

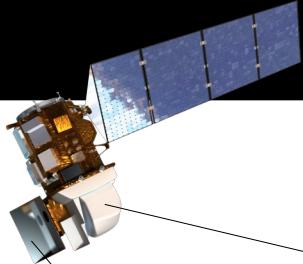


**Student:** Leandro Leal Parente

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

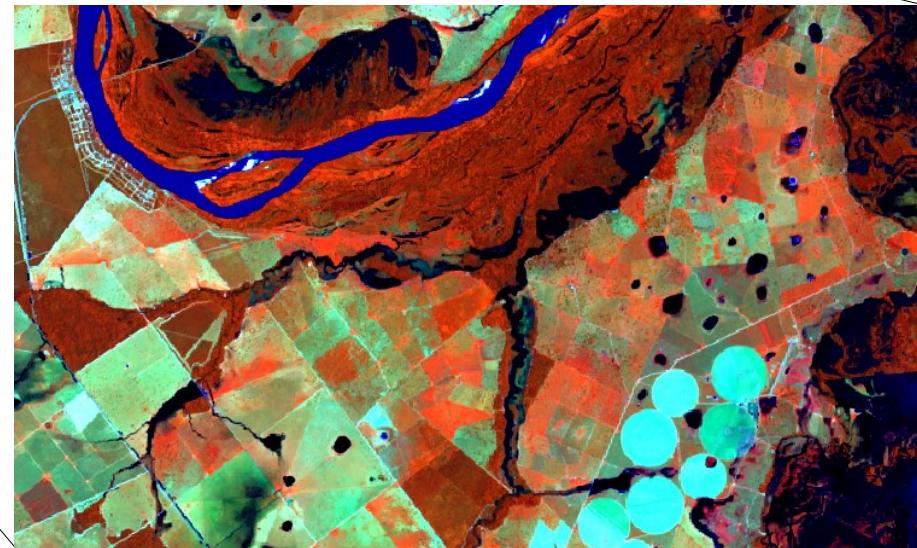
**Professor:** Anderson Soares



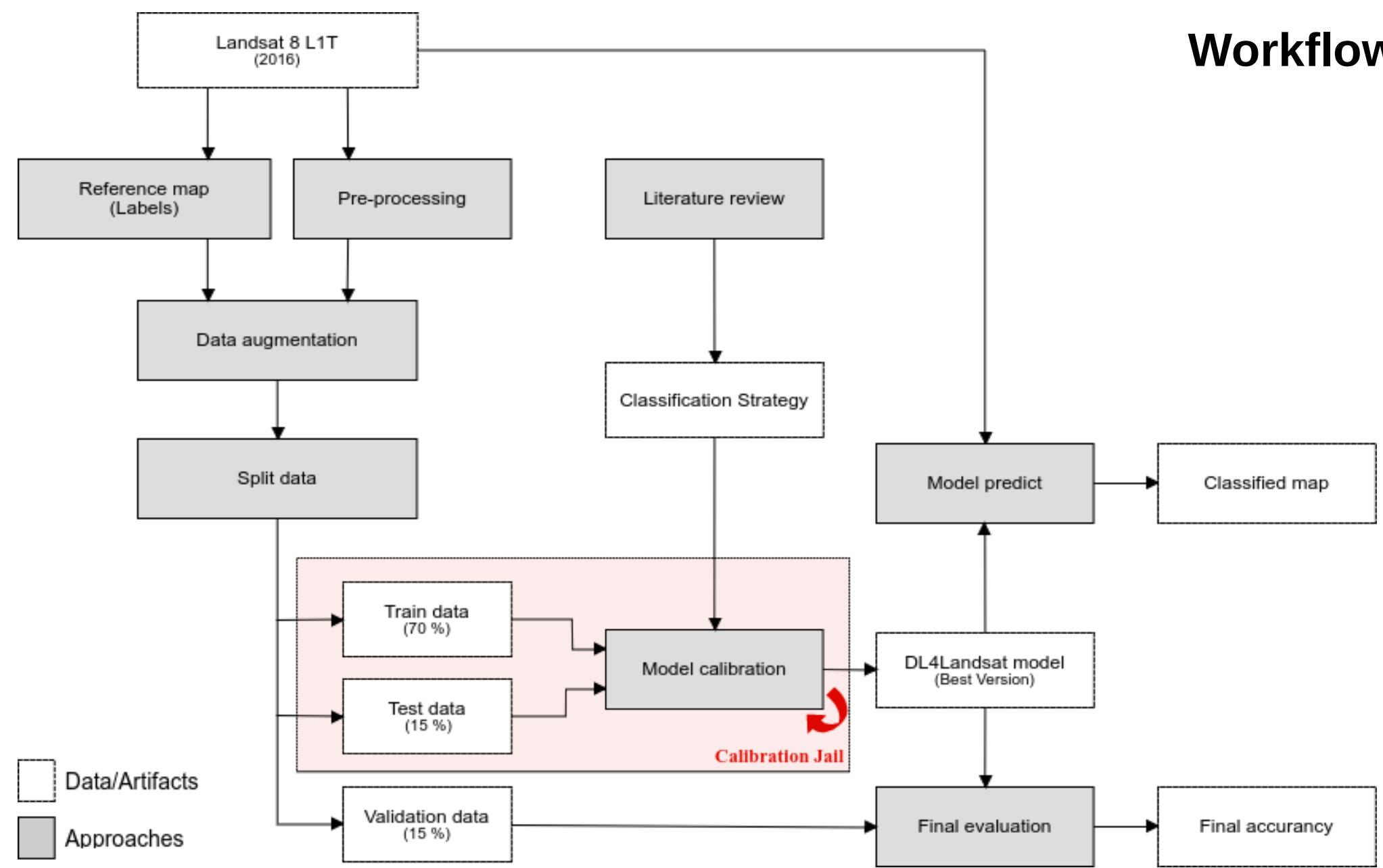


# Presentation Outline

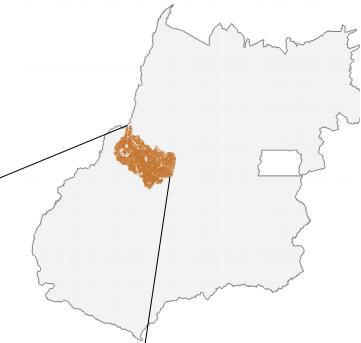
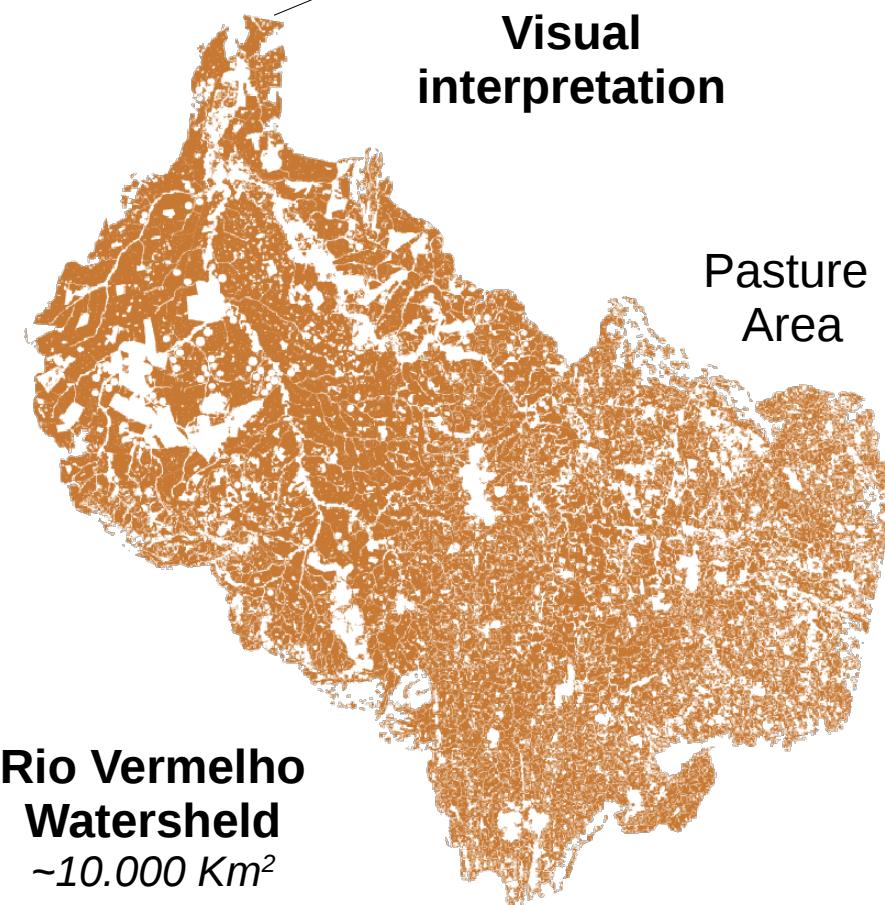
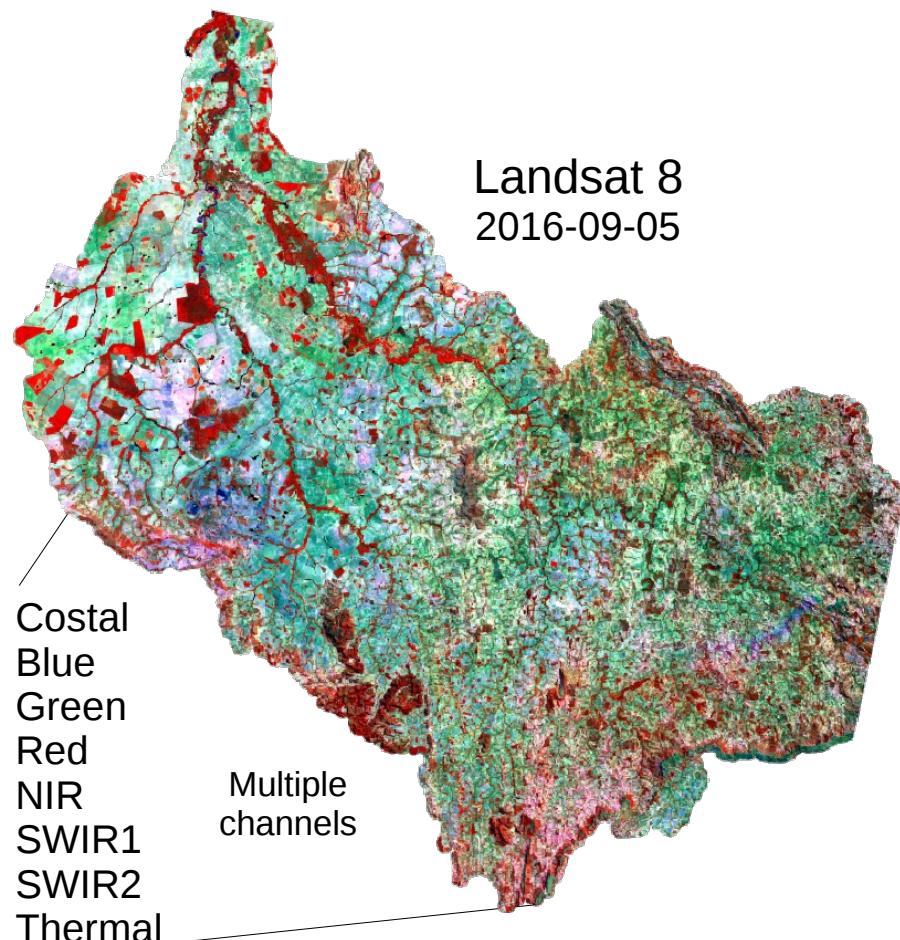
- **Workflow**
- **Results**
- **Next steps**



