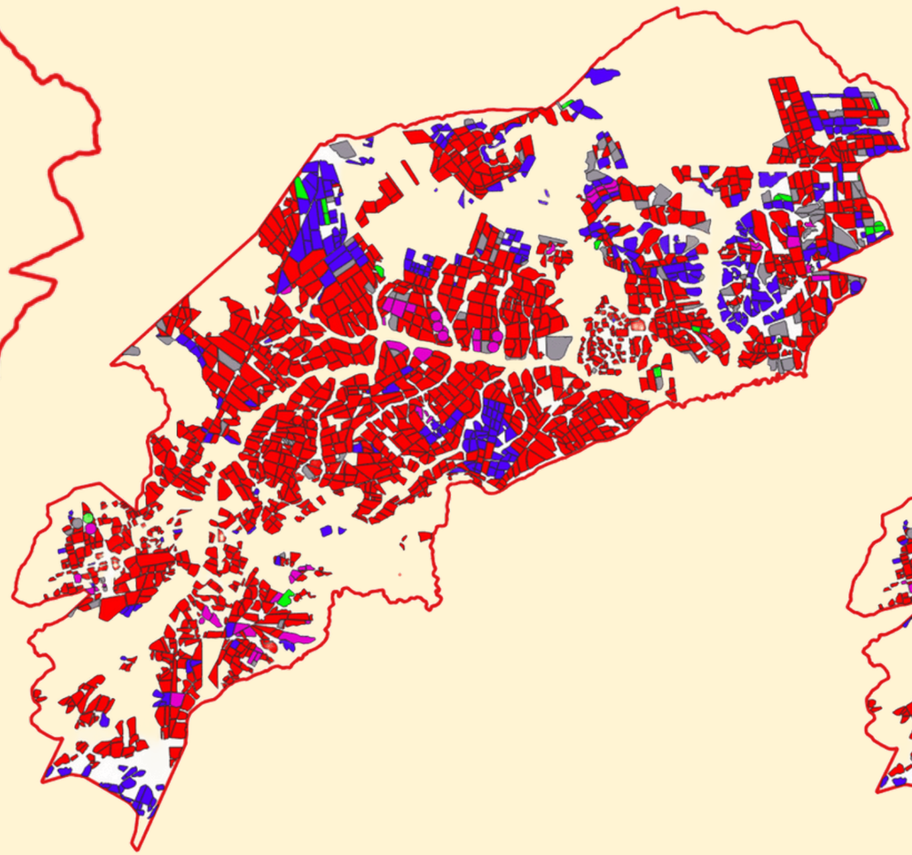
# Classification - 4 classes

## December - Generated Masks

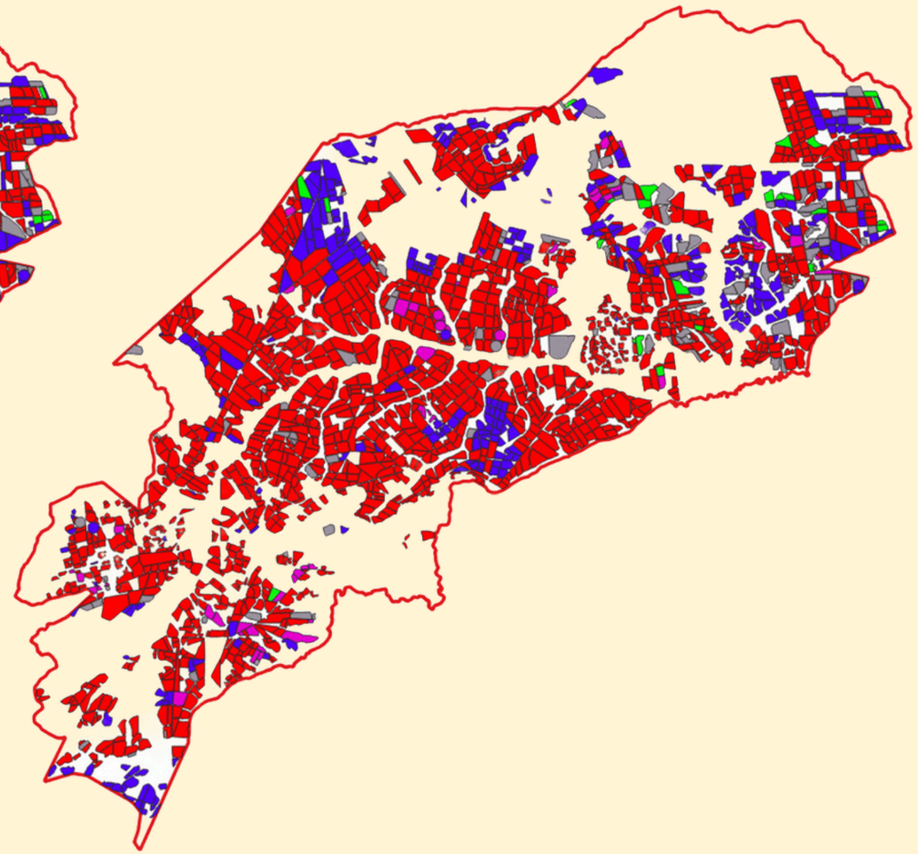
Soybean
Cotton
Not Classified
Maize
Others



