UFG
INSTITUTO DE INFORMÁTICA UFG
LAPIG
Laboratório de Processamento de Imagens e Geoprocessamento

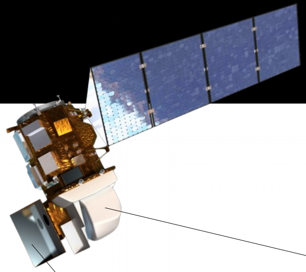
# DL4Landsat

## Deep Learning for Landsat

**Student:** Leandro Leal Parente

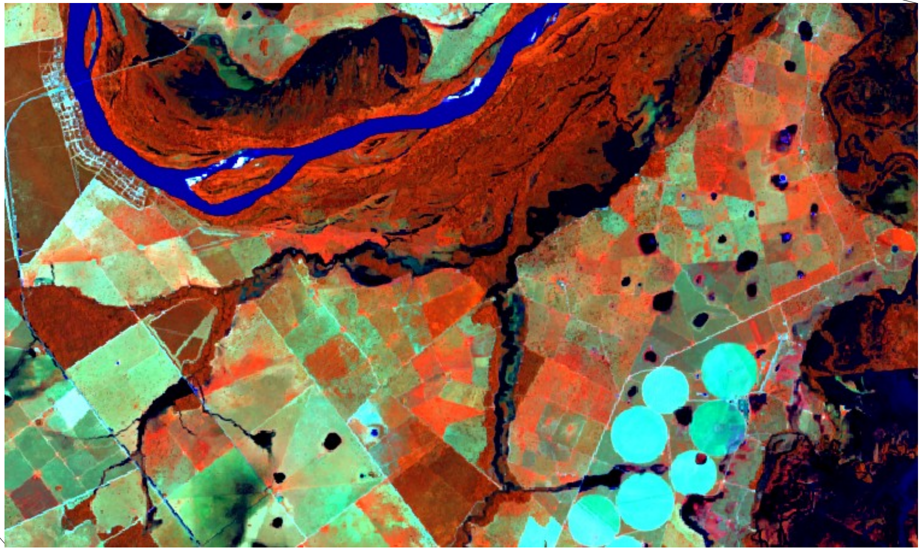
**Class:** Deep Learning (2017-02)

**Professor:** Anderson Soares

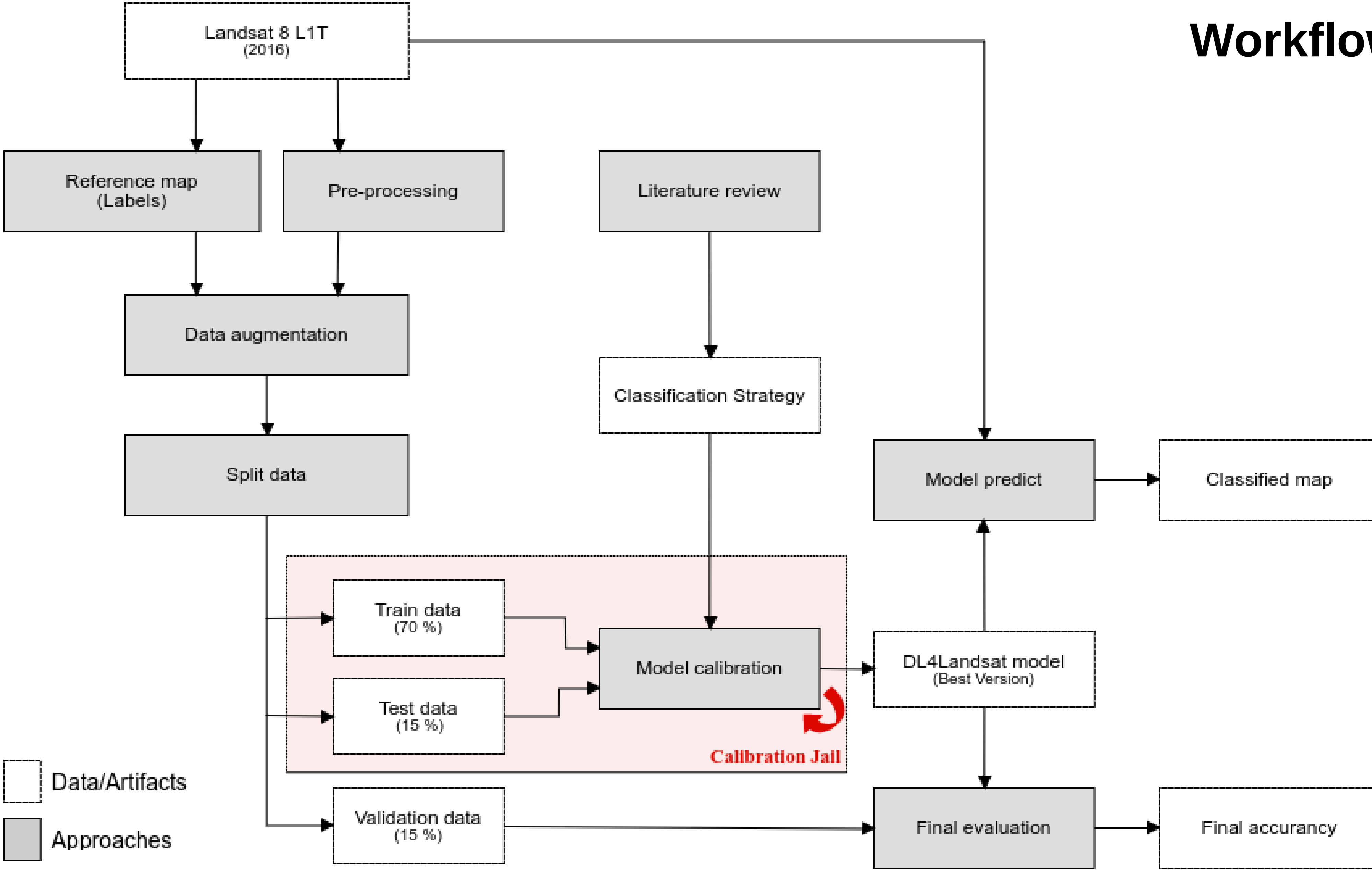


# Presentation Outline

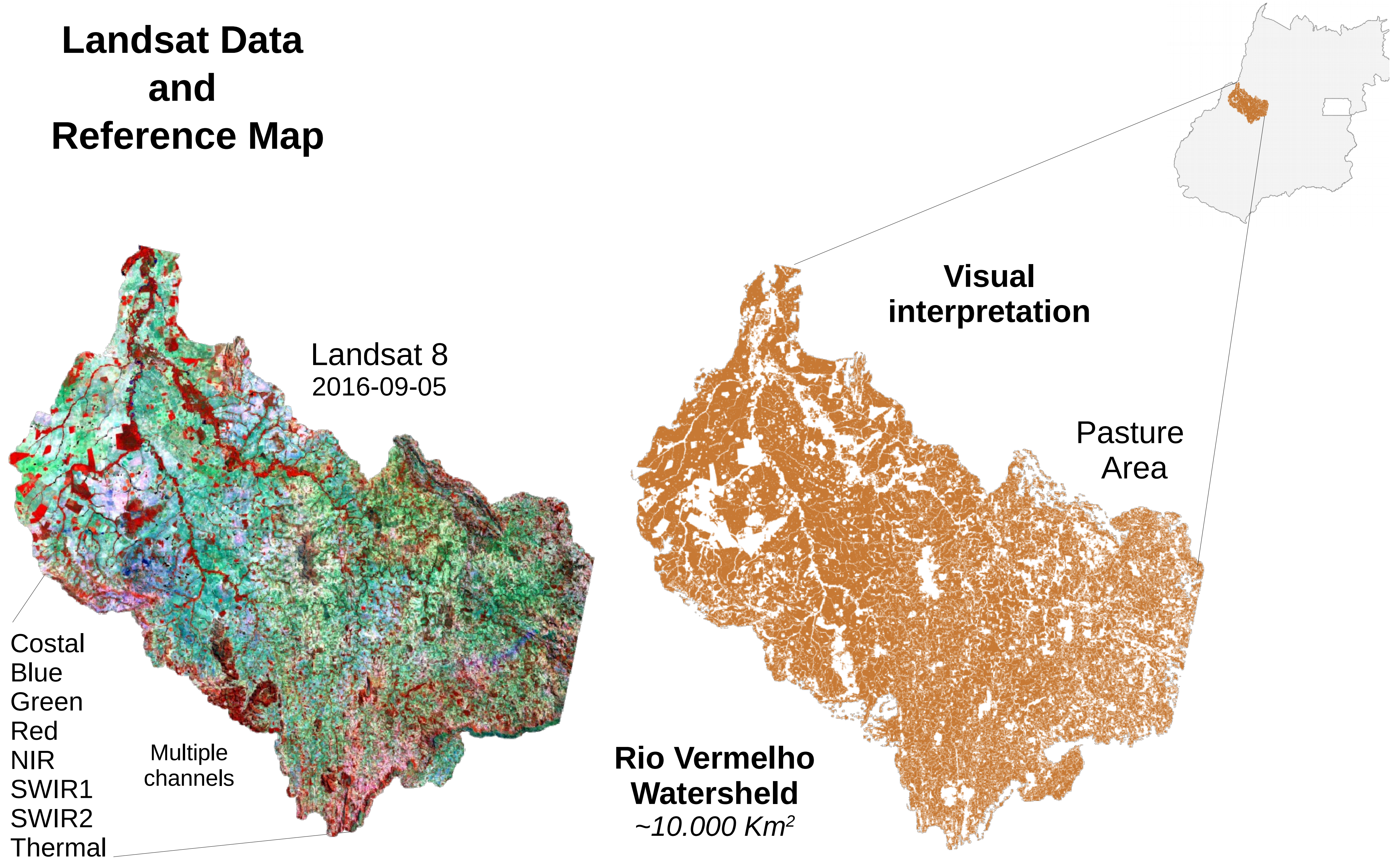
- **Workflow**
- **Results**
- **Next steps**



# Workflow

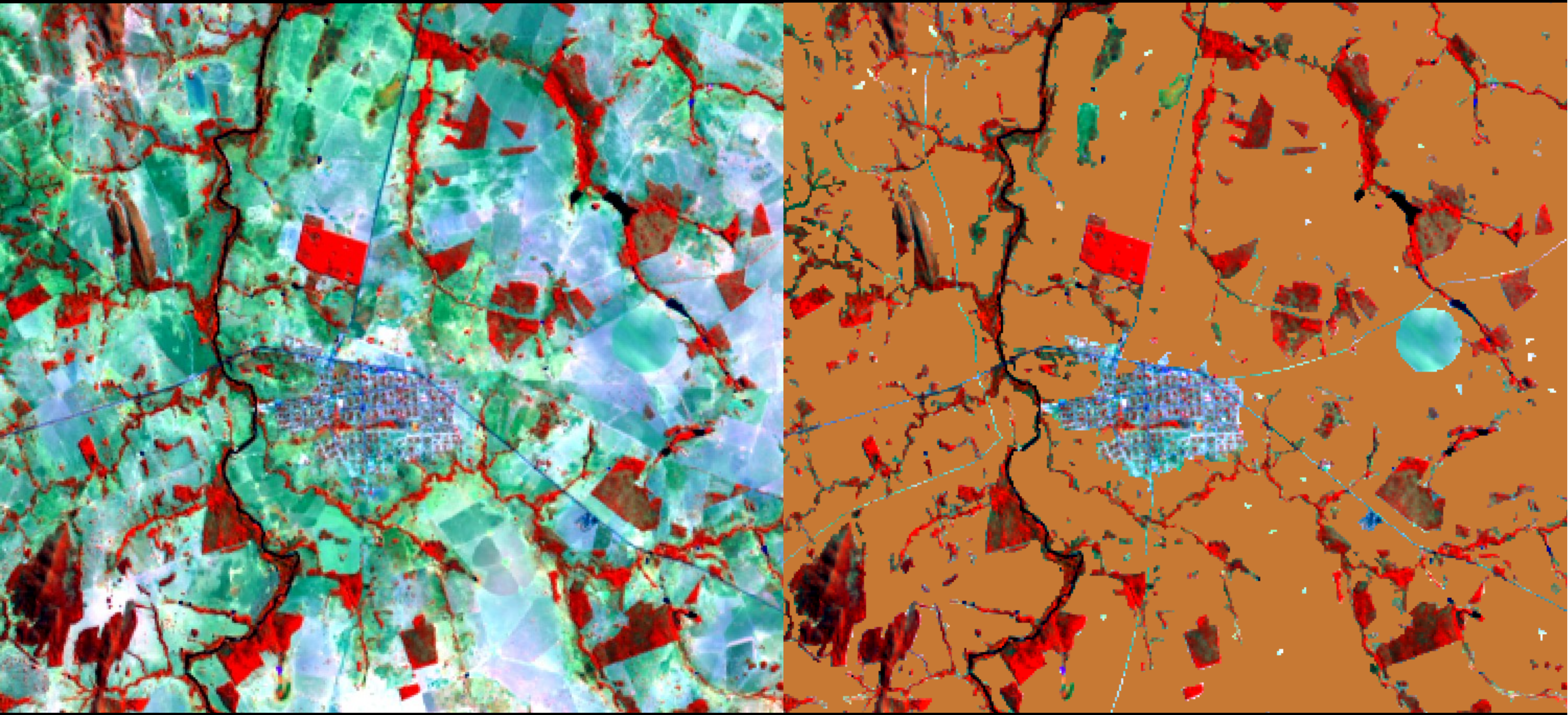


Landsat 8 L1T
(2016)
Reference map
(Labels)
Pre-processing
Literature review
Data augmentation
Classification Strategy
Split data
Model predict
Classified map
Train data
(70 %)
Model calibration
DL4Landsat model
(Best Version)
Test data
(15 %)
Calibration Jail
Data/Artifacts
Approaches
Validation data
(15 %)
Final evaluation
Final accurancy