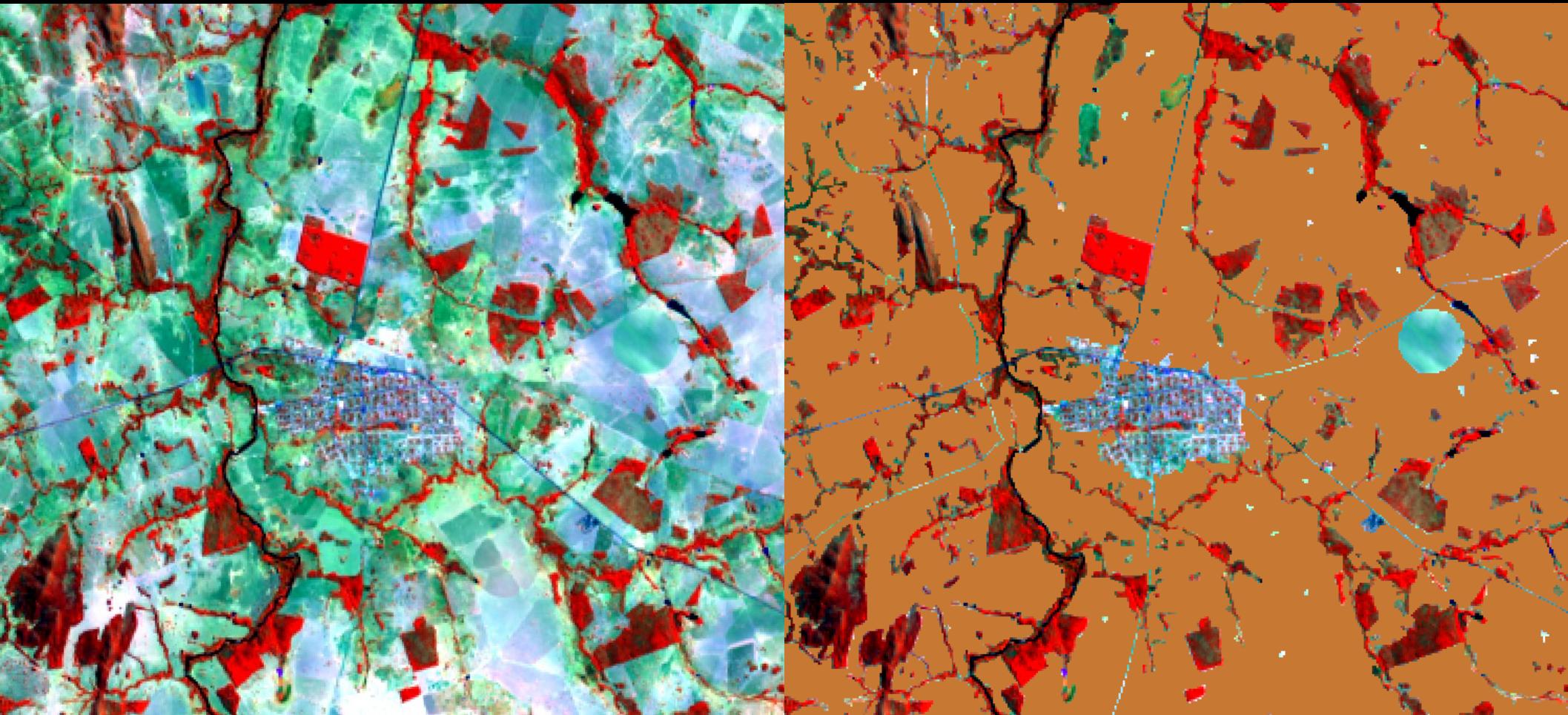
# Workflow



# Landsat Data and Reference Map

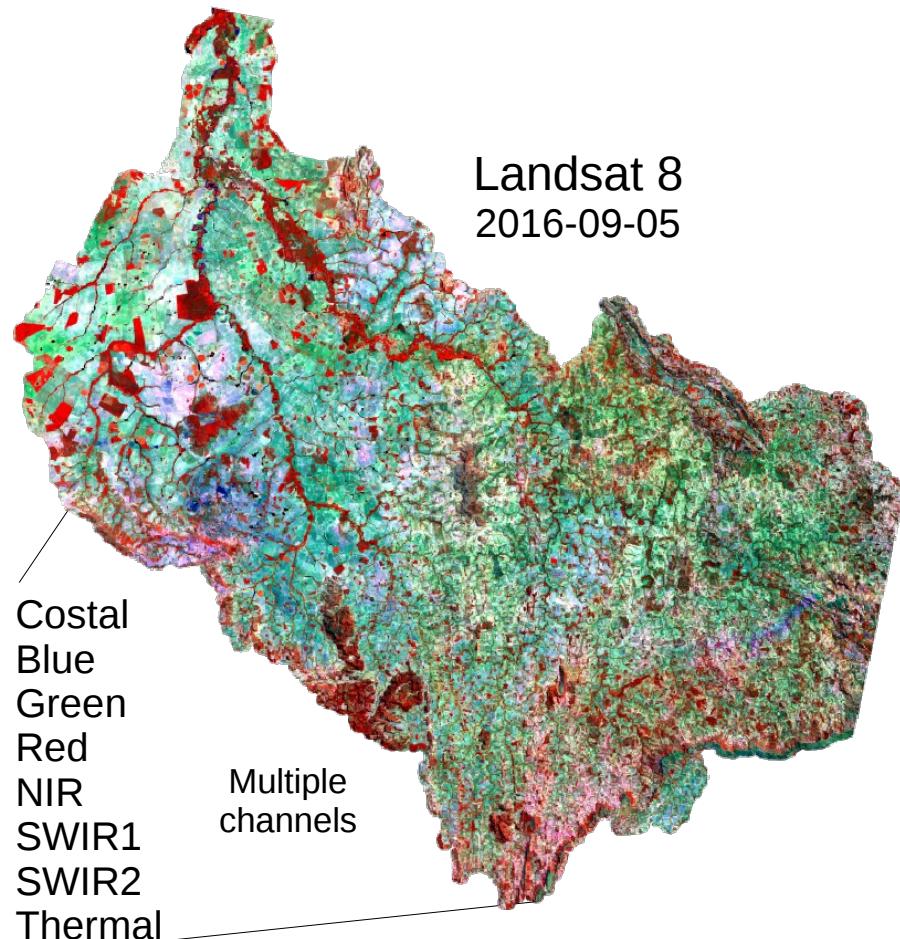


# Itapirapuã - GO

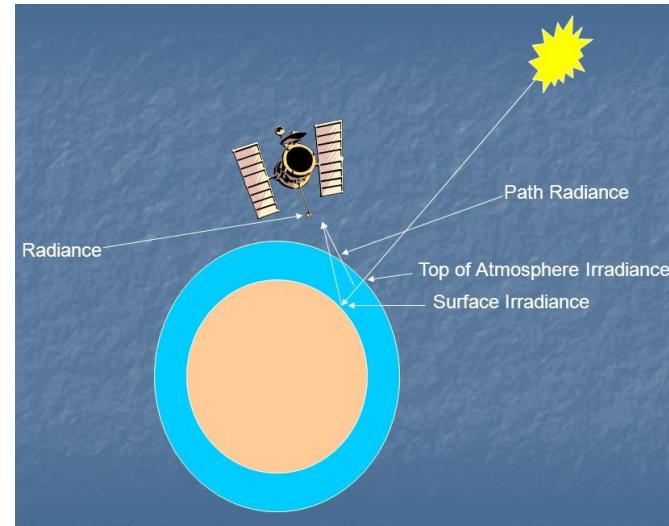


# Landsat Data

(Pre-processing)



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



## 2) Histogram equalization

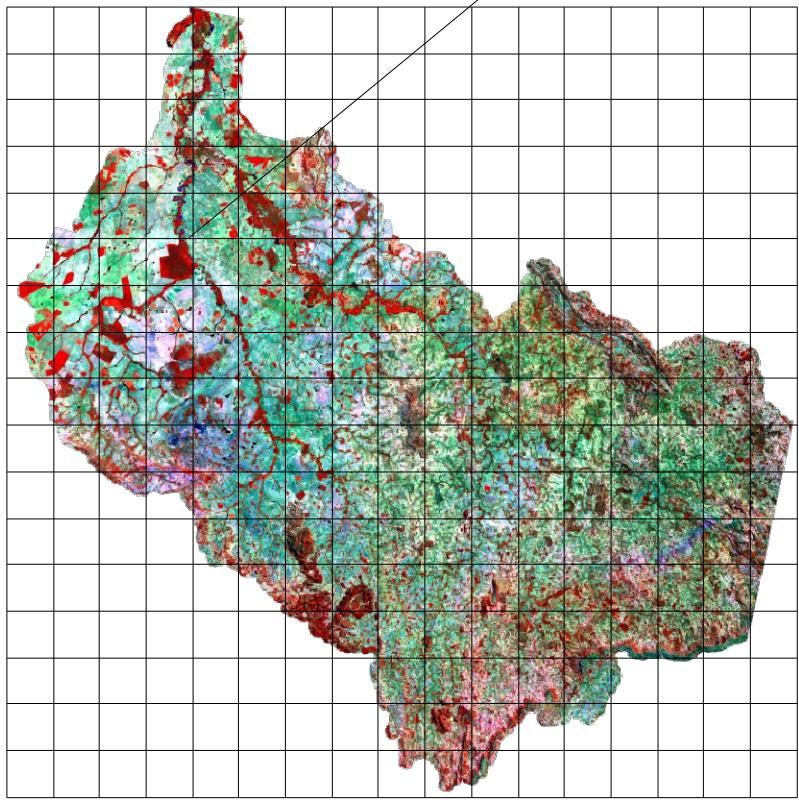
(between -1 and 1)