Labeled Data



Fine-Tuning Model

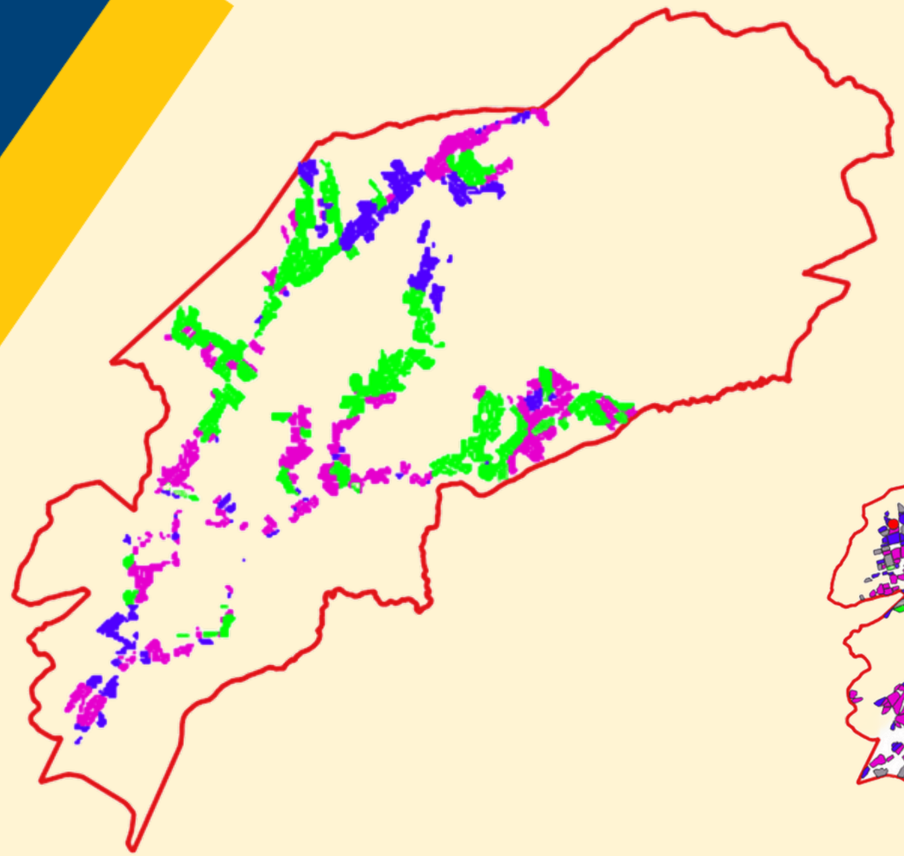


Frozen Model

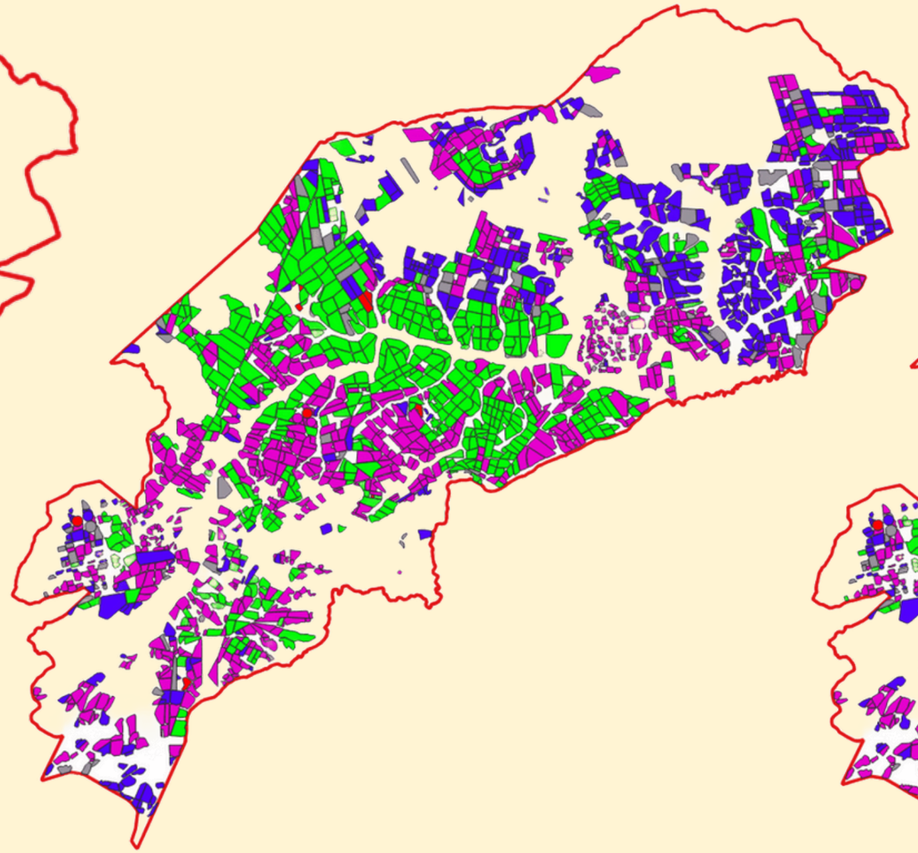
# Classification - 4 classes

## May - Generated Masks

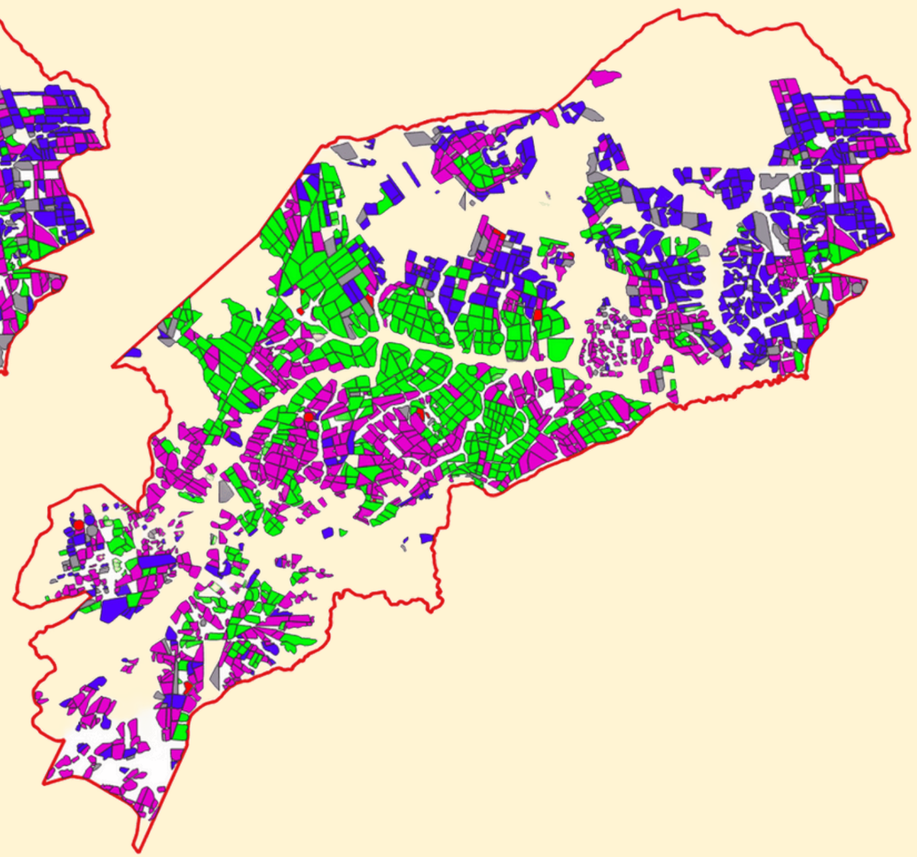
Soybean
Cotton
Not Classified
Maize
Others



Labeled Data



Fine-Tuning Model



Frozen Model

# Conclusion

# Conclusion

- We developed a scalable algorithm for field plot segmentation
- We achieved good organization of the latent space
- We successfully addressed the problem caused by cloud coverage during harvest periods
- We reached 93.41% total accuracy in crop classification
- We classified 2189.73 km² with only 520.29 km² of labeled data
- In total, we classified 4014 crop field plots, starting with only 513 labeled field plots

# Thank you! Obrigado!

# Questions?

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raullomonte13@gmail.com

@raullomontefigueiredo