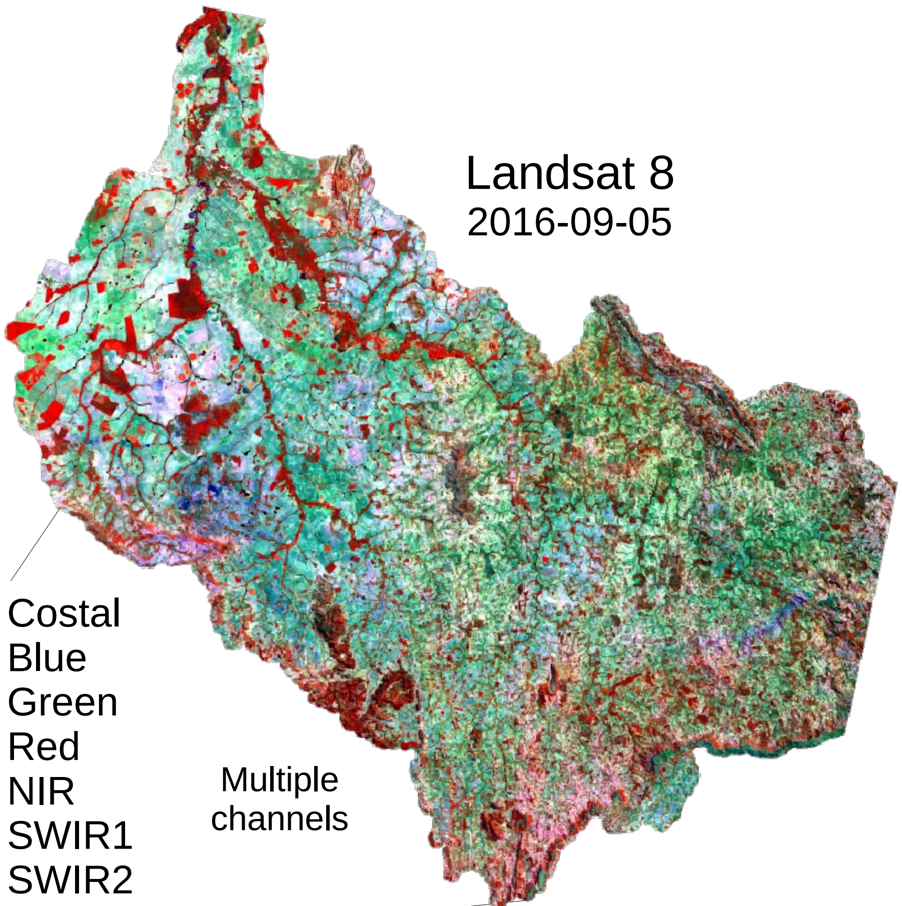
Landsat Data
and
Reference Map
Landsat 8
2016-09-05
Costal
Blue
Green
Red
NIR
SWIR1
SWIR2
Thermal
Multiple
channels
Visual
interpretation
Pasture
Area
Rio Vermelho
Watersheld
~10.000 Km²

# Itapirapuã - GO



# Landsat Data

(Pre-processing)

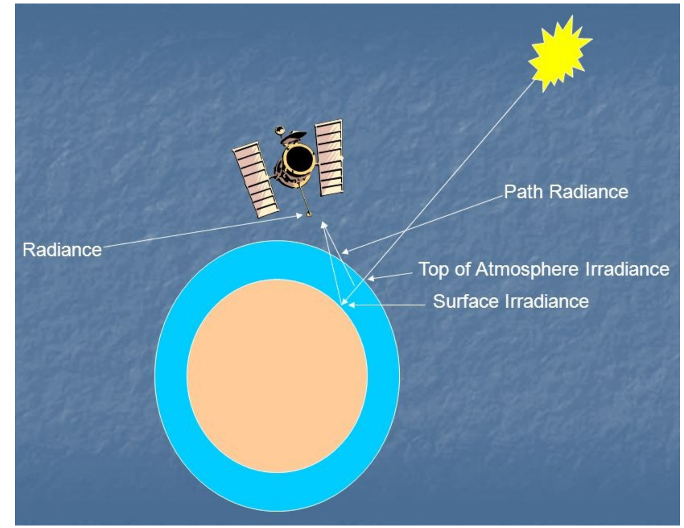


Landsat 8
2016-09-05

Costal
Blue
Green
Red
NIR
SWIR1
SWIR2
Thermal

Multiple channels

## 1) Top-of-Atosmphere (TOA) Normalization

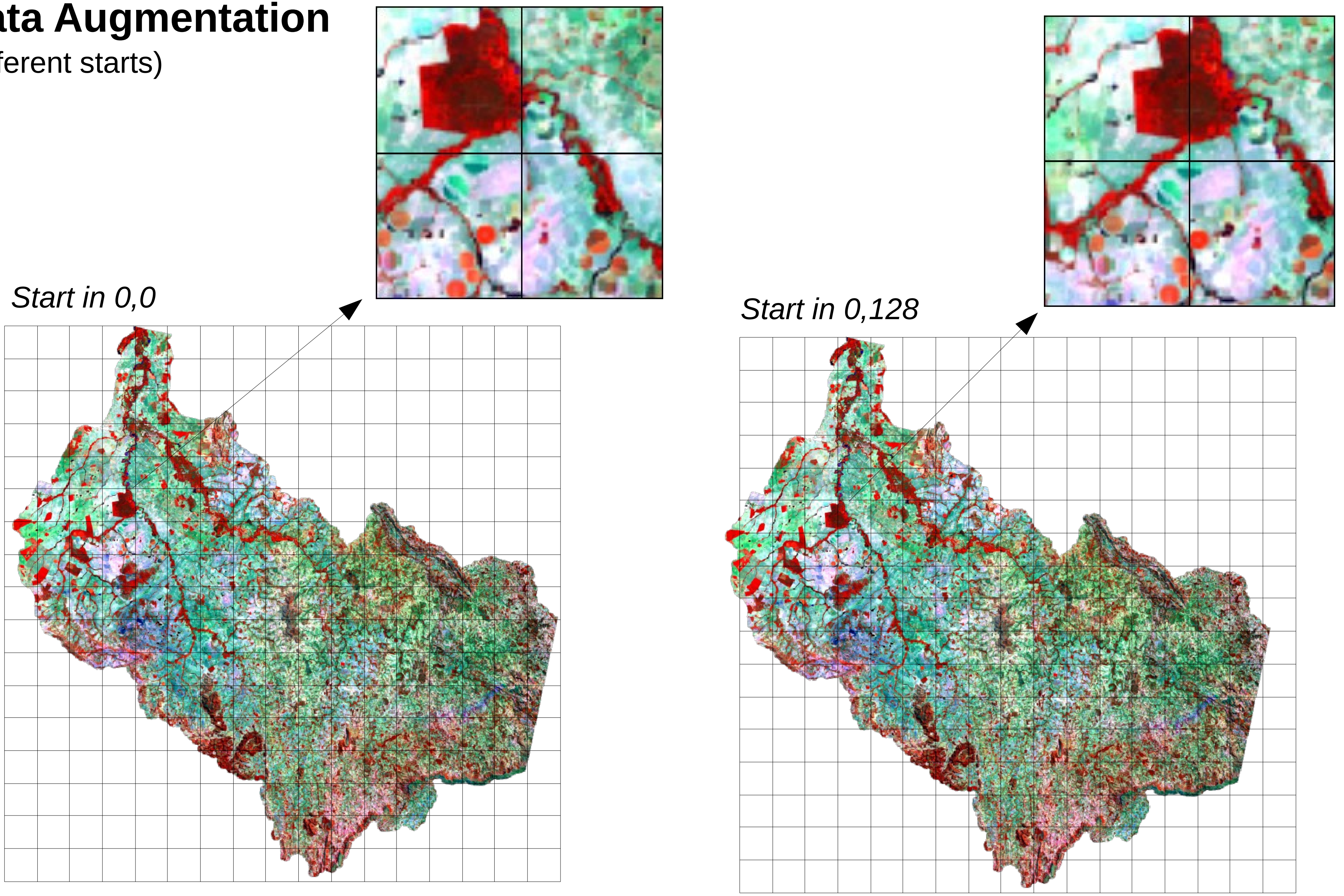



## 2) Histogram equalization

(between -1 and 1)

$$2*\left(\frac{(X-Xmin)}{(Xmax-Xmin)}\right)-1$$

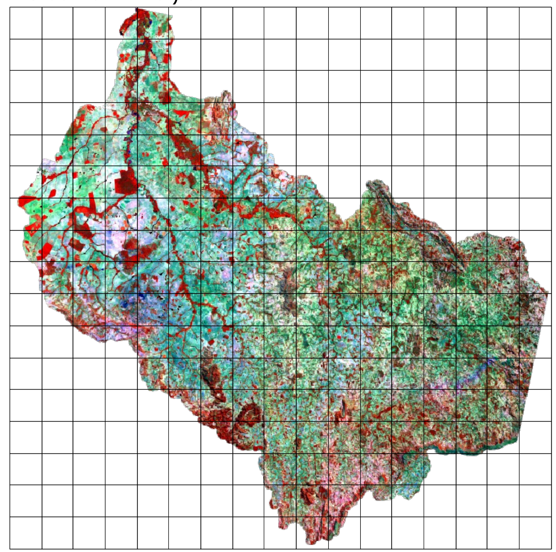
# Data Augmentation
(different starts)



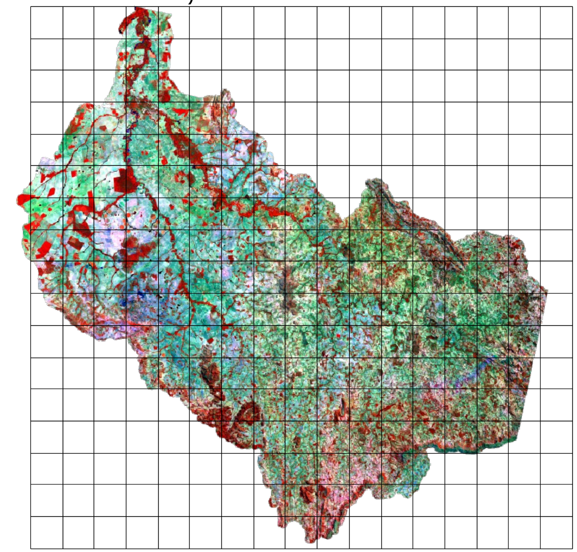
# Data Augmentation

(different starts)

*Start in 0,0*

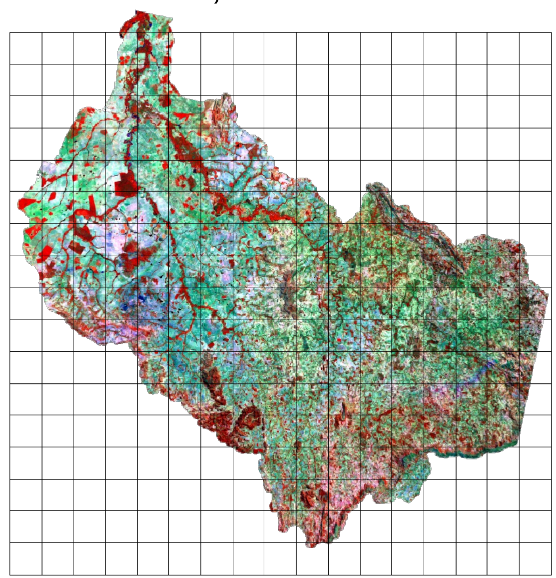


*Start in 0,128*

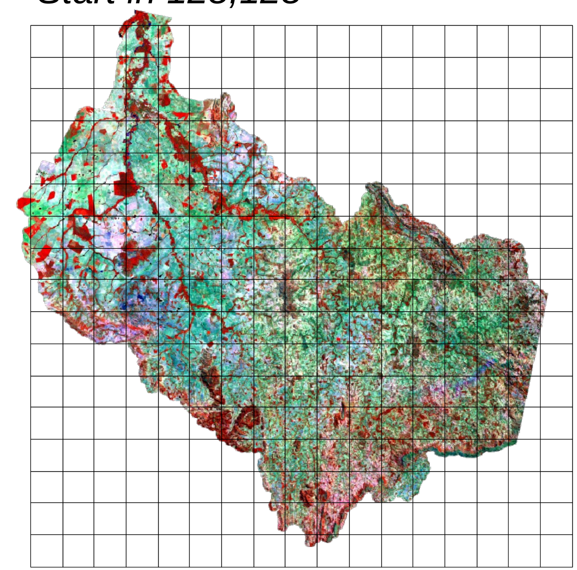


4 X

*Start in 128,0*

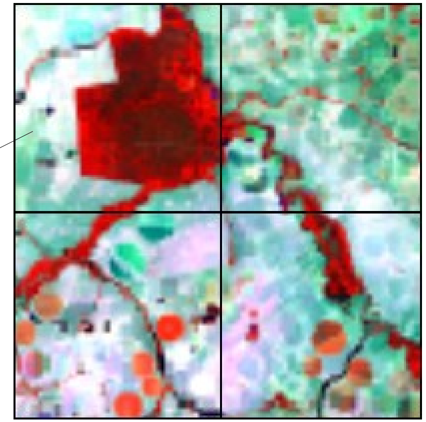


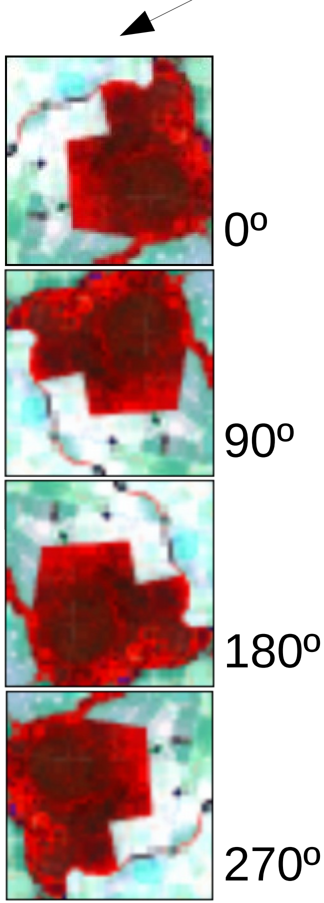
*Start in 128,128*



# Data Augmentation

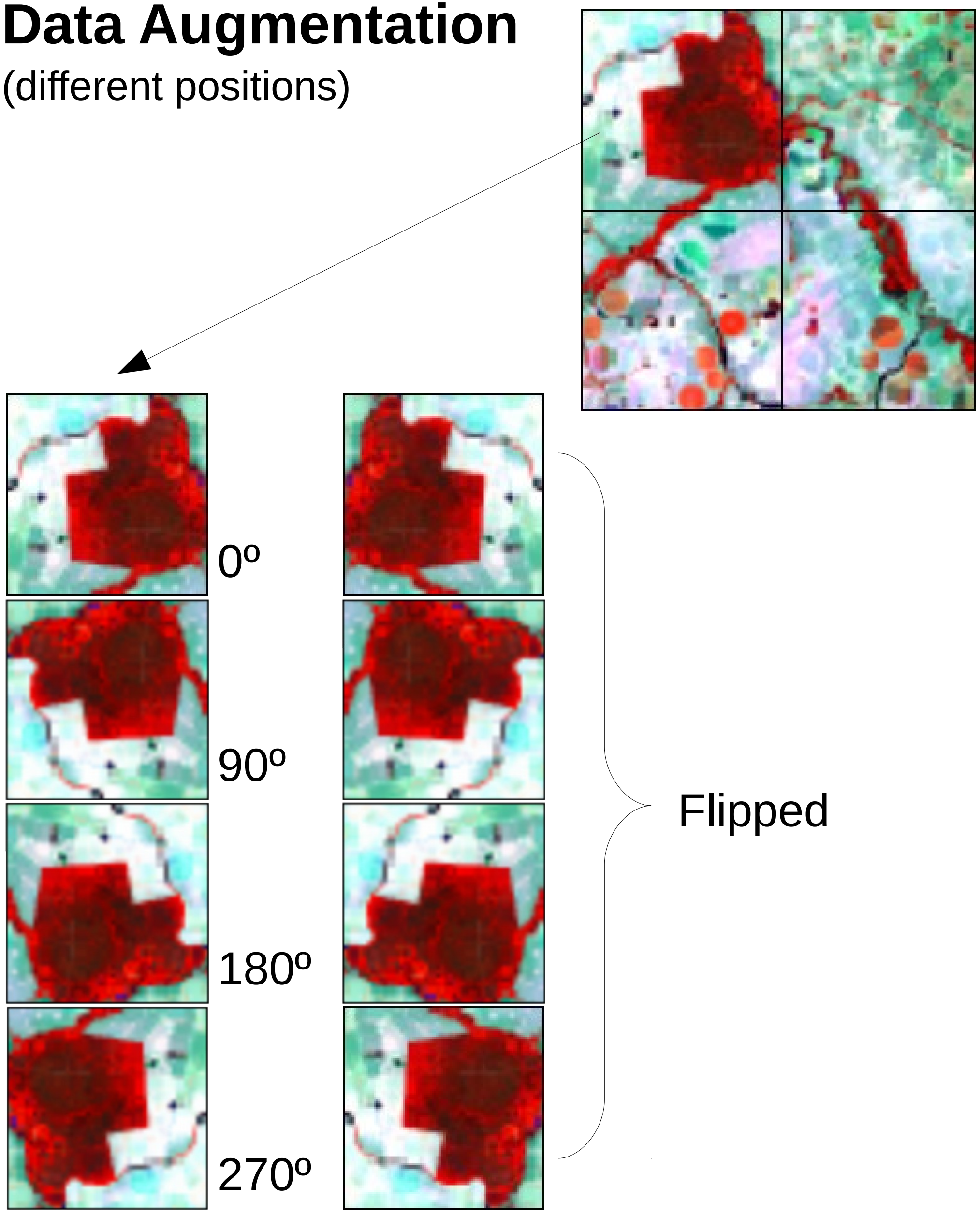
(different positions)