$$2 * \left( \frac{(X - X_{min})}{(X_{max} - X_{min})} \right) - 1$$

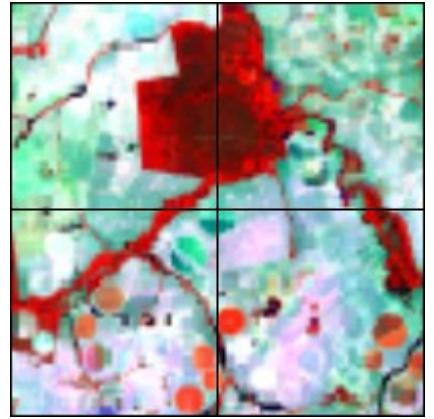
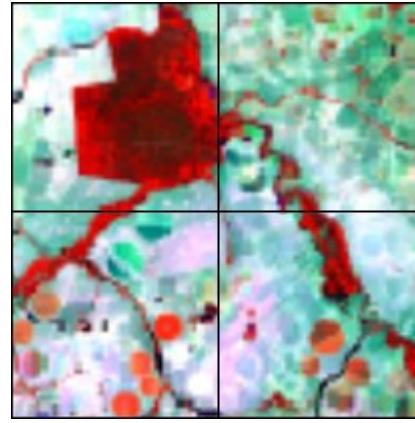
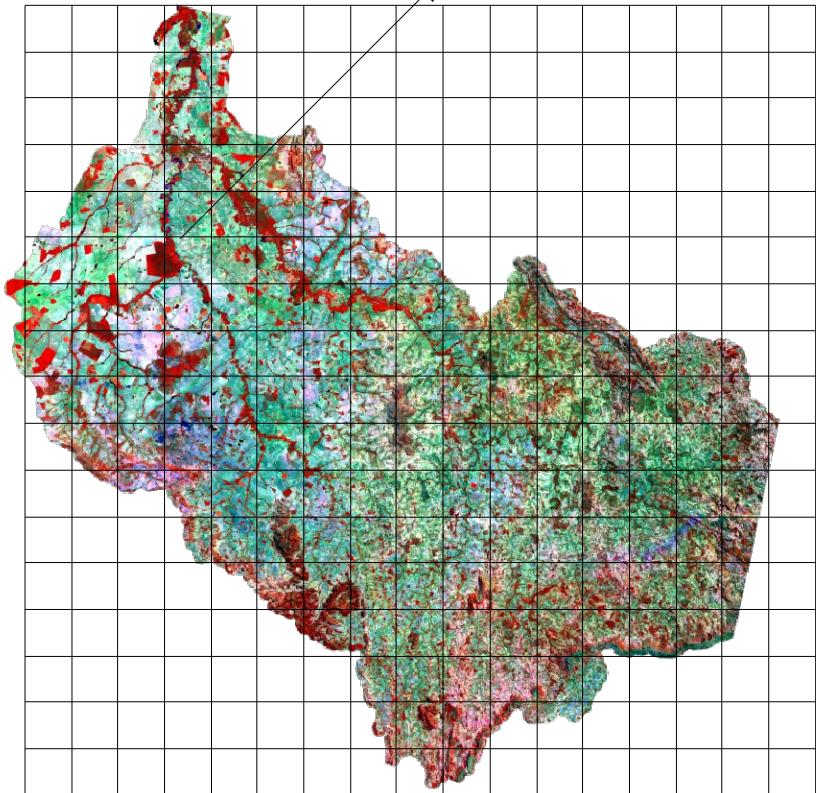
# Data Augmentation

(different starts)

*Start in 0,0*



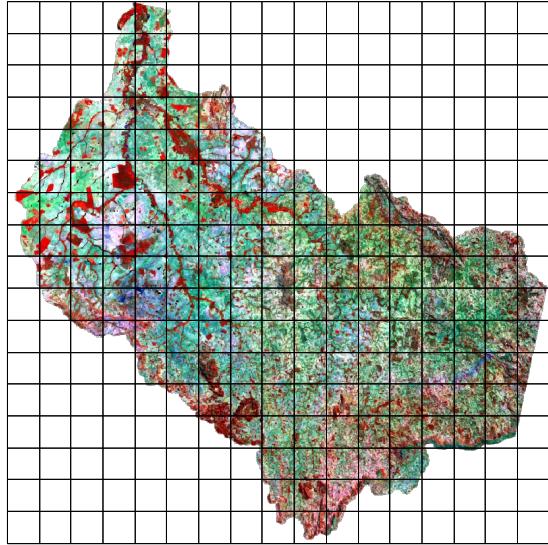
*Start in 0,128*



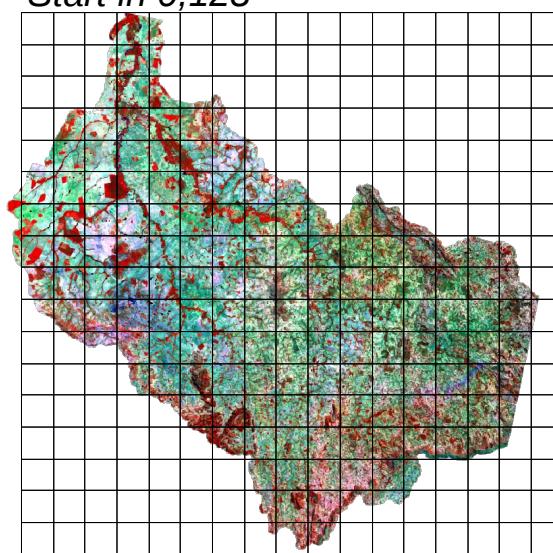
# Data Augmentation

(different starts)

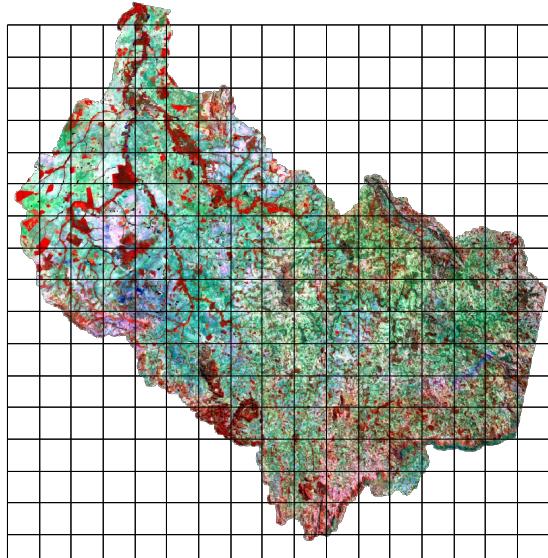
*Start in 0,0*



*Start in 0,128*

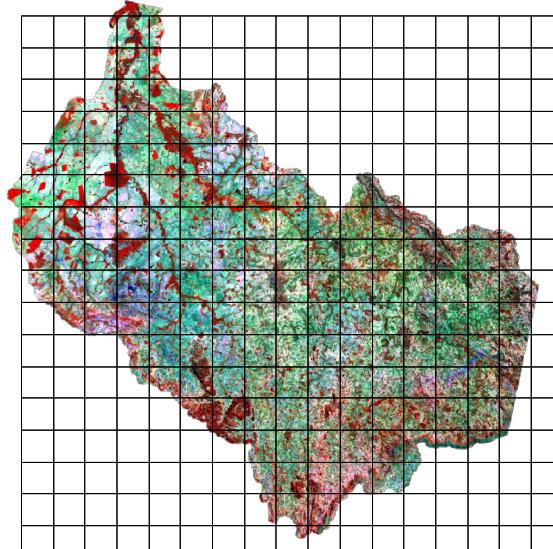


*Start in 128,0*



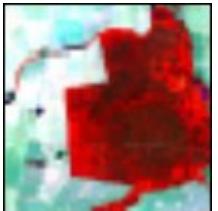
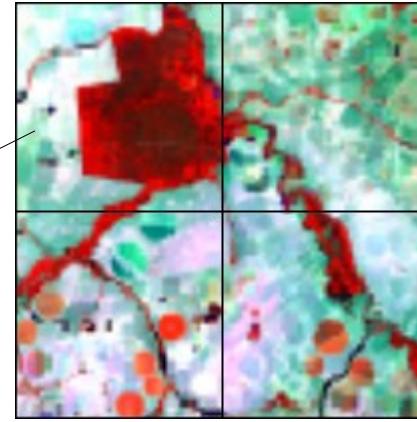
4 X

*Start in 128,128*

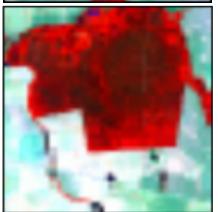


# Data Augmentation

(different positions)



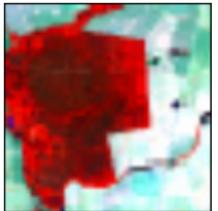
0°



90°



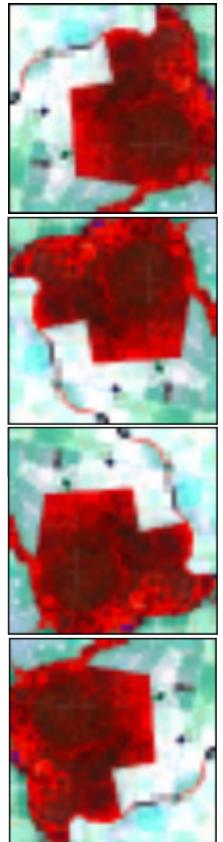
180°



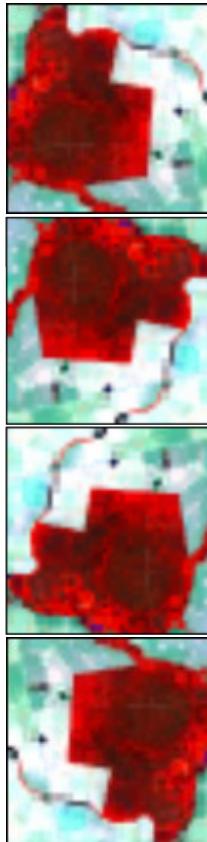
270°

# Data Augmentation

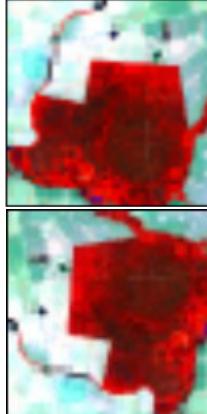
(different positions)