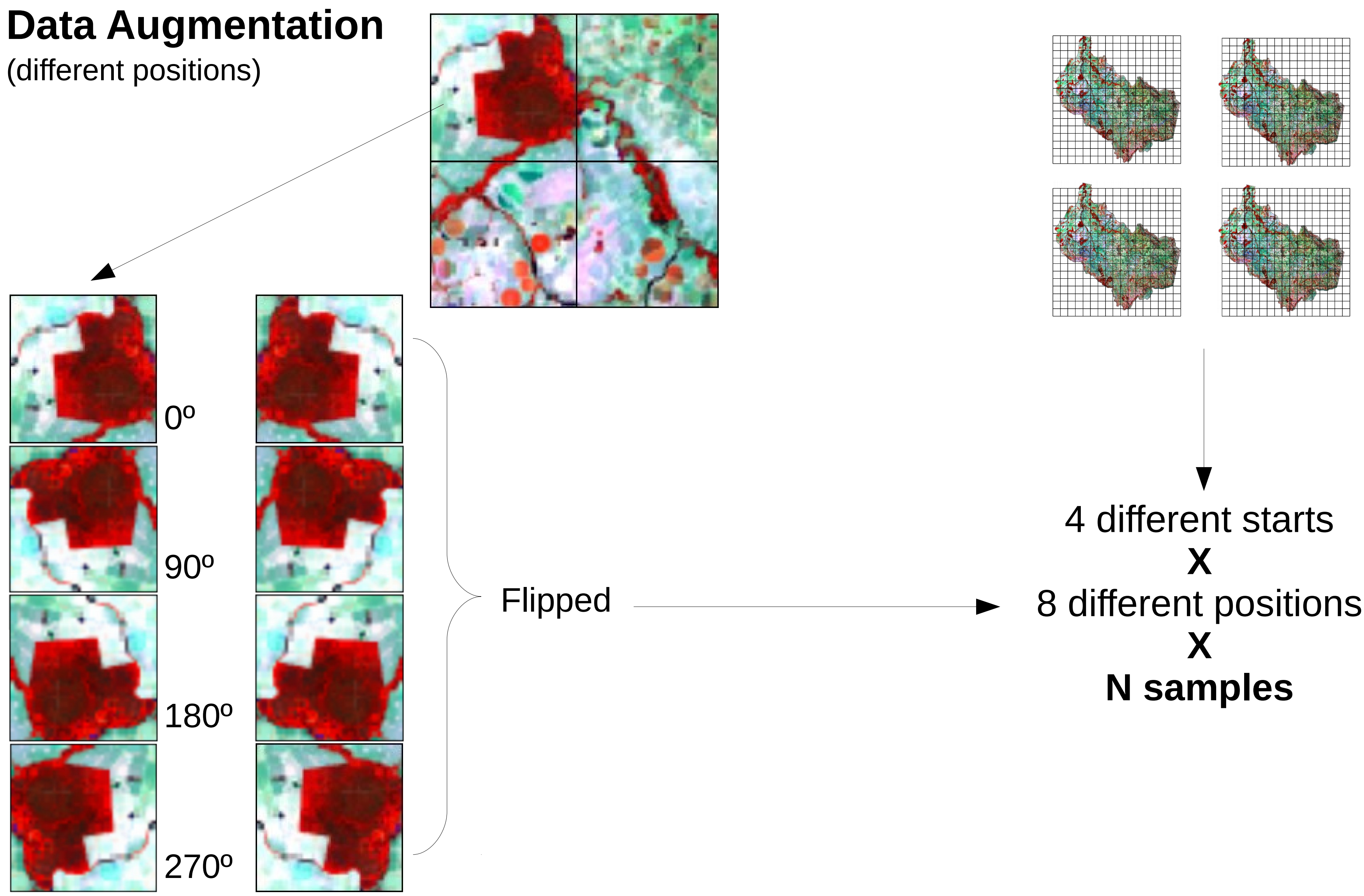


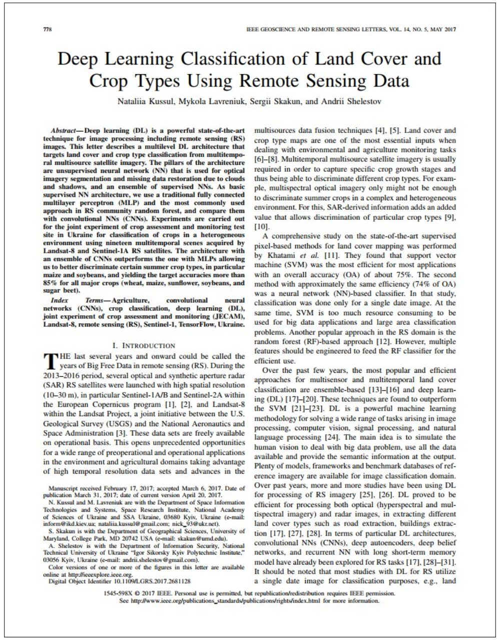


# Data Augmentation

(different positions)

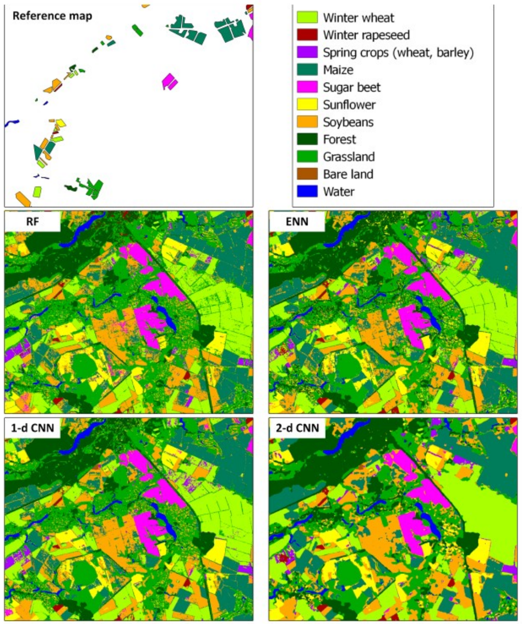


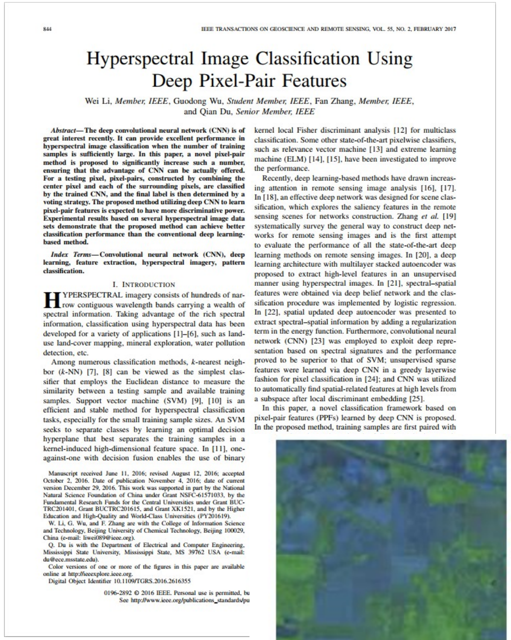

Data Augmentation
(different positions)
0º
90º
180º
270º
Flipped
4 different starts
X
8 different positions
X
N samples


IEEE GEOSCIENCE AND REMOTE SENSING LETTERS, VOL. 14, NO. 5, MAY 2017

# Deep Learning Classification of Land Cover and Crop Types Using Remote Sensing Data

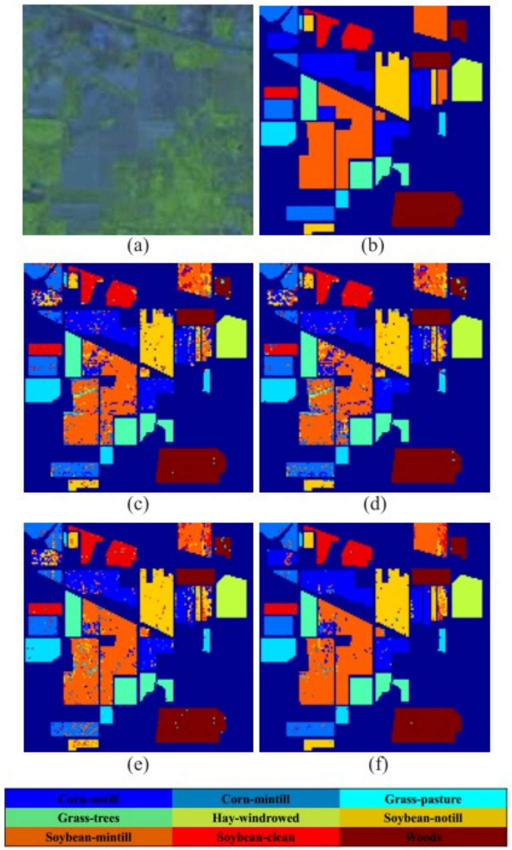
Nataliia Kussul, Mykola Lavreniuk, Sergii Skakun, and Andrii Shelestov

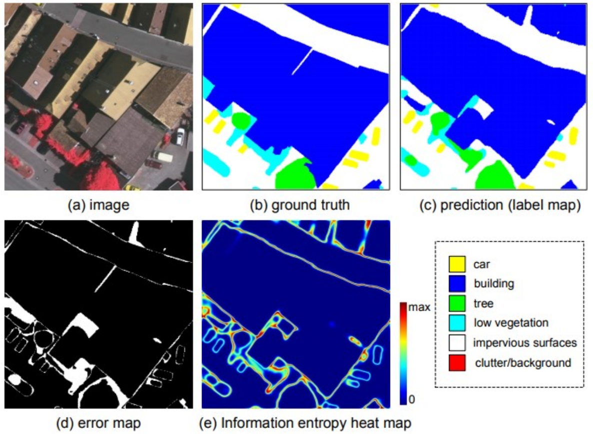


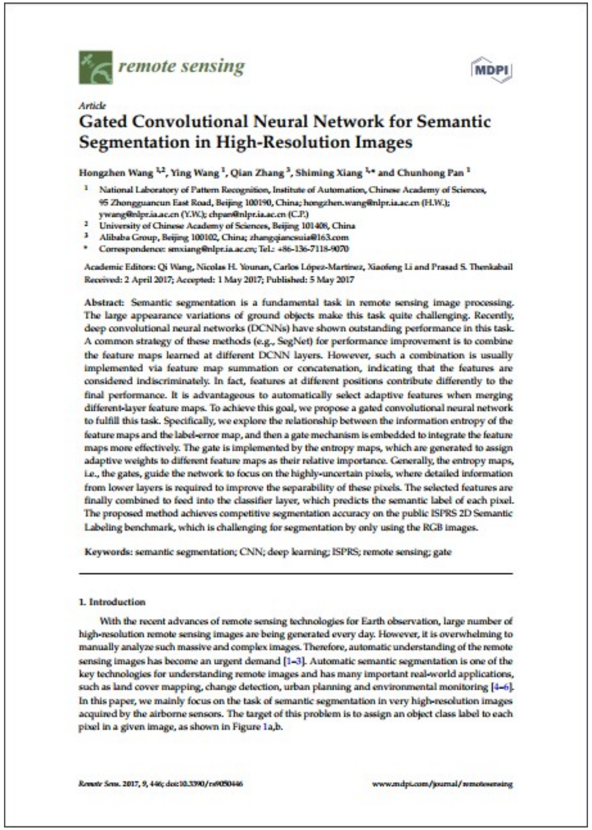


IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING, VOL. 55, NO. 2, FEBRUARY 2017

# Hyperspectral Image Classification Using Deep Pixel-Pair Features

Wei Li, *Member, IEEE*, Guodong Wu, *Student Member, IEEE*, Fan Zhang, *Member, IEEE*, and Qian Du, *Senior Member, IEEE*





remote sensing

MDPI

*Article*

# Gated Convolutional Neural Network for Semantic Segmentation in High-Resolution Images

Hongzhen Wang [1,2], Ying Wang [1], Qian Zhang [3], Shiming Xiang [1,*] and Chunhong Pan [1]

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2 University of Chinese Academy of Sciences, Beijing 101408, China
3 Alibaba Group, Beijing 100102, China; zhangqiancsuia@163.com
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Academic Editors: Qi Wang, Nicolas H. Younan, Carlos López-Martínez, Xiaofeng Li and Prasad S. Thenkabail
Received: 2 April 2017; Accepted: 1 May 2017; Published: 5 May 2017

**Abstract:** Semantic segmentation is a fundamental task in remote sensing image processing. The large appearance variations of ground objects make this task quite challenging. Recently, deep convolutional neural networks (DCNNs) have shown outstanding performance in this task. A common strategy of these methods (e.g., SegNet) for performance improvement is to combine the feature maps learned at different DCNN layers. However, such a combination is usually implemented via feature map summation or concatenation, indicating that the features are considered indiscriminately. In fact, features at different positions contribute differently to the final performance. It is advantageous to automatically select adaptive features when merging different-layer feature maps. To achieve this goal, we propose a gated convolutional neural network to fulfill this task. Specifically, we explore the relationship between the information entropy of the feature maps and the label-error map, and then a gate mechanism is embedded to integrate the feature maps more effectively. The gate is implemented by the entropy maps, which are generated to assign adaptive weights to different feature maps as their relative importance. Generally, the entropy maps, i.e., the gates, guide the network to focus on the highly-uncertain pixels, where detailed information from lower layers is required to improve the separability of these pixels. The selected features are finally combined to feed into the classifier layer, which predicts the semantic label of each pixel. The proposed method achieves competitive segmentation accuracy on the public ISPRS 2D Semantic Labeling benchmark, which is challenging for segmentation by only using the RGB images.

**Keywords:** semantic segmentation; CNN; deep learning; ISPRS; remote sensing; gate

## 1. Introduction

With the recent advances of remote sensing technologies for Earth observation, large number of high-resolution remote sensing images are being generated every day. However, it is overwhelming to manually analyze such massive and complex images. Therefore, automatic understanding of the remote sensing images has become an urgent demand [1–3]. Automatic semantic segmentation is one of the key technologies for understanding remote images and has many important real-world applications, such as land cover mapping, change detection, urban planning and environmental monitoring [4–6]. In this paper, we mainly focus on the task of semantic segmentation in very high-resolution images acquired by the airborne sensors. The target of this problem is to assign an object class label to each pixel in a given image, as shown in Figure 1a,b.

*Remote Sens.* 2017, 9, 446; doi:10.3390/rs9050446 www.mdpi.com/journal/remotesensing

# Classification Strategy

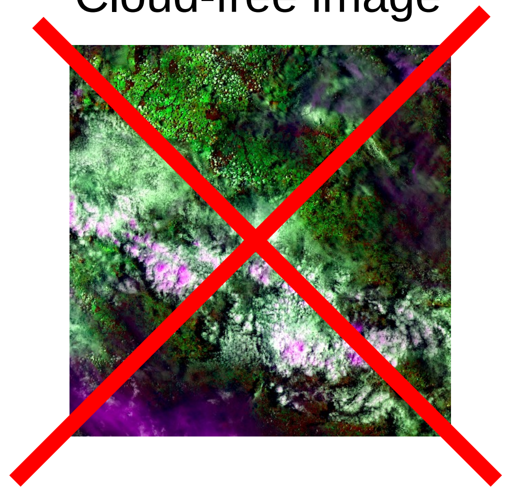
Input data (normalized)

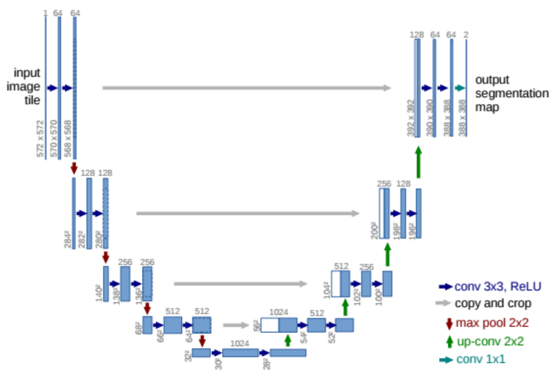
2016-09-05

8 Channels

~~Costal~~
**Blue**
**Green**
**Red**
**NIR**
**SWIR1**
**SWIR2**
**NDVI**
**Thermal**

Cloud-free image



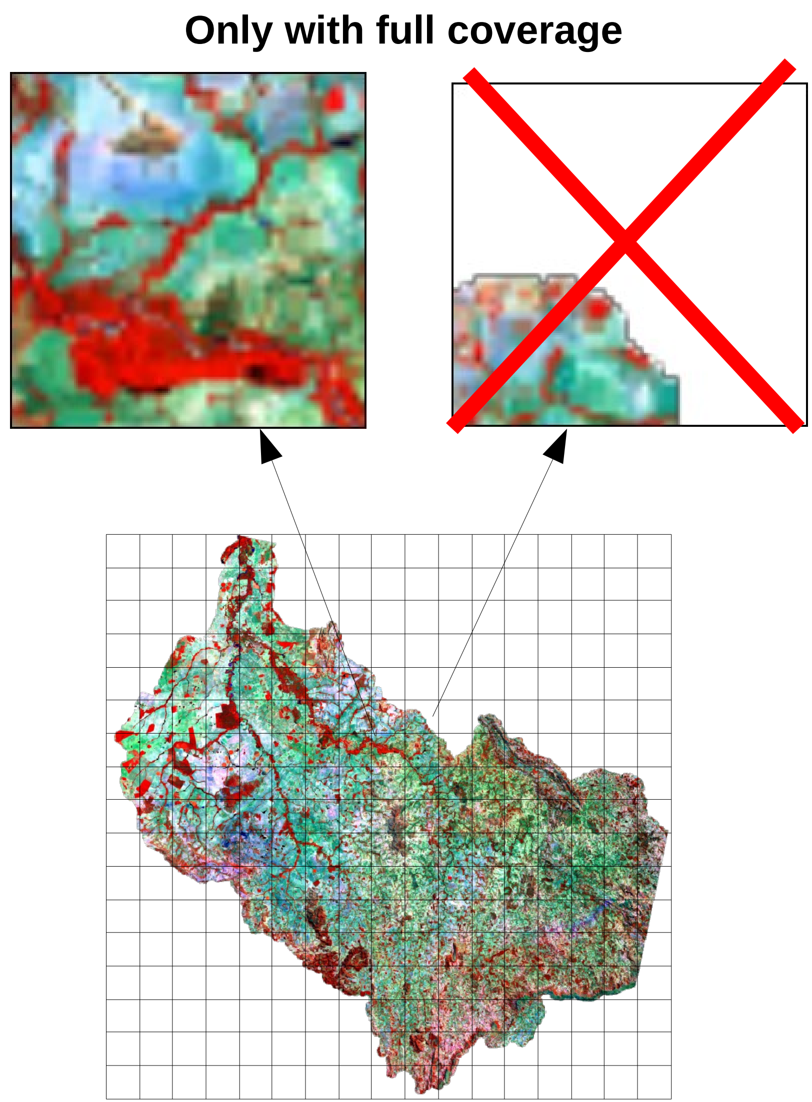



U-Net Model

- Spectral and spatial domain exploration
- One image classification (without temporal domain)
- Cloud-free image (without gaps or null values)
- Binary classification (pasture and not-pasture)
- Produce a pasture map for entire Landsat scene

# Model calibration

(Input data)



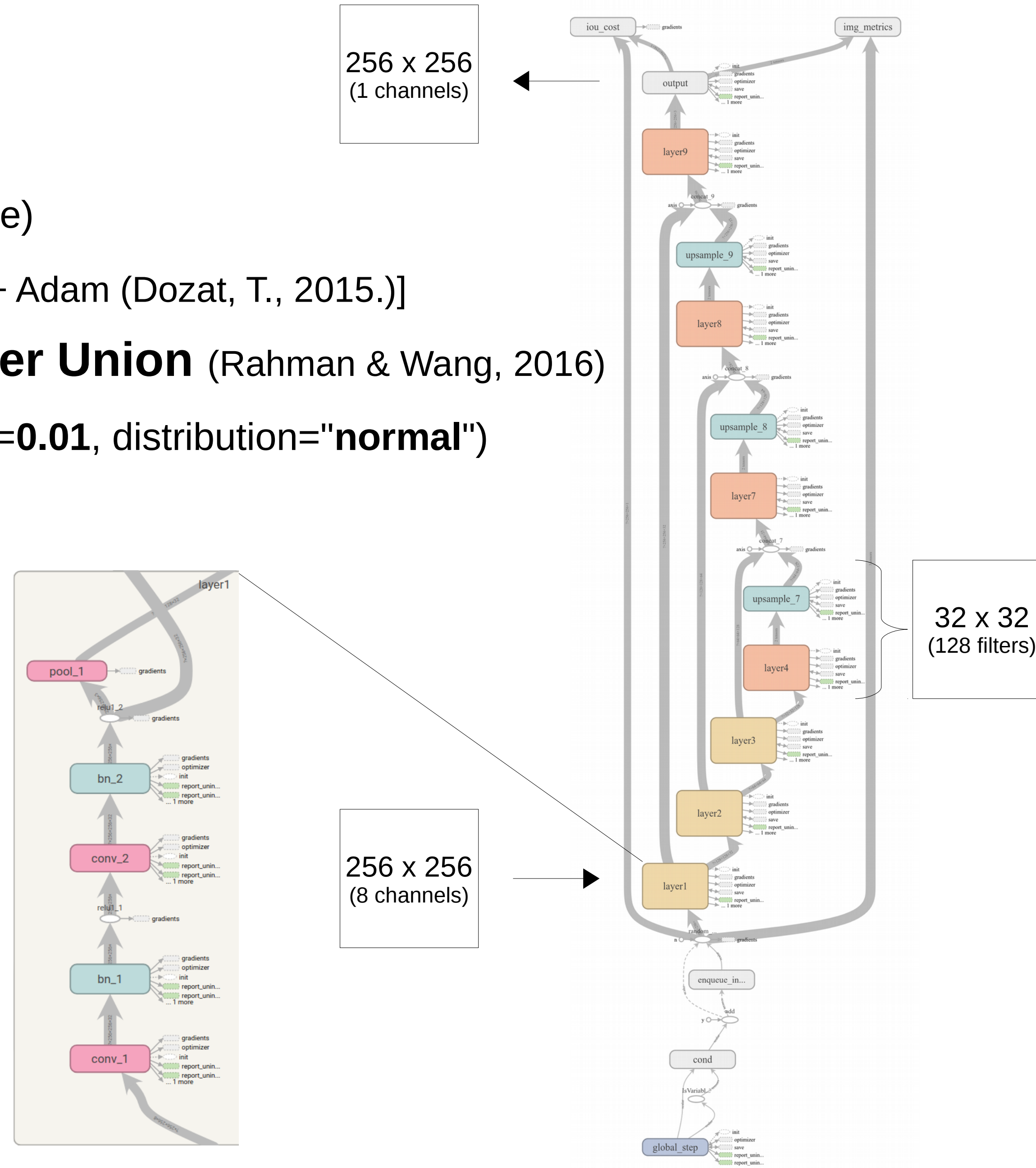

- Image size: 256 x 256
- Format: Float32
- Size in memory: 5,5 GB

- Train: (**1638**, 256, 256, 8)
- Test: (**351**, 256, 256, 8)
- Validation: (**351**, 256, 256, 8)

# Model calibration
(Hyperparameters)

- Number of epochs: **200** (2h 48m runtime)
- Optimizer: **Nadam** [Nesterov Momentum + Adam (Dozat, T., 2015.)]
- Cost function: **IoU - Intersection over Union** (Rahman & Wang, 2016)
- Weight initializer: variance_scaling(scale=**0.01**, distribution="**normal**")

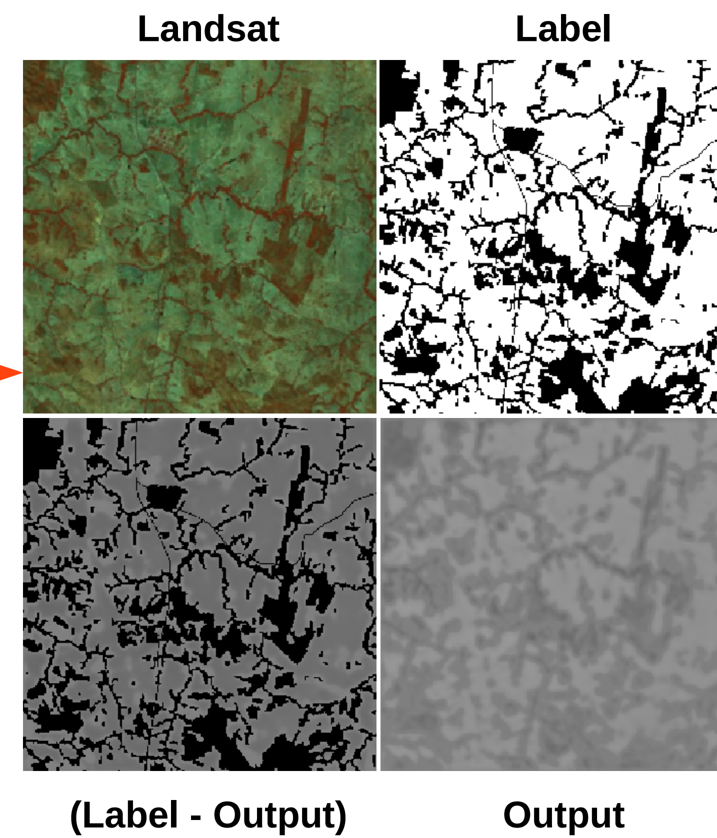
- **Convolution layers:**
  - L2_regularizer: 0.3
  - Batch normalization
  - Activation function: ReLU
- **Output layer:**
  - Activation function: Sigmoid

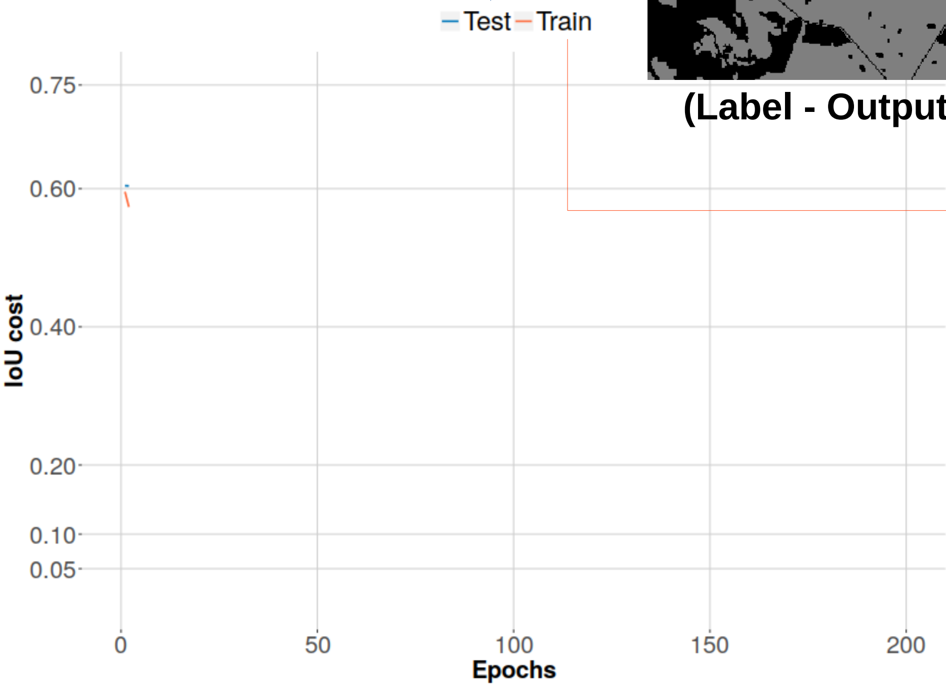


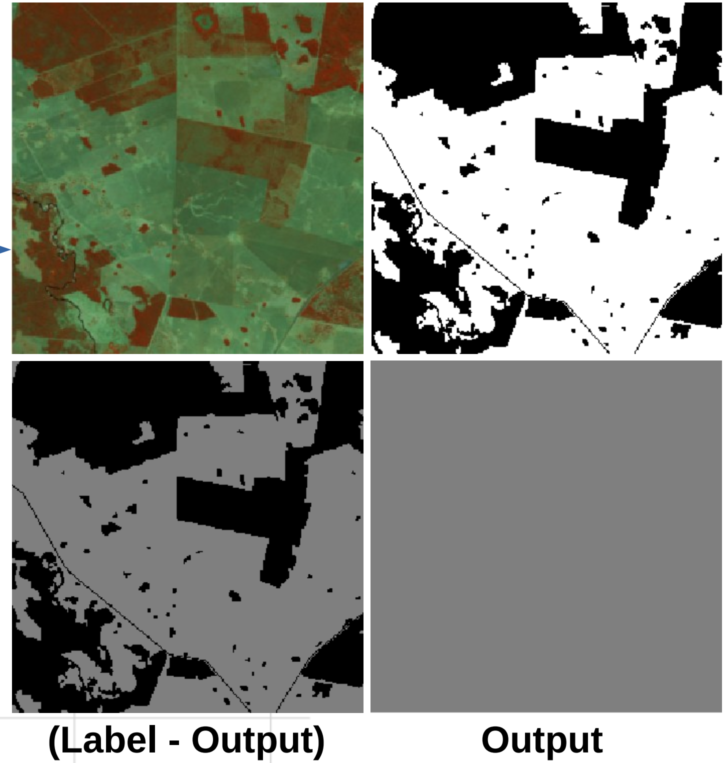
# Model calibration

(Tensorboard)