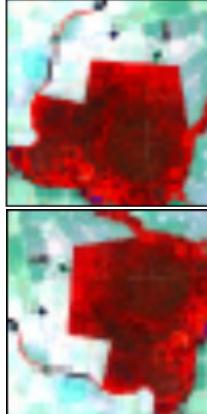
0°



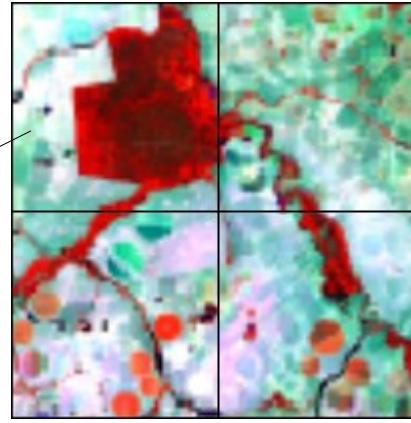
90°



180°

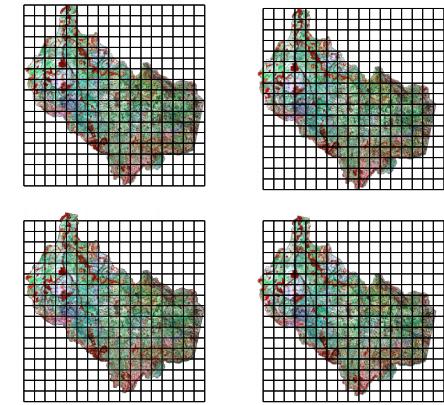
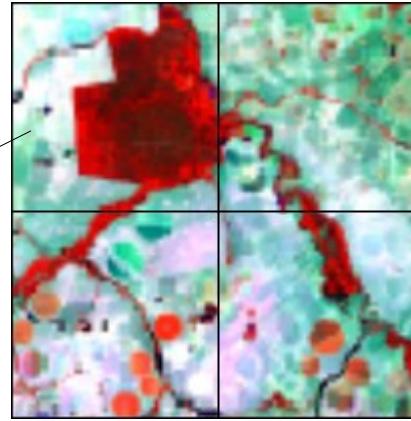
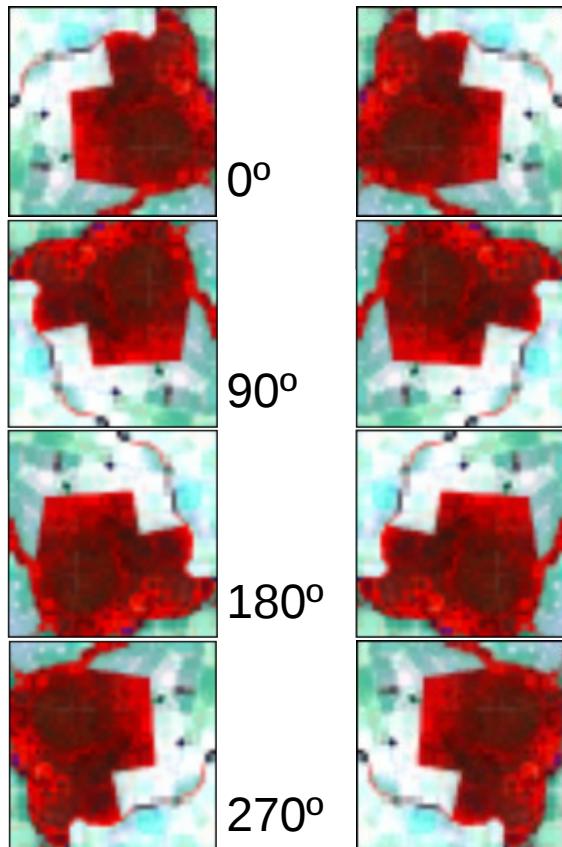


270°



# Data Augmentation

(different positions)



4 different starts  
X  
8 different positions  
X  
**N samples**

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

Natalia Kusul, Mykola Lavreniuk, Sergii Skakan, and Andrii Shelestov

**Abstract**—Deep learning (DL) is a powerful state-of-the-art technique for image processing including remote sensing (RS) images. In this letter, we propose a deep learning framework for targets land cover and crop type classification from multispectral and hyperspectral satellite imagery. The pillars of the architecture are unsupervised pretraining, feature extraction, and optical imagery segmentation and missing data restoration due to clouds and atmospheric artifacts. The proposed framework uses a supervised NN architecture; we use a traditional fully connected network (FCN) for semantic segmentation. The main idea of the approach in RS community random forest, and compare them with FCN. SAR-derived experiments are carried out using testing site in Ukraine for classification of crops in a heterogeneous environment. The experiments show that the proposed framework and LandSat-8 and Sentinel-1A RS satellites. The architecture with an encoder-decoder structure and skip connections is able to us to better discriminate certain summer crop types, in particular maize and soybeans, and yielding the target accuracies more than 90% for both crops. The proposed framework is able to classify sugar beet.

**Index Terms**—Agriculture, convolutional neural networks (CNNs), crop classification, deep learning (DL), joint learning, land cover classification, land use, LandSat-8 remote sensing (RS), Sentinel-1, TensorFlow, Ukraine.

The last several years and onward could be called the 2010s years of Big Data in remote sensing (RS). During the 2010–16 period, several optical and synthetic aperture radar (SAR) RS datasets have been collected at different spatial (10–30 m), in particular Sentinel-1A and Sentinel-2A within the European Copernicus program [1], [2], and LandSat-8 within the US Landsat program [3]. These datasets are freely available, and they are used for a wide range of operational and operational applications in the environment and agricultural domains taking advantage of high temporal resolution data sets and advances in the

multisource data fusion techniques [4], [5]. Land cover and crop type maps are one of the most essential inputs when dealing with environmental and agricultural monitoring tasks [6]. Multispectral and hyperspectral imagery are usually required in order to capture specific crop growth stages and thus being able to discriminate different crop types. For example, the use of optical imagery is not enough to be enough to discriminate summer crops in a complex and heterogeneous environment. For this, SAR-derived experiments adds an additional dimension for the joint experiments of particular crop types [6].

A deep learning (DL) may be the best choice for the classification of land cover mapping. A deep learning-based methods for land cover mapping was performed by Khattan et al. [11]. They found that support vector machine (SVM) was the most efficient for most applications with an overall accuracy (OA) of about 79%, while CNNs with approximately the same efficiency (74% of OA) was a neural network (NN)-based classifier. In that study, classification was done for a single RS image. Although SVM is too much time-consuming to be used for big data applications and large area classification problems. Another popular approach in the RS domain is the random forest (RF) classifier [12]. RF classifier is a multiple features should be engineered to feed the RF classifier for the efficient use.

In the past few years, the most popular and efficient approaches for multispectral and multitemporal land cover classification are ensemble-based [13]–[16] and deep learning-based [17]–[20]. In this letter, we propose a deep learning methodology for solving a wide range of tasks arising in image processing, including semantic segmentation and optical language processing [24]. The main idea is to simulate the human vision to deal with big data problem, use all the data available, and extract the most important information from it. Plenty of models, frameworks and benchmark databases of reference maps are available for image classification domain. Over past years, many studies have been performed on the classification of RS images [25], [26]. DL, proved to be efficient for processing both optical hyperspectral and multitemporal images and RS images, in including different crop cover types such as maize, soybean, barley, rapeseed [17], [27], [28]. In terms of particular DL architectures, convolutional NN (CNN), deep autoencoder, deep belief networks, recurrent NNs, and generative adversarial network model have already been explored for RS tasks [17], [28]–[31]. It should be noted that our studies with DL for RS utilize optical RS image for classification purposes, e.g., land

multisource data fusion and semantic segmentation.

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A. Shelestov is with the Department of Information Sciences, National Technical University of Ukraine "Kyiv Polytechnic Institute," 03056 Kyiv, Ukraine (e-mail: andrii.shelestov@gmail.com).

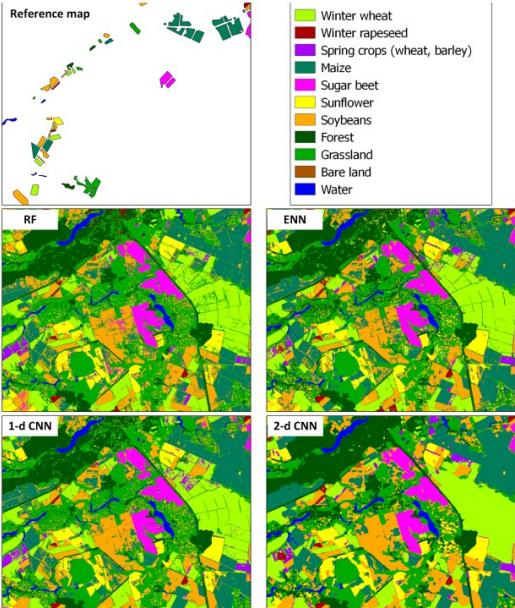
C. Li is with the Institute of Geomatics, China University of Geosciences.

Y. Zhang is with the Institute of Geomatics, China University of Geosciences.

Digital Object Identifier 10.1109/LGRS.2017.2681113

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# 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

**Abstract**—The deep convolutional neural network (CNN) is of great interest recently. It can provide excellent performance in hyperspectral image classification. However, the training samples is sufficiently large. In this paper, a novel pixel-pair method is proposed to significantly increase such a number, making the training process more efficient. Convolutional neural network (CNN) is used to extract features from optical imagery segmentation and missing data restoration due to clouds and atmospheric artifacts. The proposed framework uses a supervised NN architecture; we use a traditional fully connected network (FCN) for semantic segmentation.

Recently, deep learning methods have drawn increasing attention in remote sensing image analysis [16], [17]. For the testing pixel, pixel-pairs, constructed by combining the center pixel with its neighbors, are generated only by the trained CNN, and the final label is determined by a voting mechanism. The pixel-pair features are expected to have more discriminative power. Experimental results based on several hyperspectral image data sets show that the proposed framework can obtain better classification performance than the conventional deep learning baseline.

**Index Terms**—Convolutional neural network (CNN), deep learning, feature extraction, hyperspectral imagery, pattern classification.

## I. INTRODUCTION

HYPERSPECTRAL imagery consists of hundreds of narrow contiguous wavelength bands capturing a wealth of spectral information. By using the spectral information, classification using hyperspectral data has been developed for a variety of applications [1]–[6], such as land use/land cover mapping, mineral exploration, water pollution detection, etc.

A deep learning [7], [8] can be viewed as the simplest classifier that employs the Euclidean distance to measure the similarity between a testing sample and available training samples. Support vector machine (SVM) [9], [10] is an often-used classifier for hyperspectral classification tasks, especially for small training sample sizes. SVM seeks to separate classes by learning an optimal decision hyperplane that separates the two classes in a kernel-induced high-dimensional feature space. In [11], oneagainst-with decision fusion enables the use of binary

Masering map. June 11, 2016, revised August 12, 2016, accepted August 12, 2017. This work was supported by the National Natural Science Foundation of China under Grant 41671363, the Fundamental Research Fund for the Central Universities under Grant BUC-XJ-2016-05, and the National Education Commission of Education and High-Quality and World-Class Universities (PV201619).