## Epoch 2



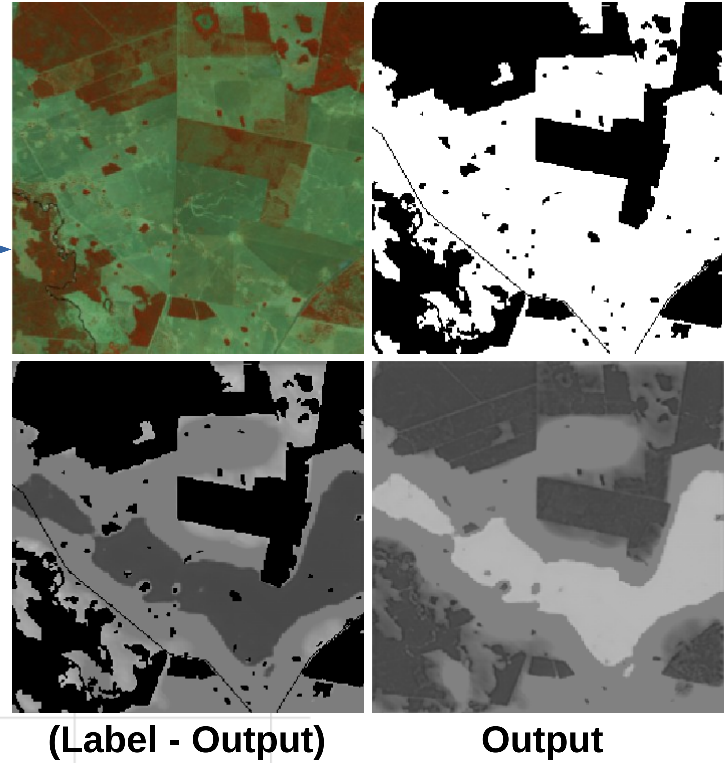



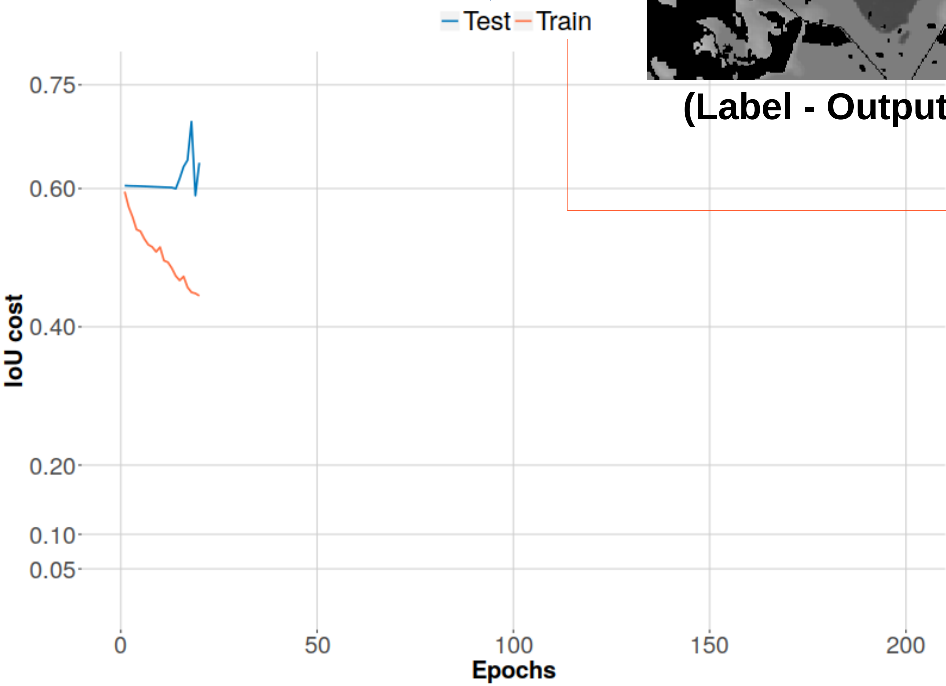



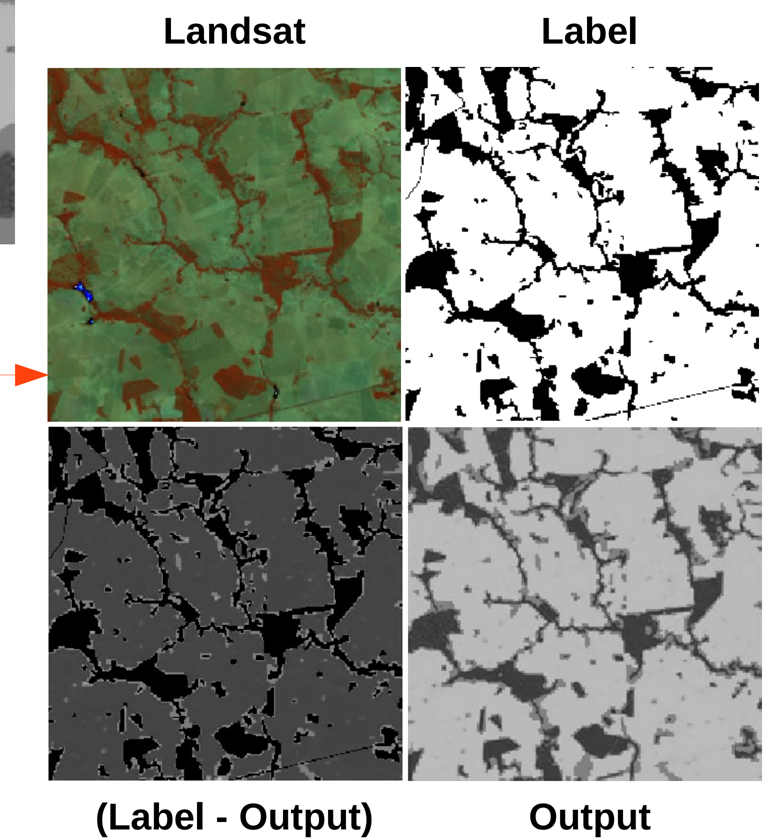
# Model calibration

(Tensorboard)

## Epoch 20



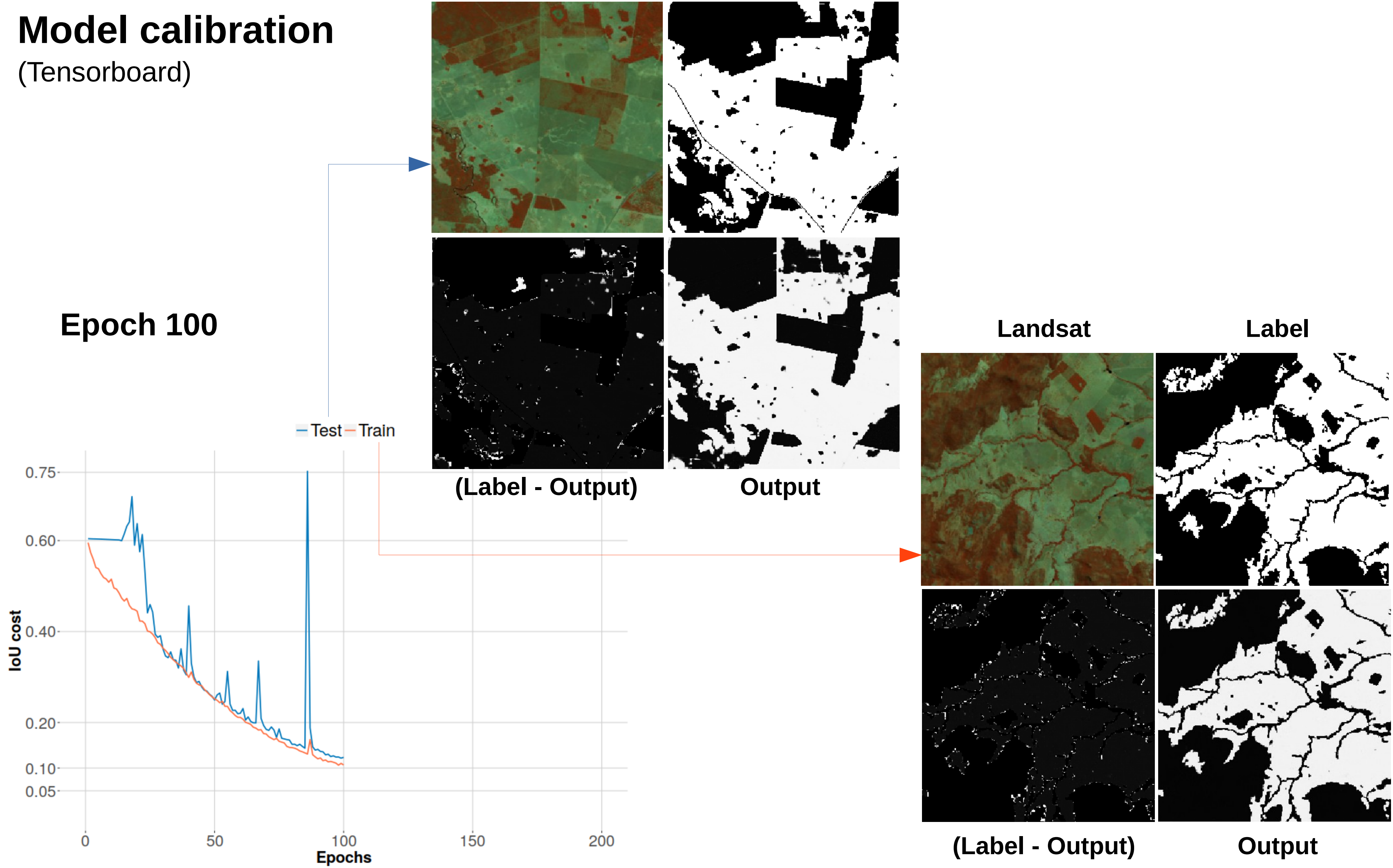



# Model calibration

(Tensorboard)