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Q. Du is with the Department of Electrical and Computer Engineering, Shanghai Jiao Tong University, Shanghai 200030, China (e-mail: duq@sjtu.edu.cn).

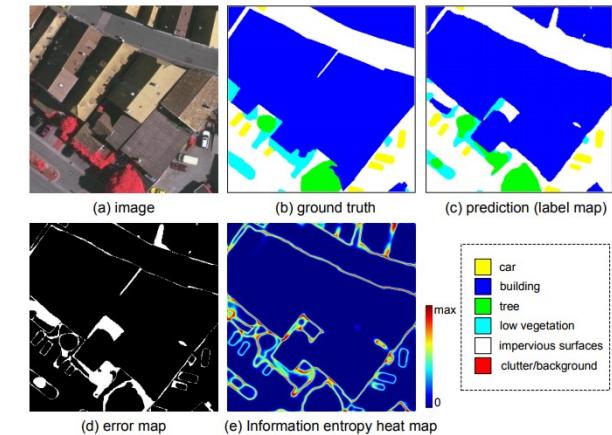
C. Li is with the Institute of Geomatics, China University of Geosciences.

Digital Object Identifier 10.1109/LGRS.2016.266315

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Corn-mintill	Corn-mintill	Grass-pasture
Grass-trees	Hay-windrowed	Grass-notill
Soybean-mintill	Soybean-clean	Woods



remote sensing

MDPI

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

Hongchen Wang<sup>1,2</sup>, Ying Wang<sup>1</sup>, Qian Zhang<sup>1</sup>, Shiming Xiang<sup>3,4\*</sup> and Chunhang Pan<sup>1</sup>

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<sup>2</sup> University of Chinese Academy of Sciences, Beijing 100049, China; zhengqianzhang@163.com

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\* Correspondence: xmsx@nlpr.ac.cn; Tel.: +86-136-7118-9070

Academic Editors: H. Wang, N. Yousef, C. Lopez-Martinez, X. Li and P. Thenskabani Received: 2 April 2017; Accepted: 1 May 2017; Published: 5 May 2017

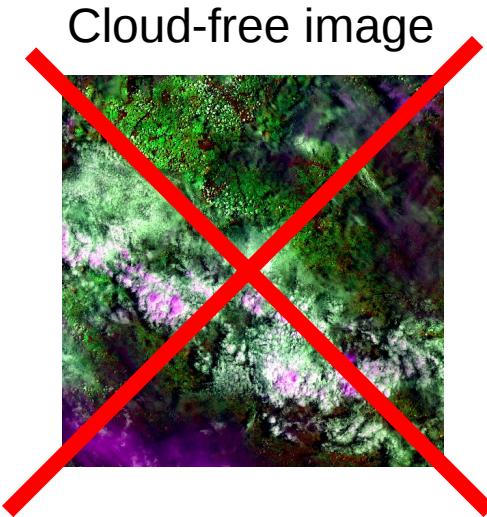
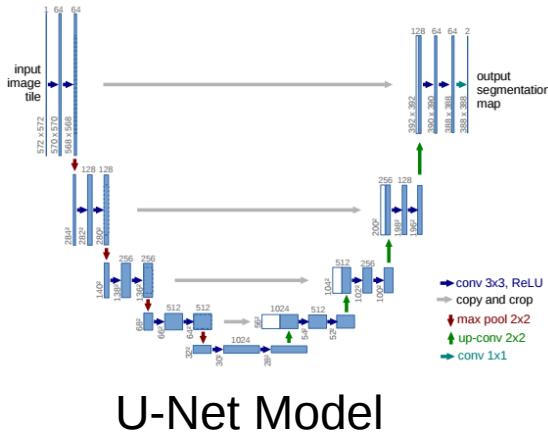
**Abstract**—Semantic segmentation is a fundamental task in remote sensing image processing. The large appearance variations of ground objects make this task quite challenging. Recently, deep convolutional neural networks (DCNNs) have shown outstanding performance in this task. A common strategy of these methods is to sequentially improve the 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 predict 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

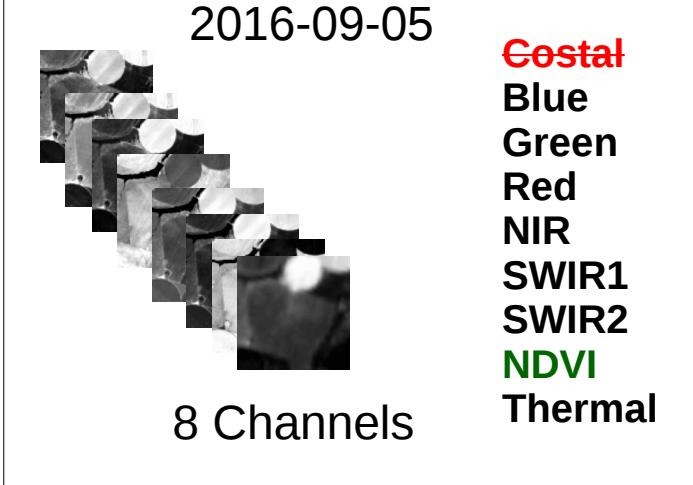
## 1. Introduction

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.

# Classification Strategy



Input data (normalized)



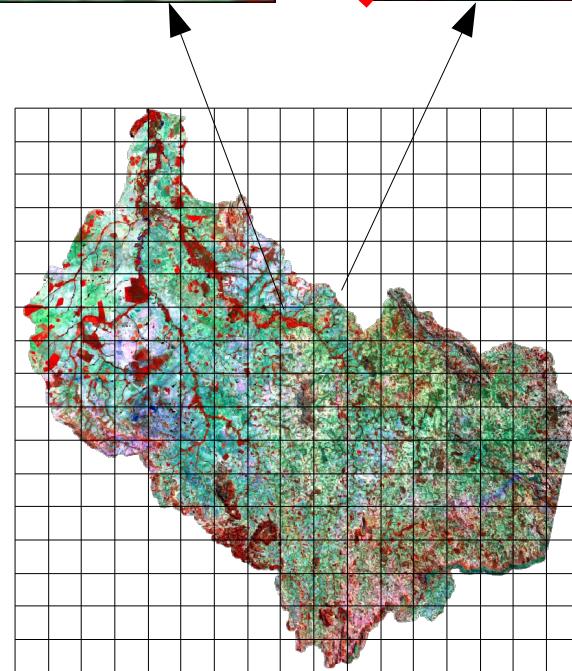
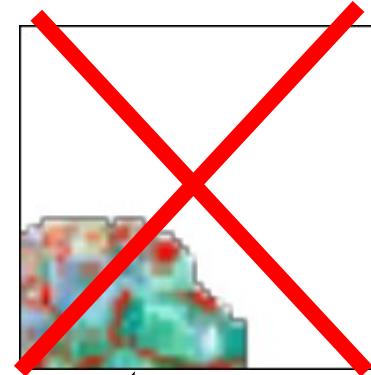
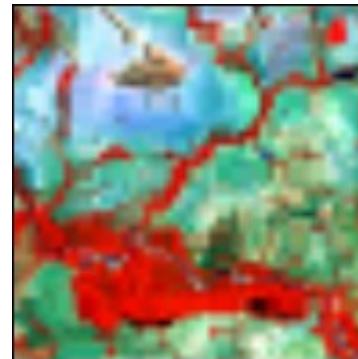
- Spectral and spatial domain exploration
- One image classification (without temporal domain)
- Cloud-free image (without gaps or null values)
- Binary classification (pasture and not-pasture)
- Produce a pasture map for entire Landsat scene

# 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)**

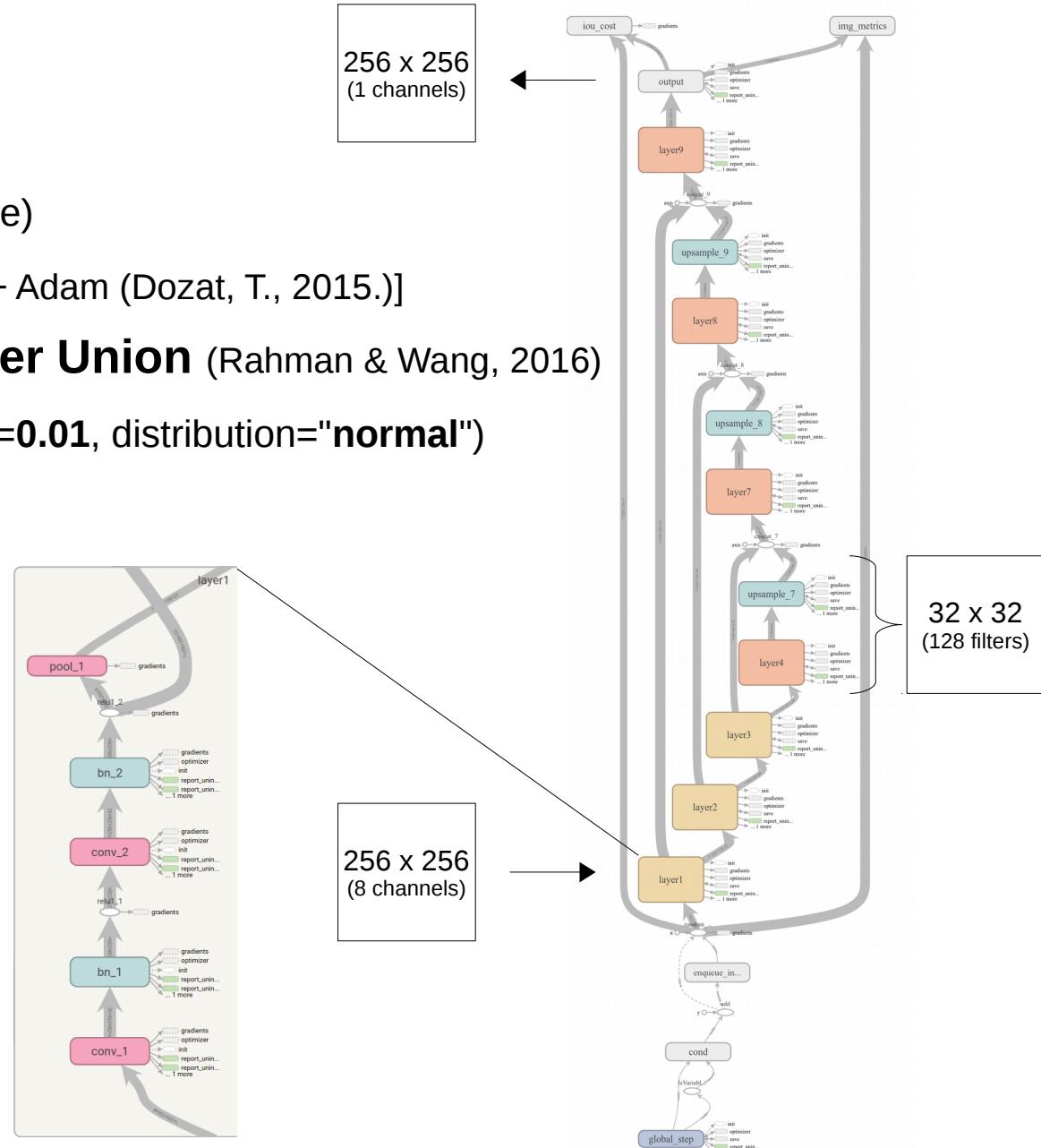
Only with full coverage



# Model calibration

(Hyperparameters)

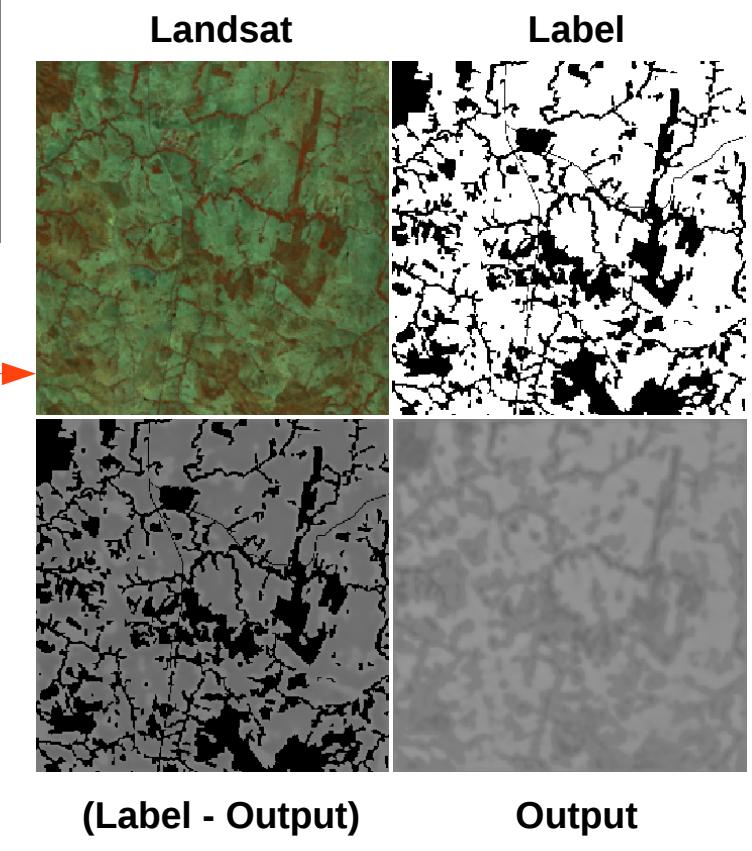
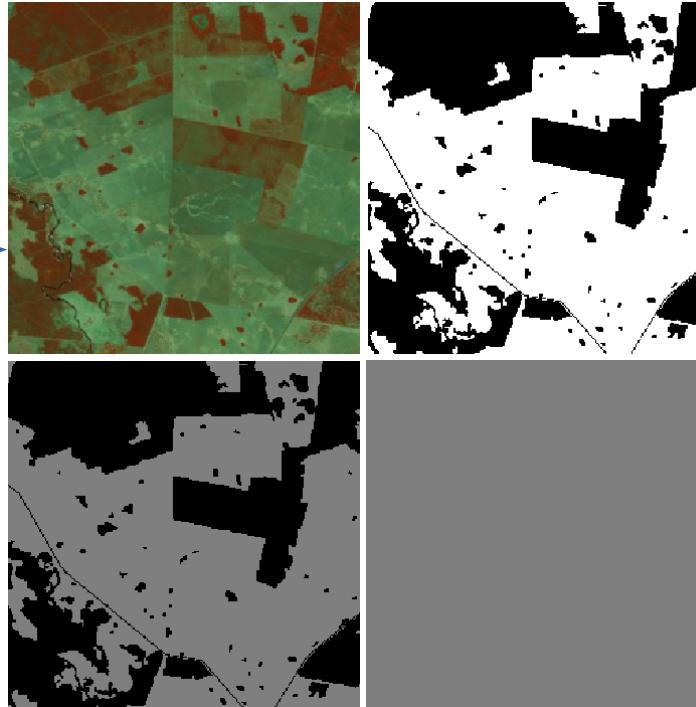
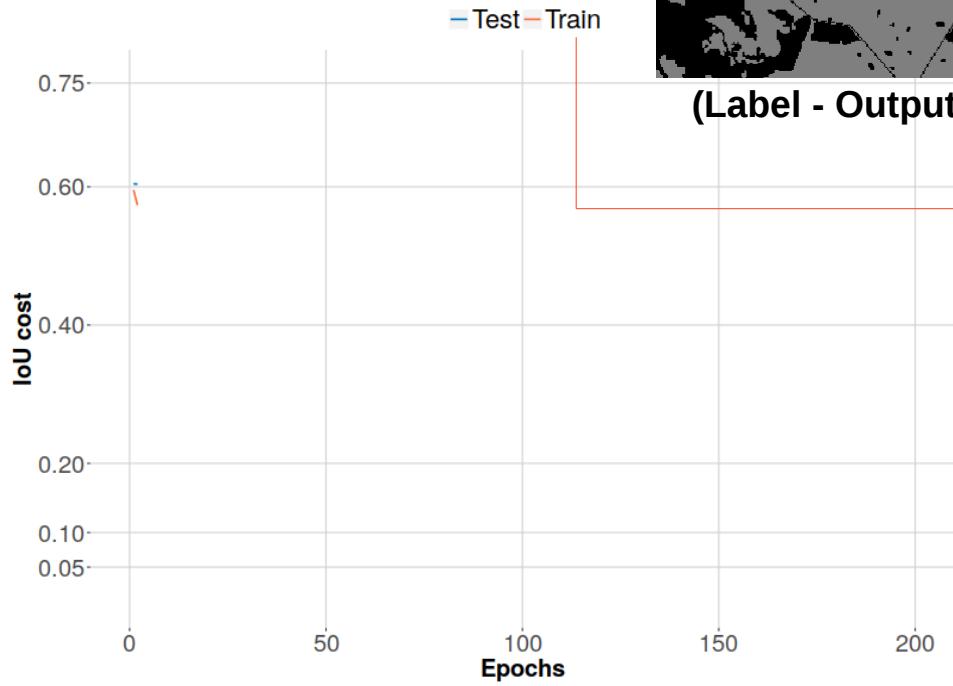
- Number of epochs: **200** (2h 48m runtime)
- Optimizer: **Nadam** [Nesterov Momentum + Adam (Dozat, T., 2015.)]
- Cost function: **IoU - Intersection over Union** (Rahman & Wang, 2016)
- Weight initializer: variance\_scaling(scale=0.01, distribution="normal")
- **Convolution layers:**
  - L2\_regularizer: 0.3
  - Batch normalization
  - Activation function: ReLU
- **Output layer:**
  - Activation function: Sigmoid



# Model calibration

(Tensorboard)

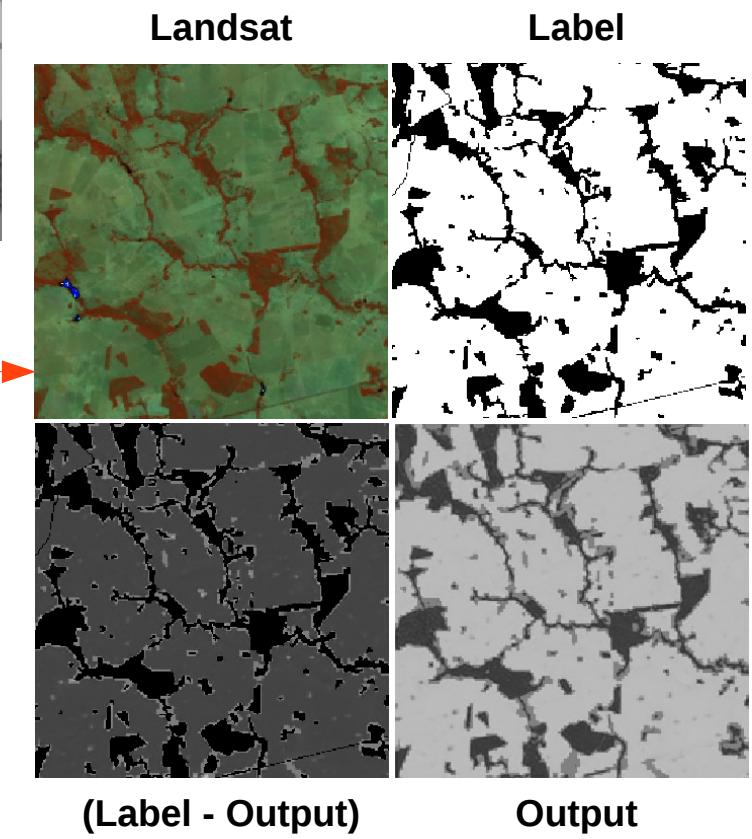
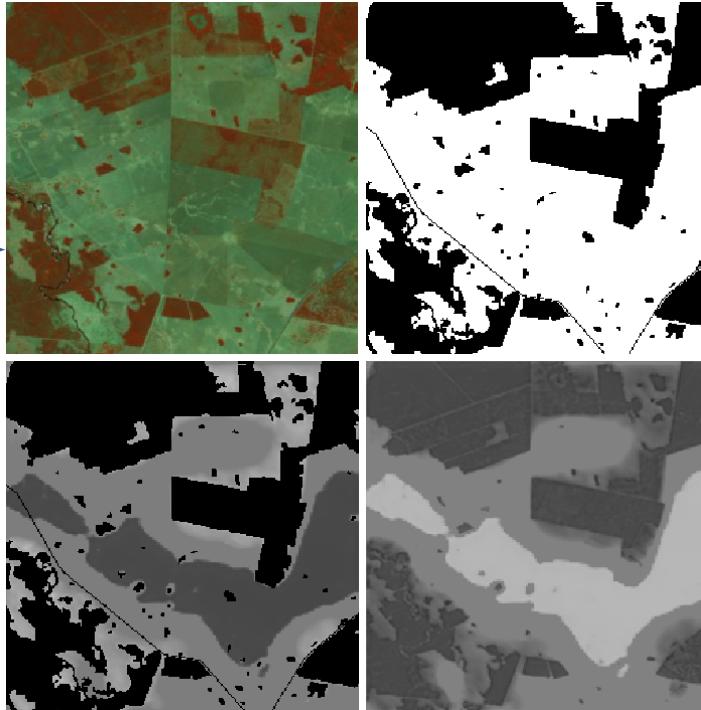
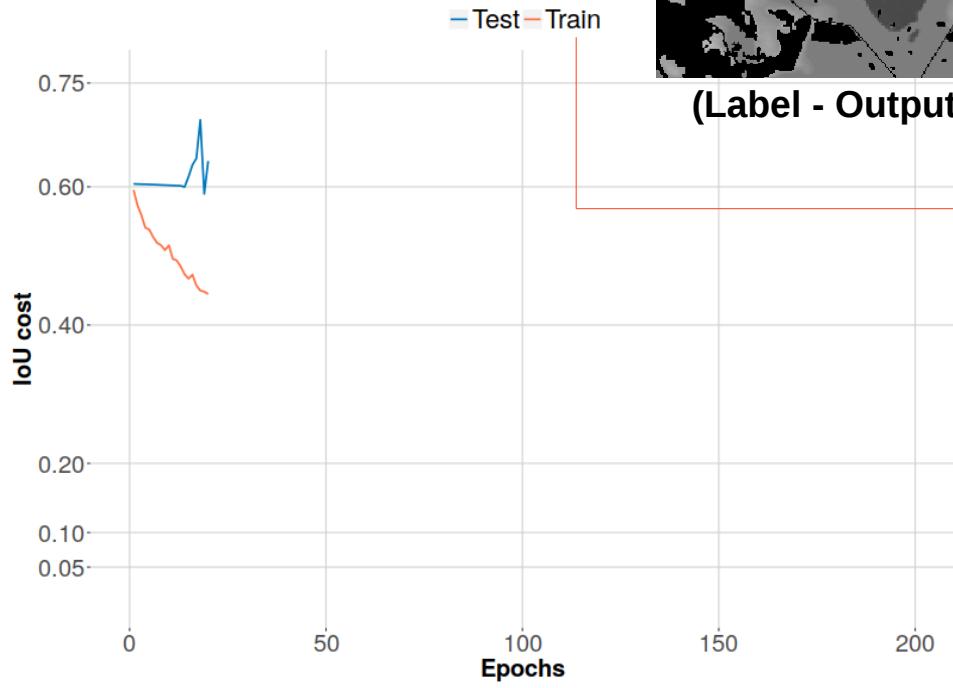
Epoch 2