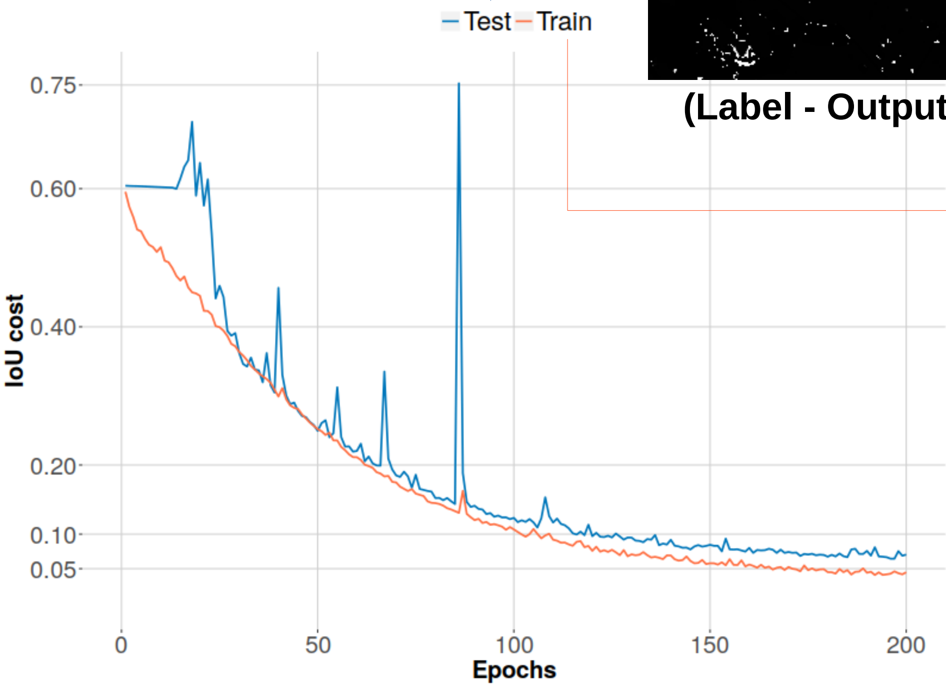
## Epoch 100

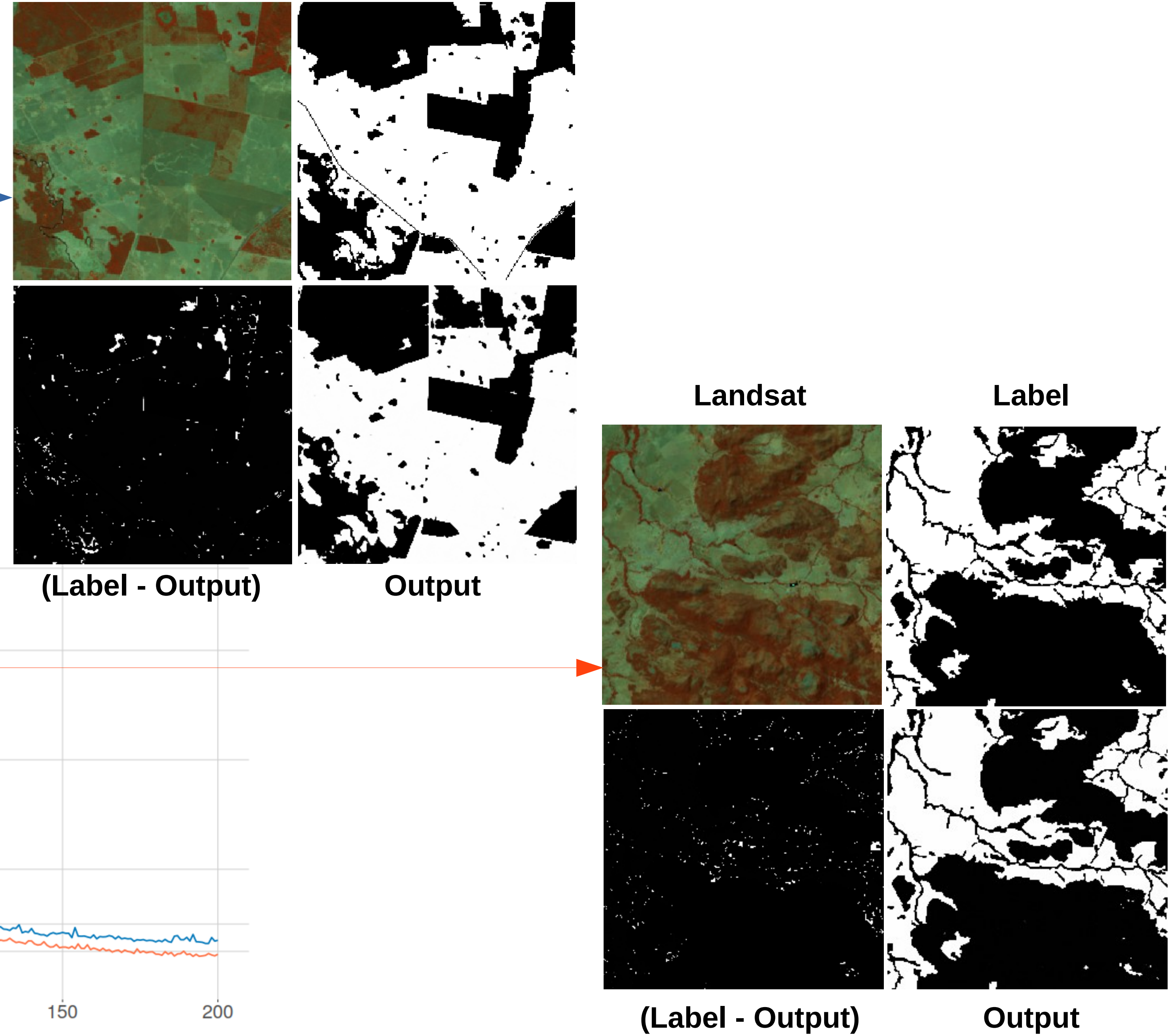


# Model calibration

(Tensorboard)

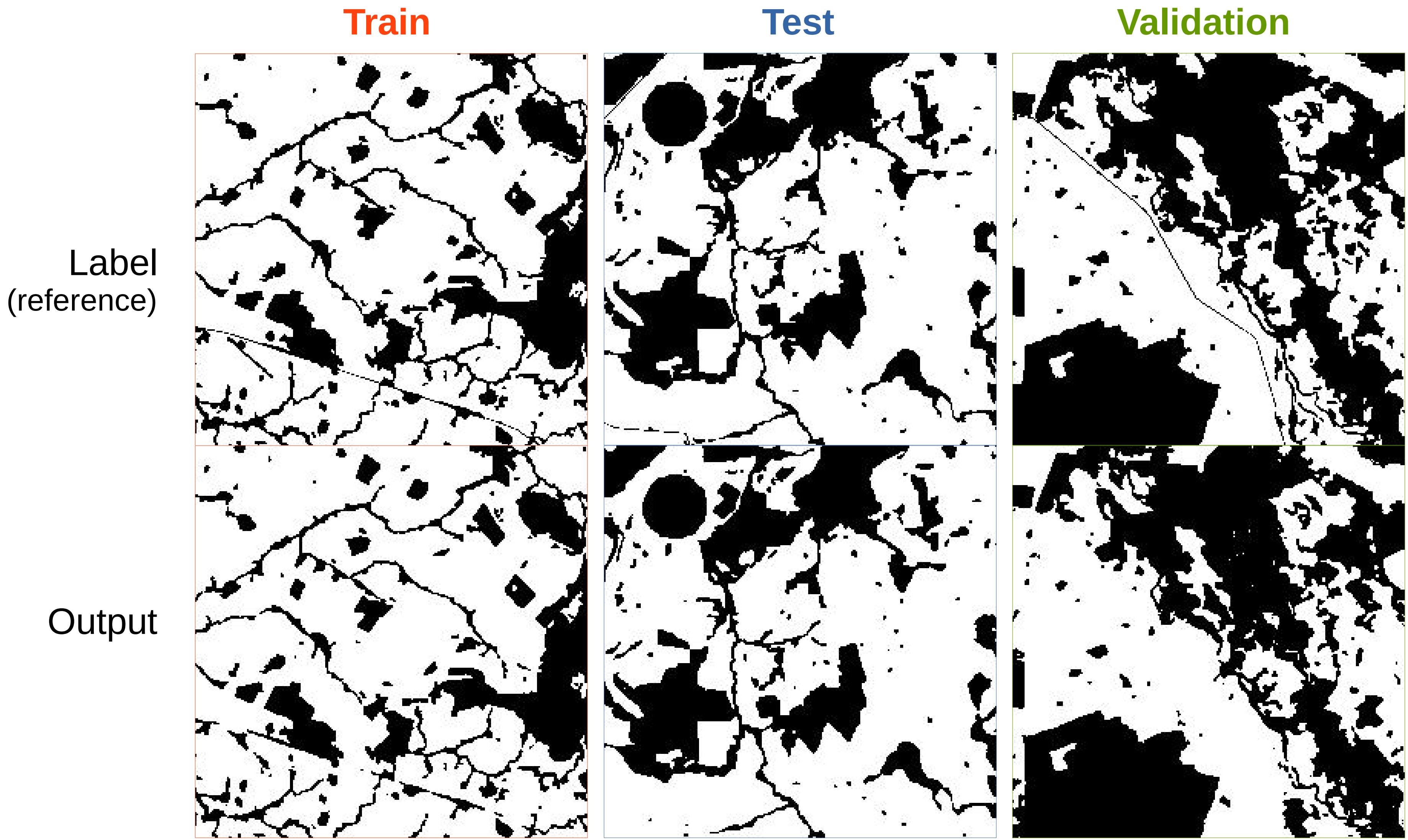
## Epoch 200



# DL4Landsat Model

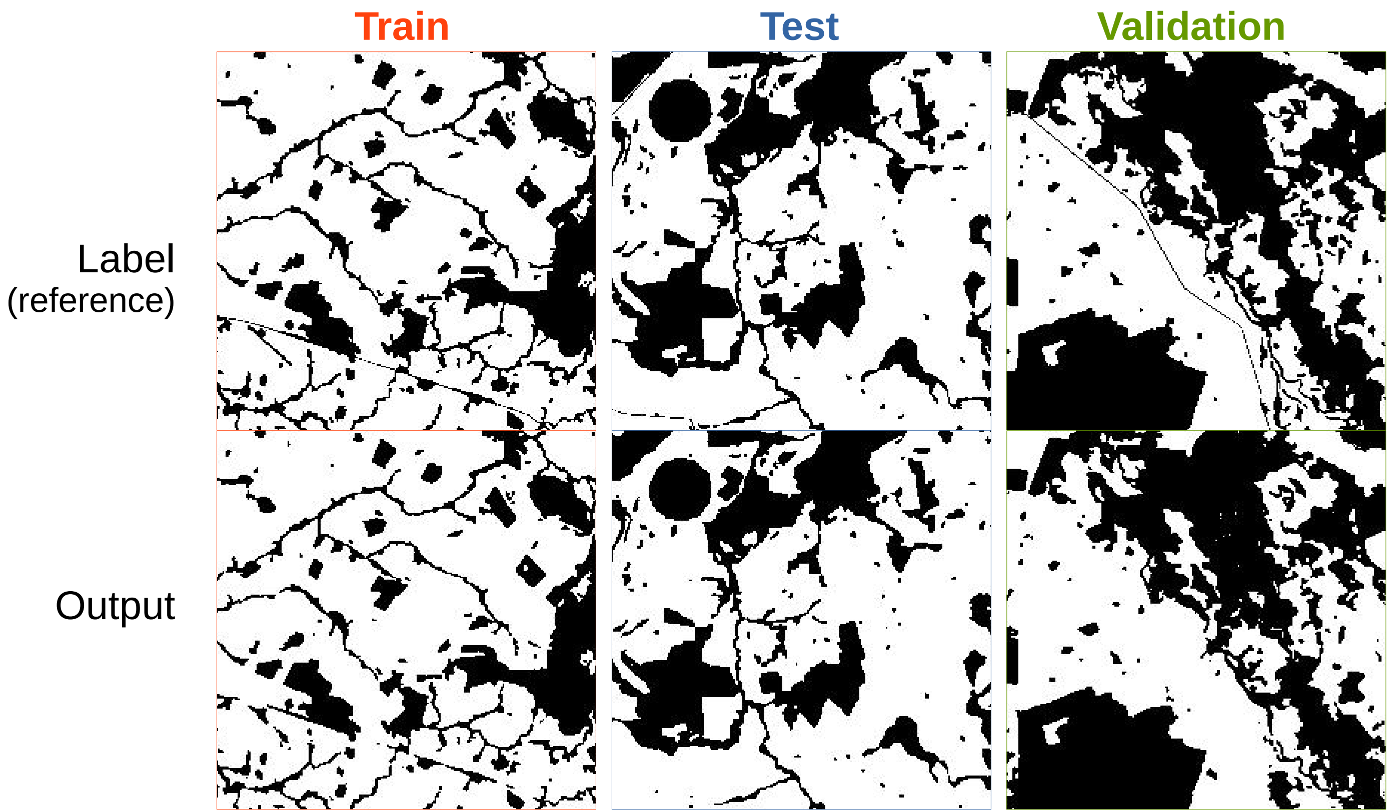
(Final evaluation)



# DL4Landsat Model

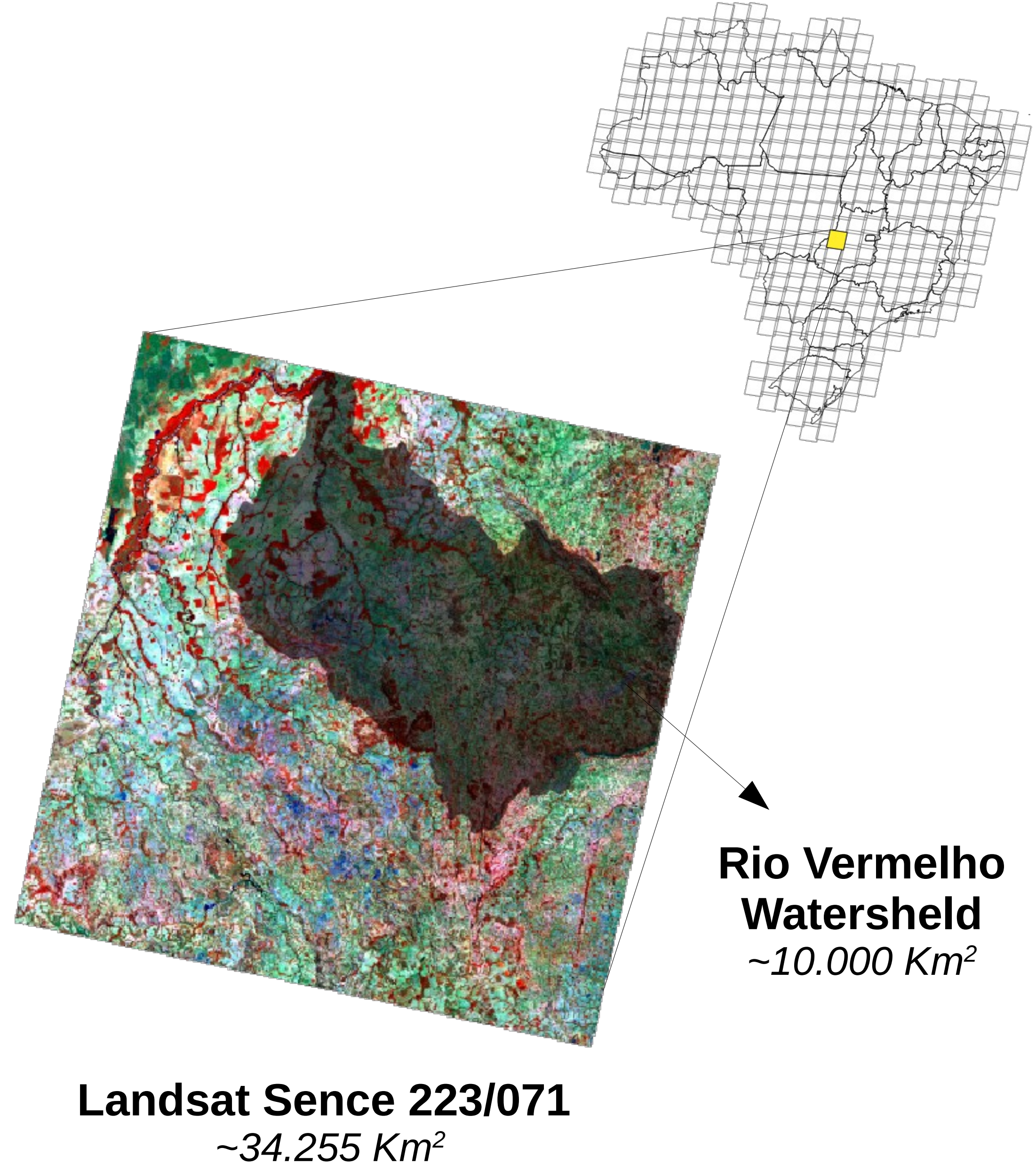
(Final accuracy)

| # | Accuracy | Error | |
|---|---|---|---|
| | | Pasture Omission | Pasture Comission |
| Train | 97.18% | 2.36% | 2.16% |
| Test | 96.05% | 3.43% | 3.02% |
| validation | 96.16% | 3.25% | 2.92% |