# Model calibration

(Tensorboard)

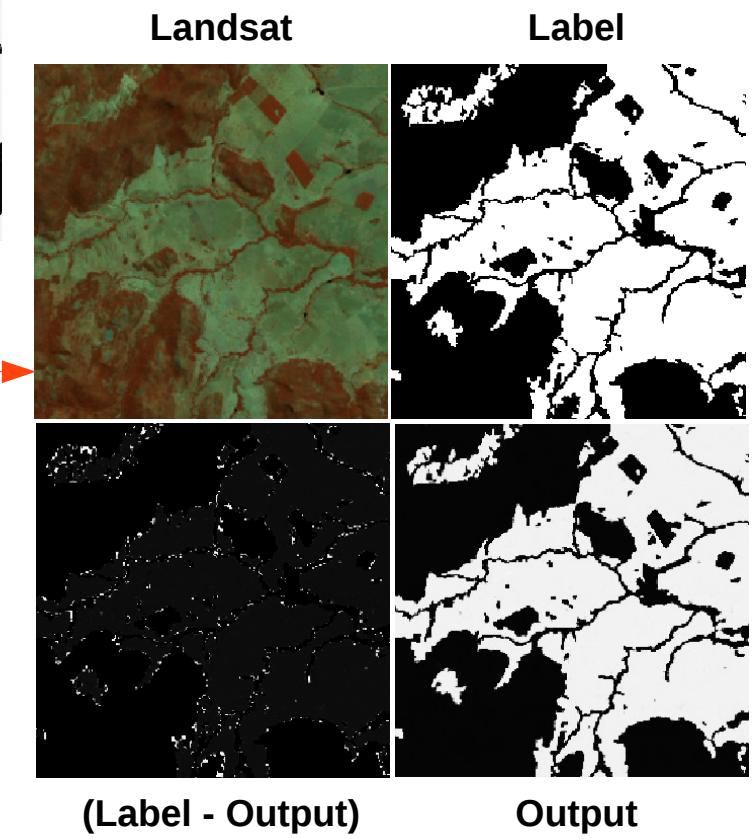
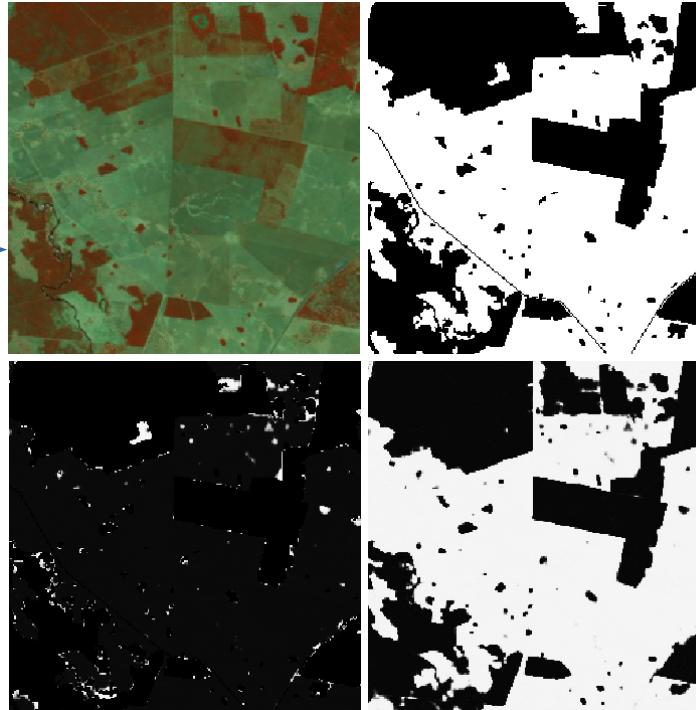
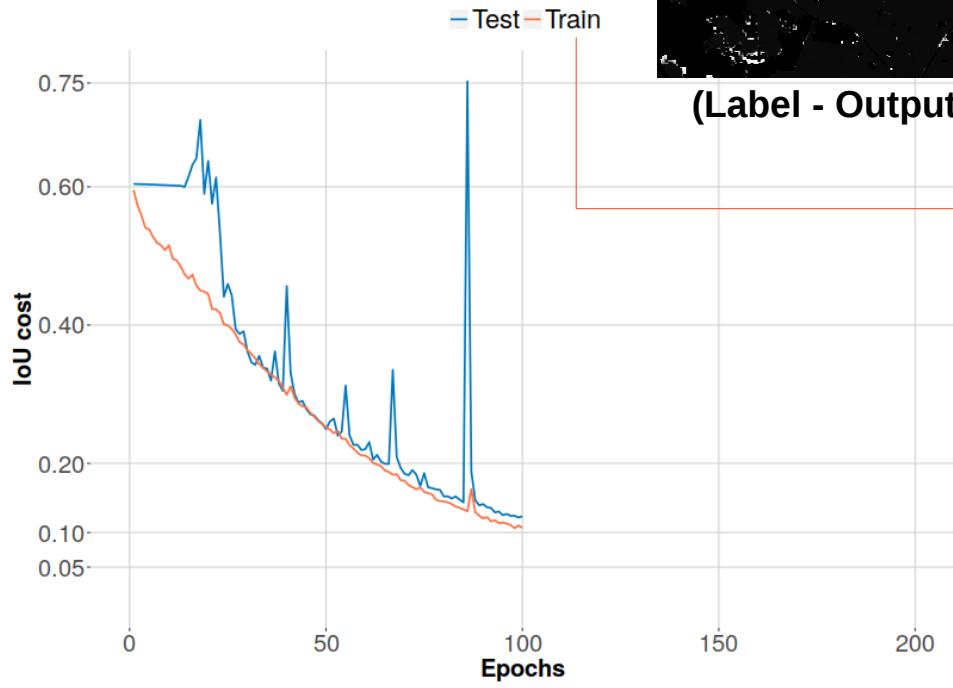
Epoch 20



# Model calibration

(Tensorboard)