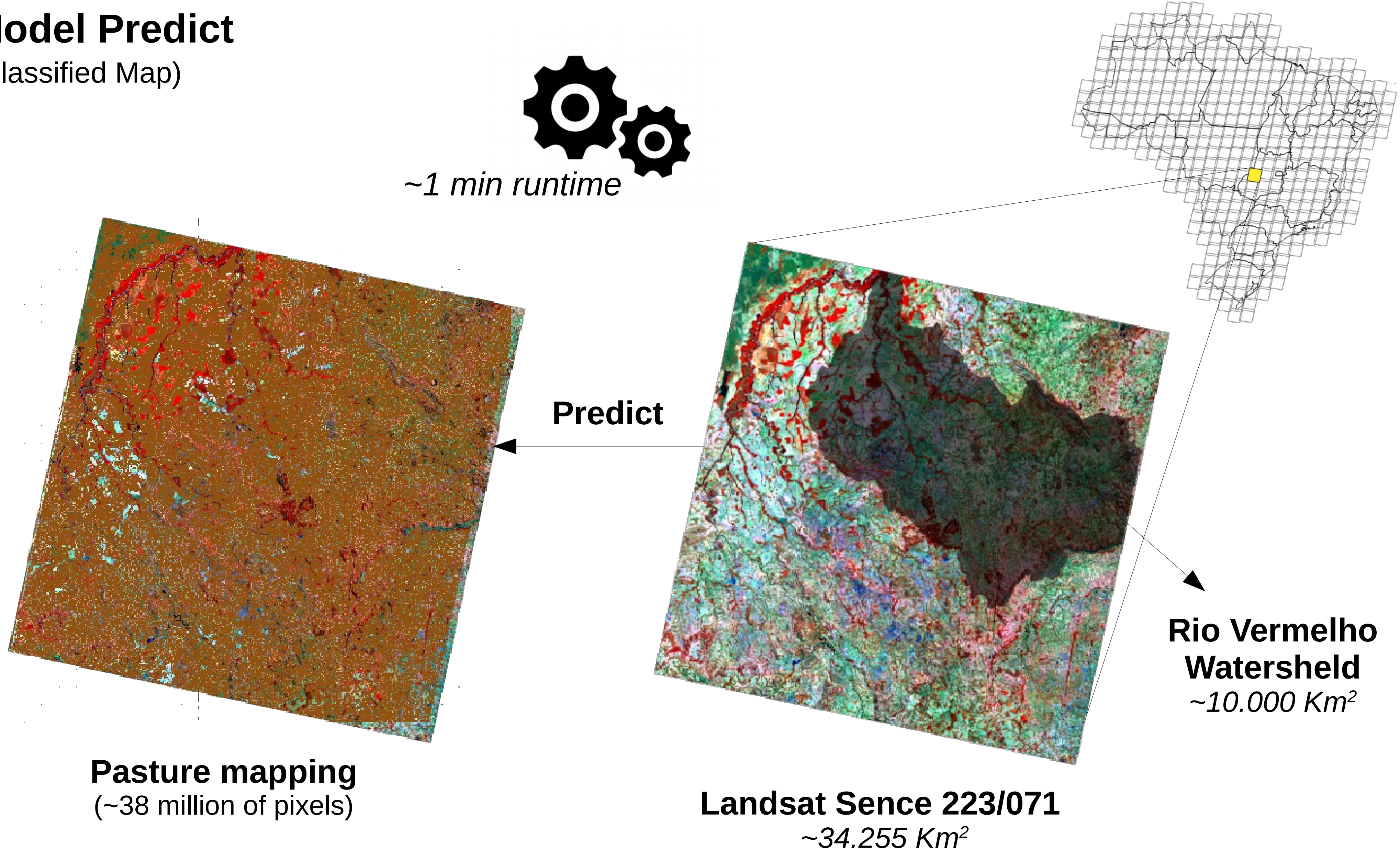


# Model Predict

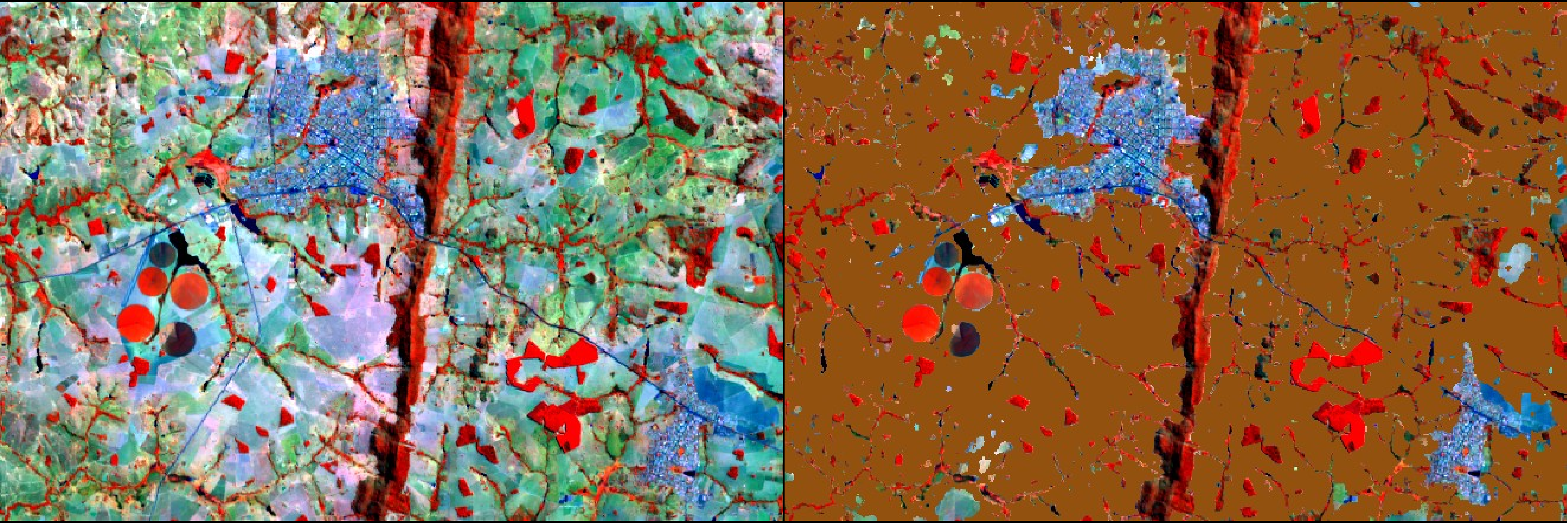
(Classified Map)



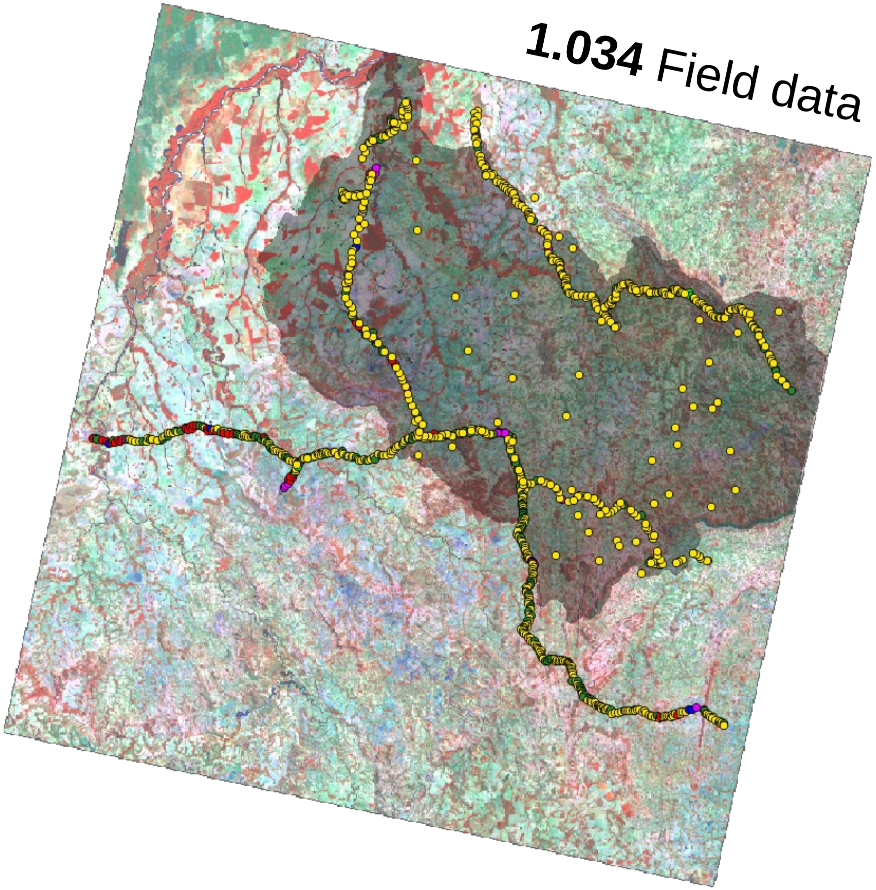
# Model Predict
(Classified Map)



# São Luís dos Montes Belos - GO



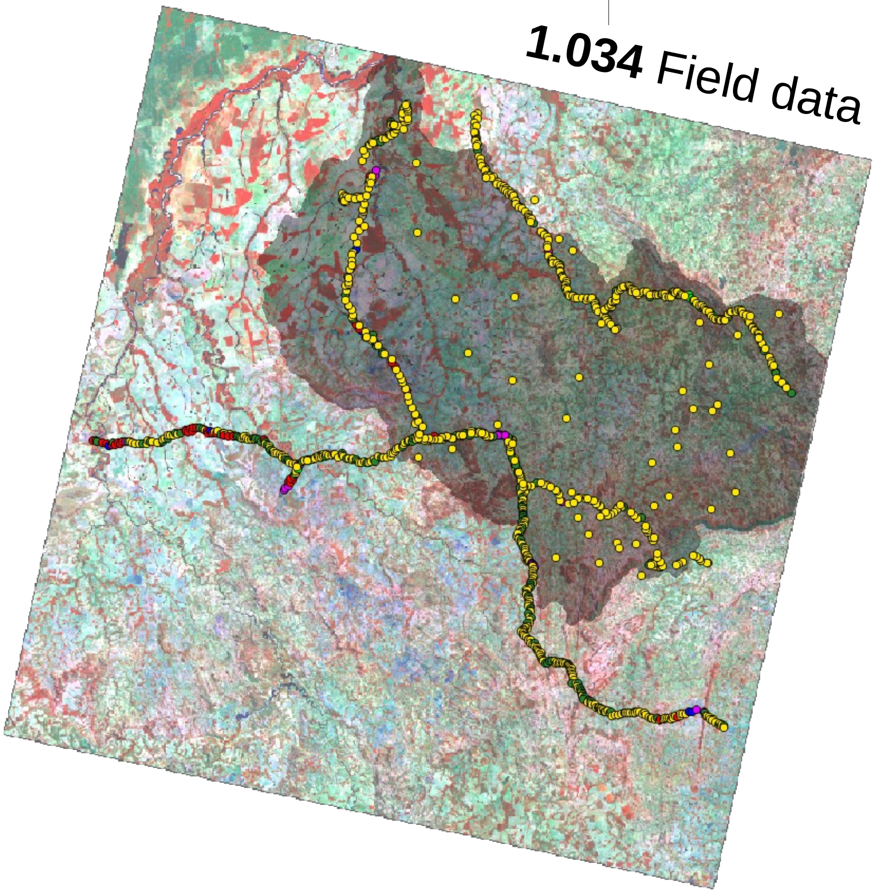
# Model Predict
(Classified Map)



# Model Predict

(Classified Map)

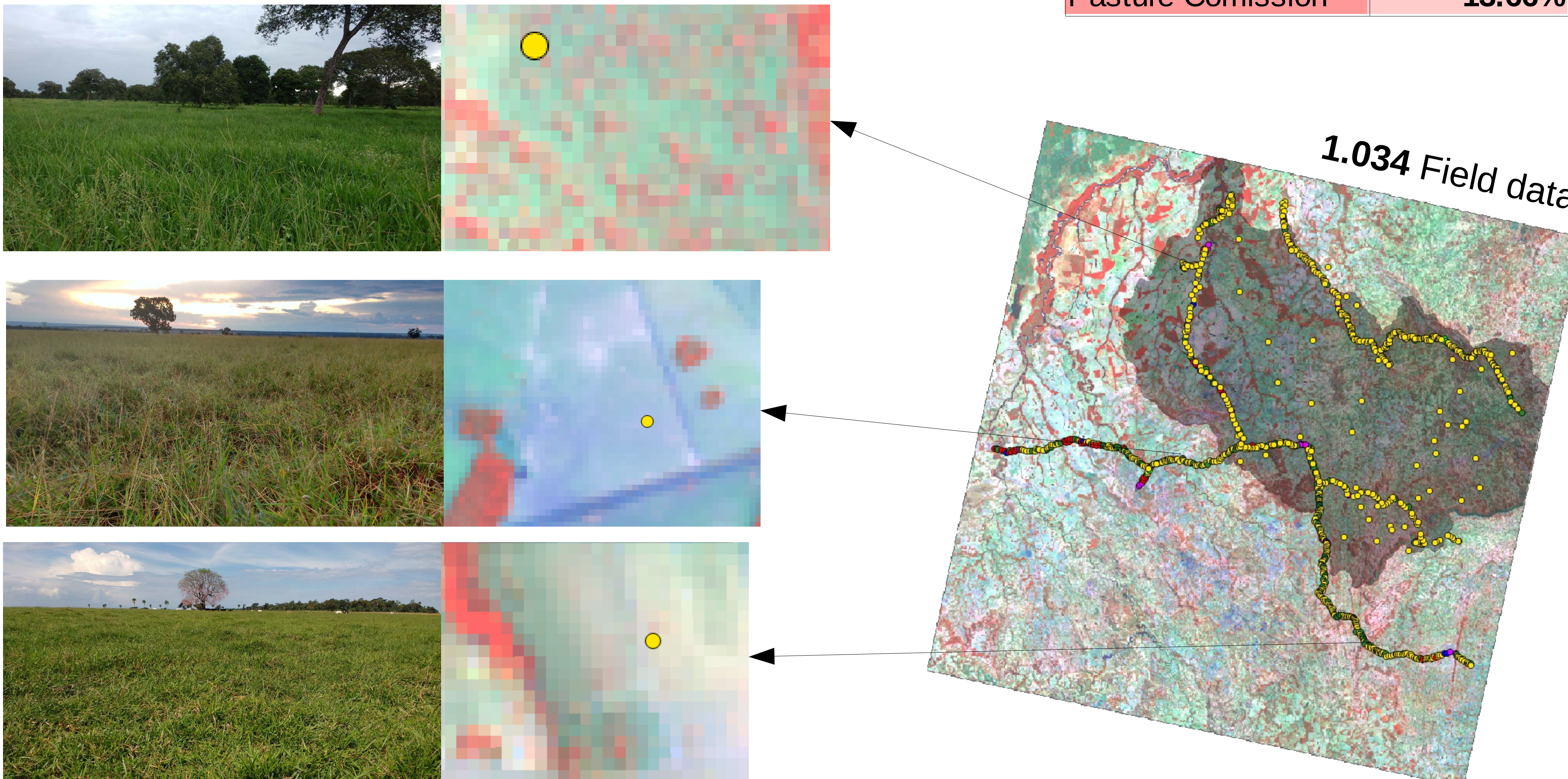
| | |
|---|---|
| Accurancy | **93.91%** |
| Pasture Omission | **4.30%** |
| Pasture Comission | **13.66%** |



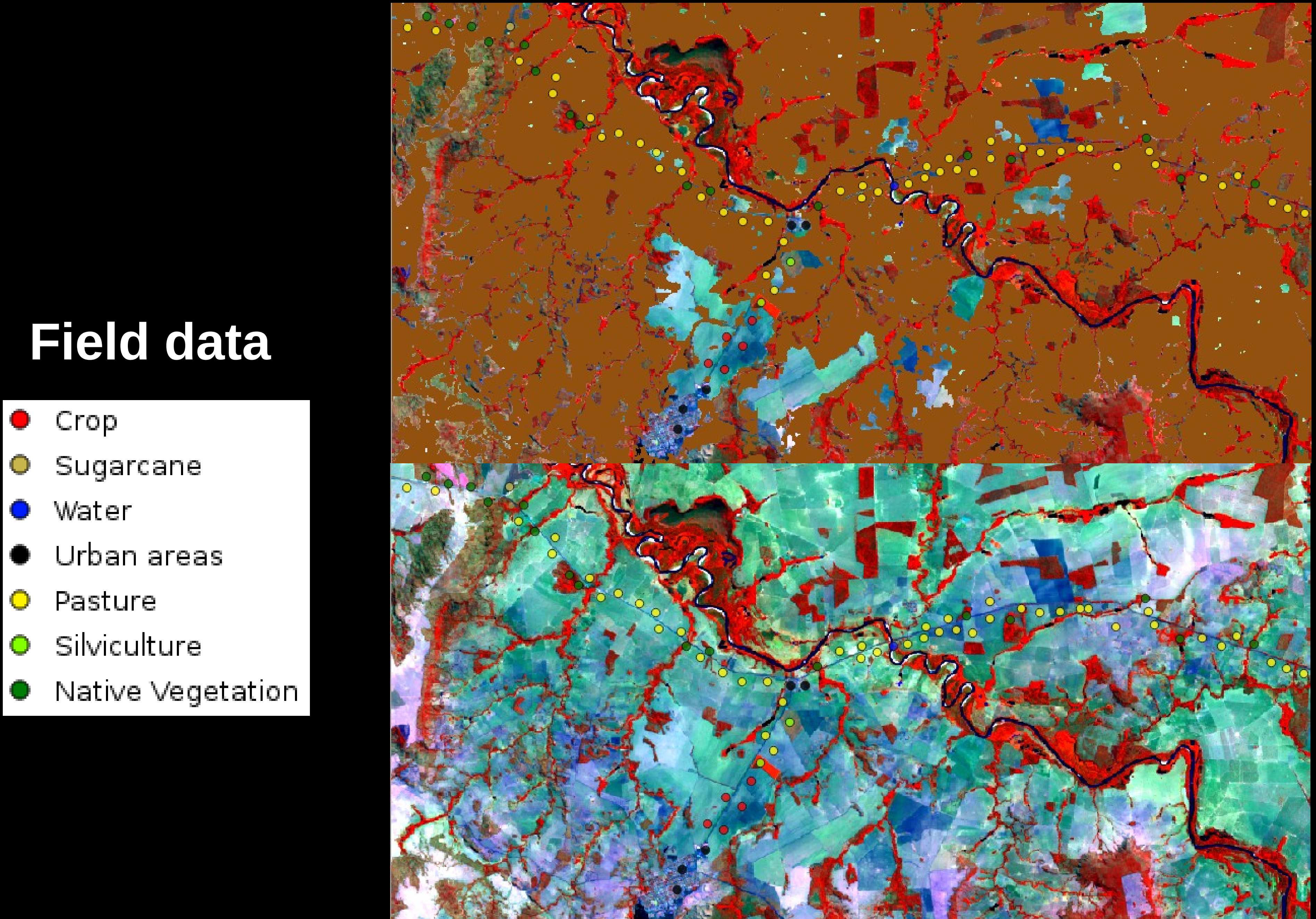
# Model Predict

(Classified Map)

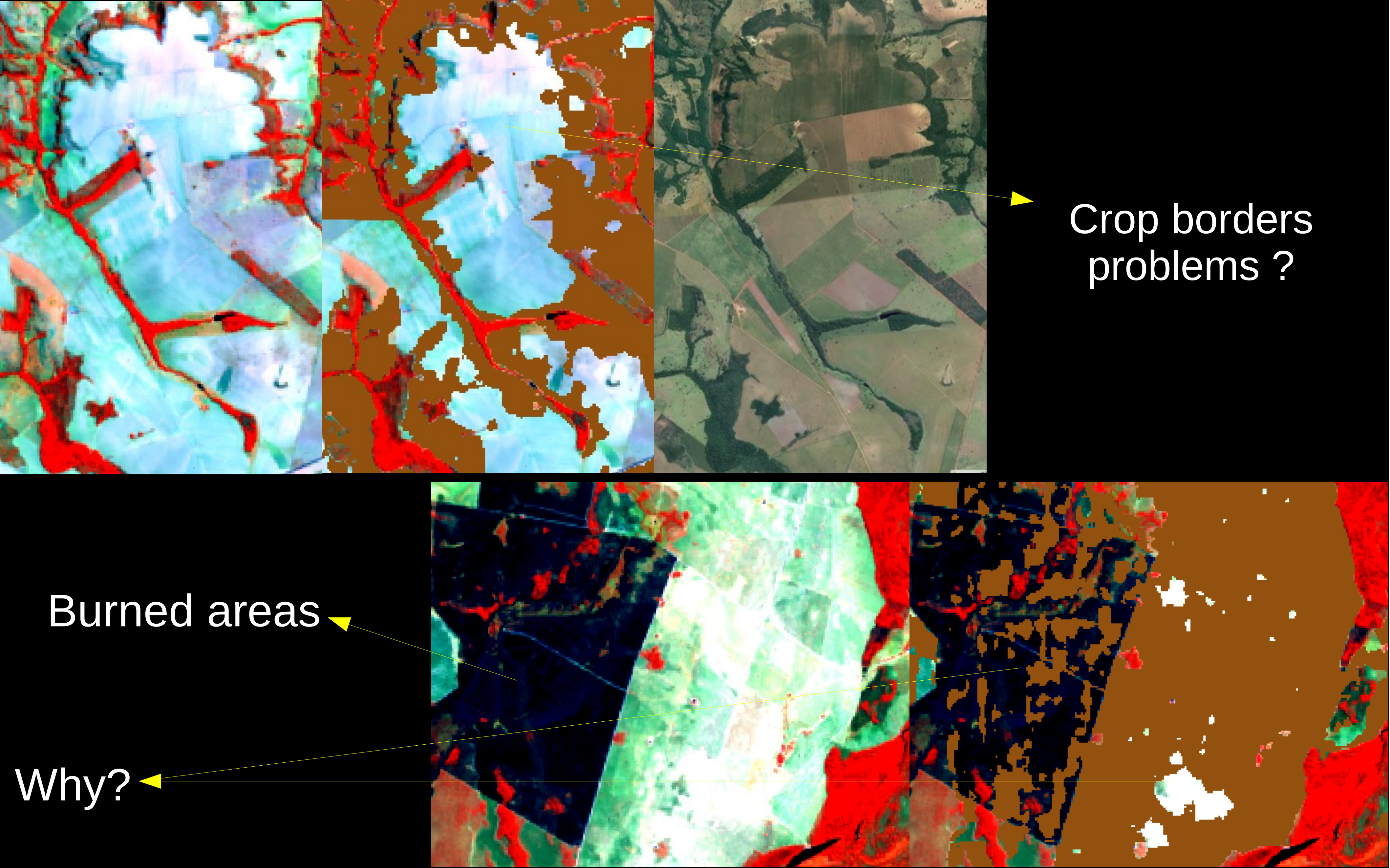
| | |
|---|---|
| Accurancy | **93.91%** |
| Pasture Omission | **4.30%** |
| Pasture Comission | **13.66%** |



# Field data



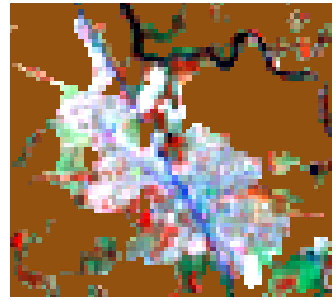
Crop
Sugarcane
Water
Urban areas
Pasture
Silviculture
Native Vegetation



Crop borders problems ?
Burned areas
Why?

## Model Predict

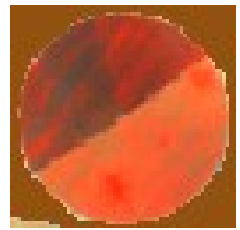
(Classified Map)



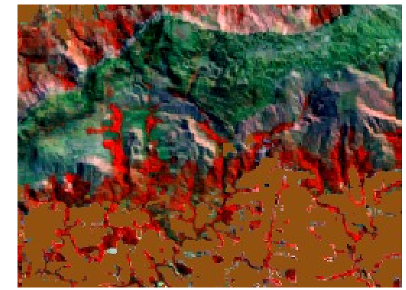
Urban Areas

*(Faina)*

Silviculture

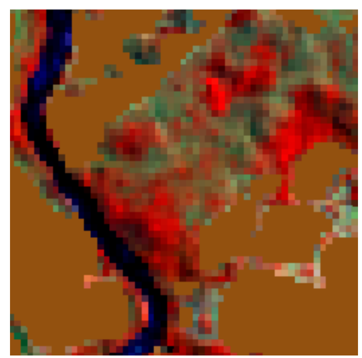


Pivots



Hillshade areas

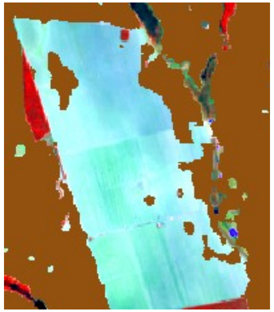
(Serra dourada)



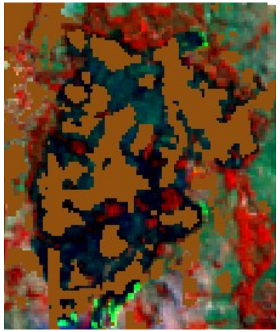
Native vegetation
and water

**Model Predict**
(Classified Map)

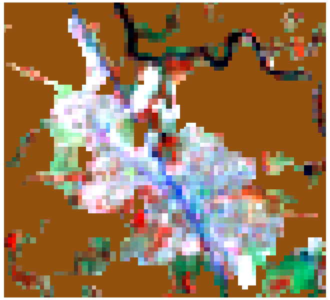
Rangelands



Crop areas

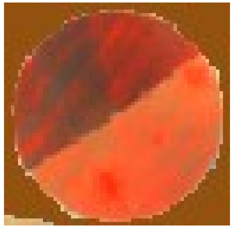


Burned
areas

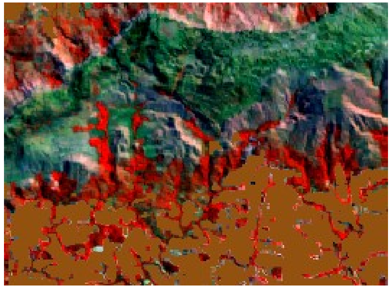


Urban Areas
*(Faina)*

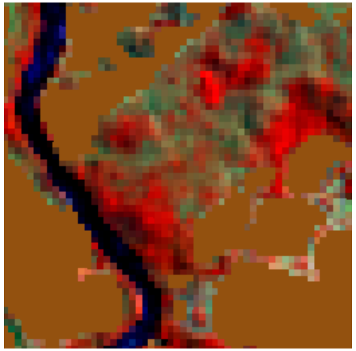
Silviculture



Pivots



Hillshade areas
(Serra dourada)



Native vegetation
and water

**Consider temporal domain:**

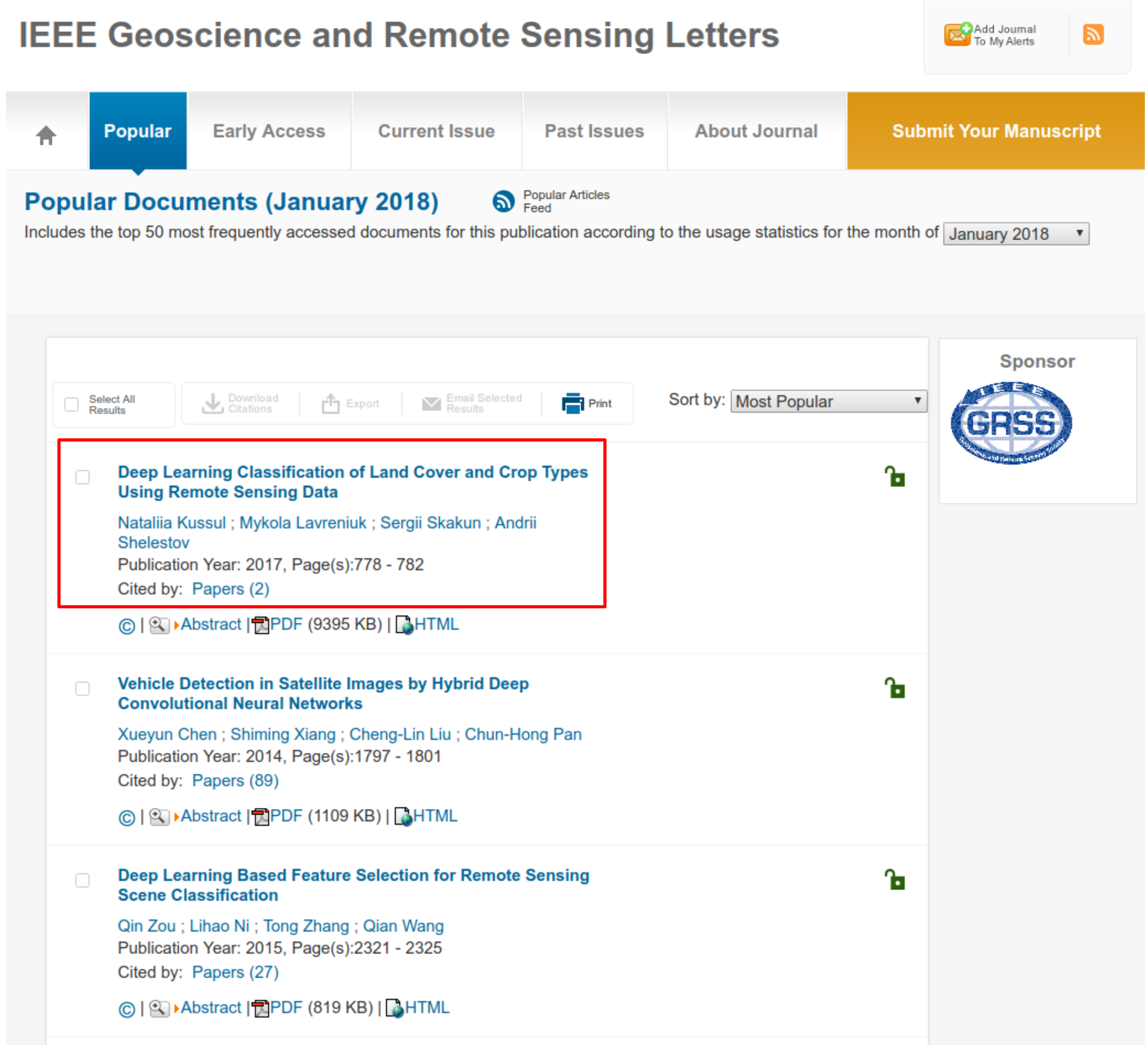
- Multiple images
- Cloud screening
- Time series analysis
- Encode-decoder (LSTM/GRU)

**Generalization over time and space:**

- Consider others regions and Landsat scenes
- Consider multiple years

**Compare with other ML approaches:**

- Random Forest
- SVM



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