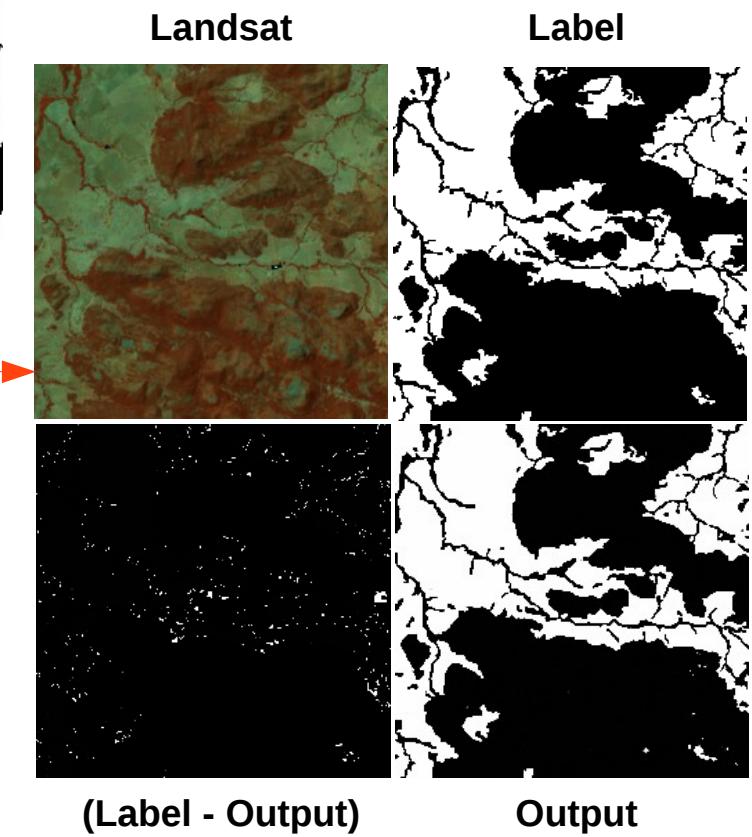
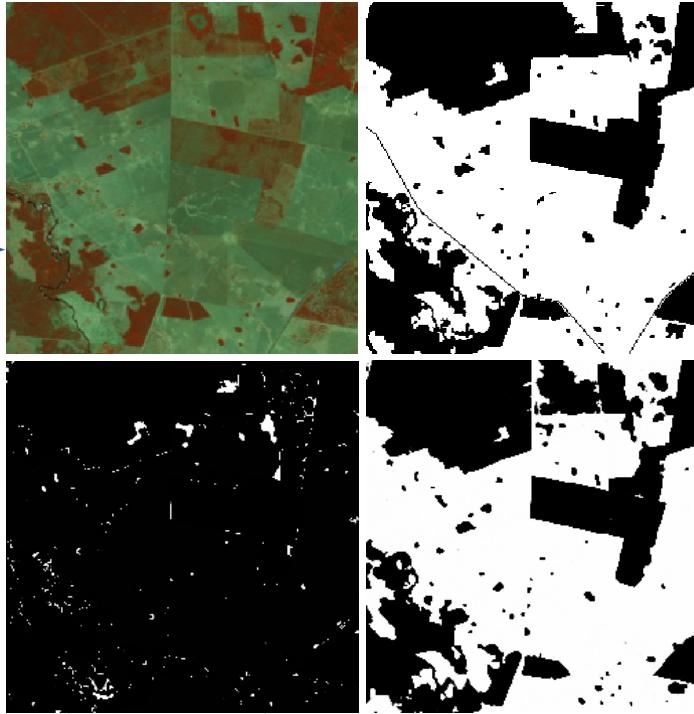
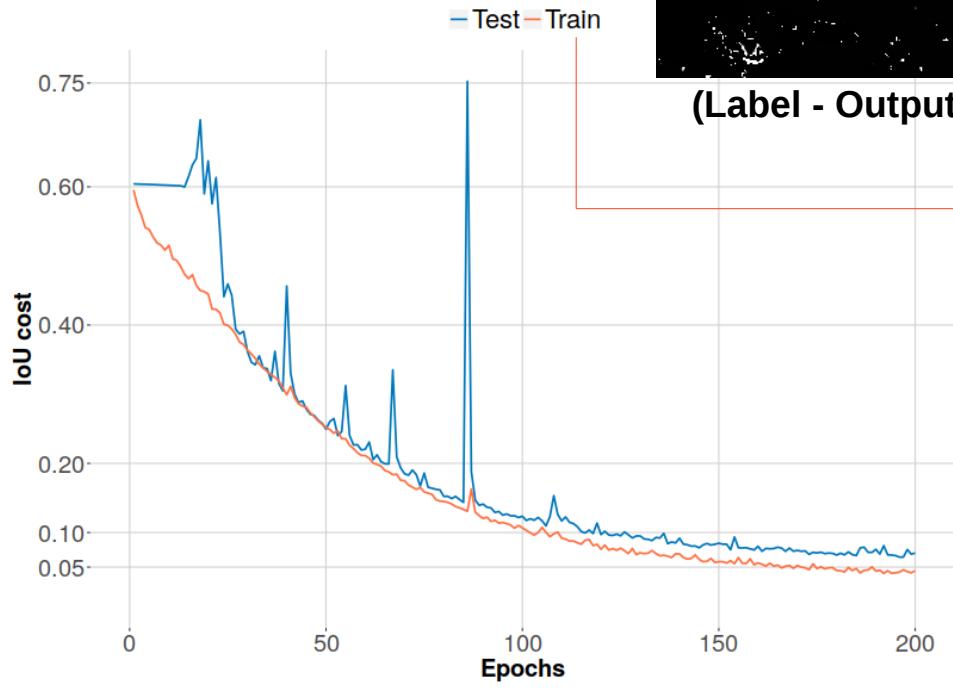
Epoch 100



# Model calibration

(Tensorboard)

Epoch 200

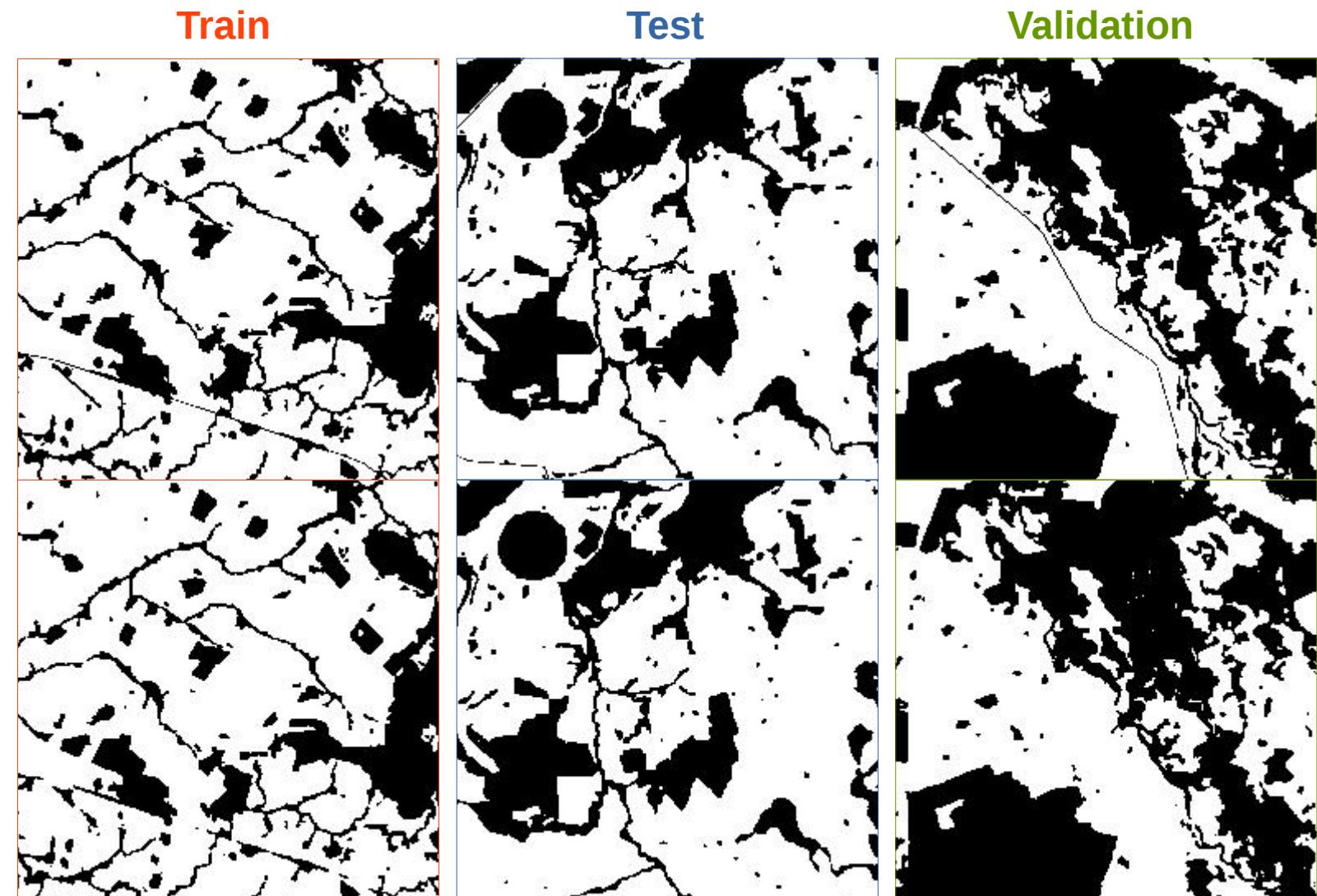


# DL4Landsat Model

(Final evaluation)

Label  
(reference)

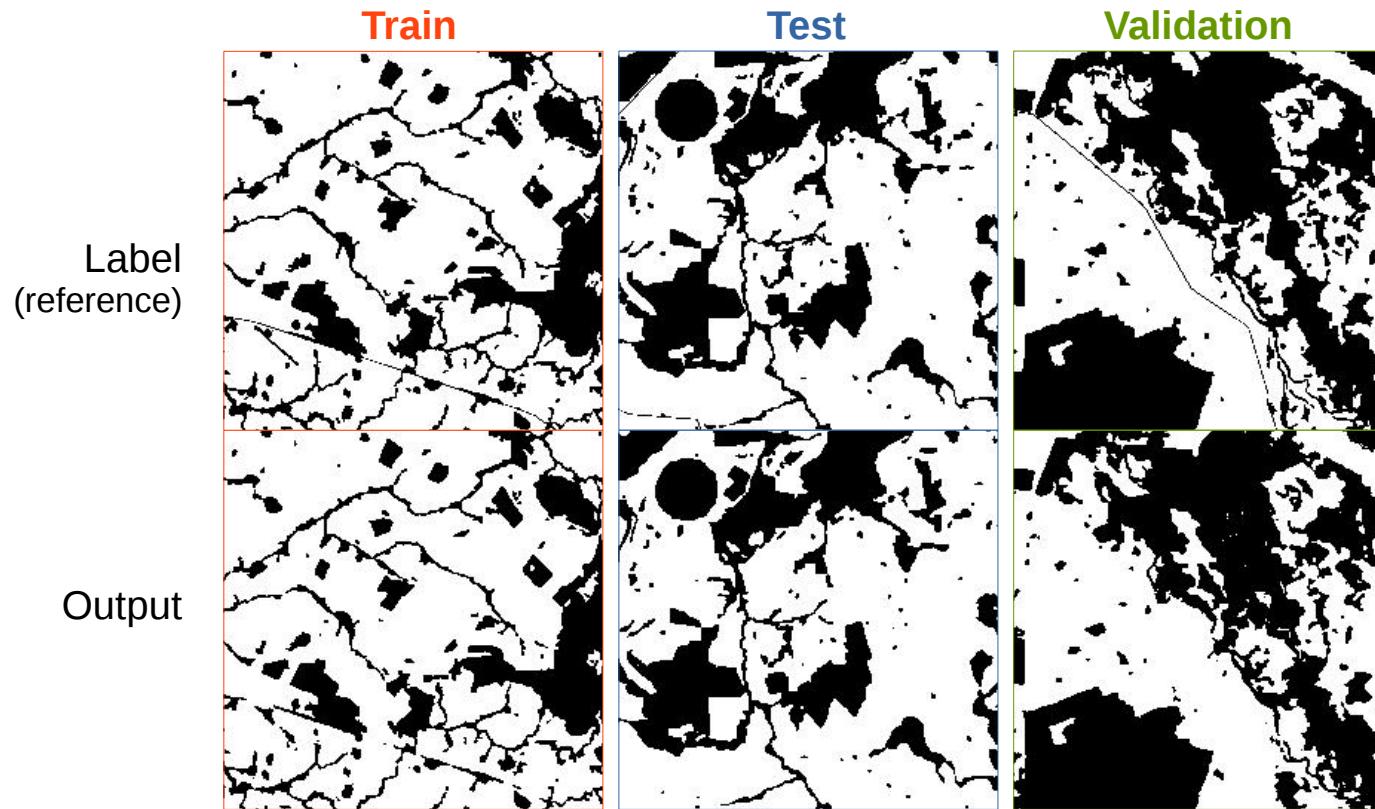
Output



# DL4Landsat Model

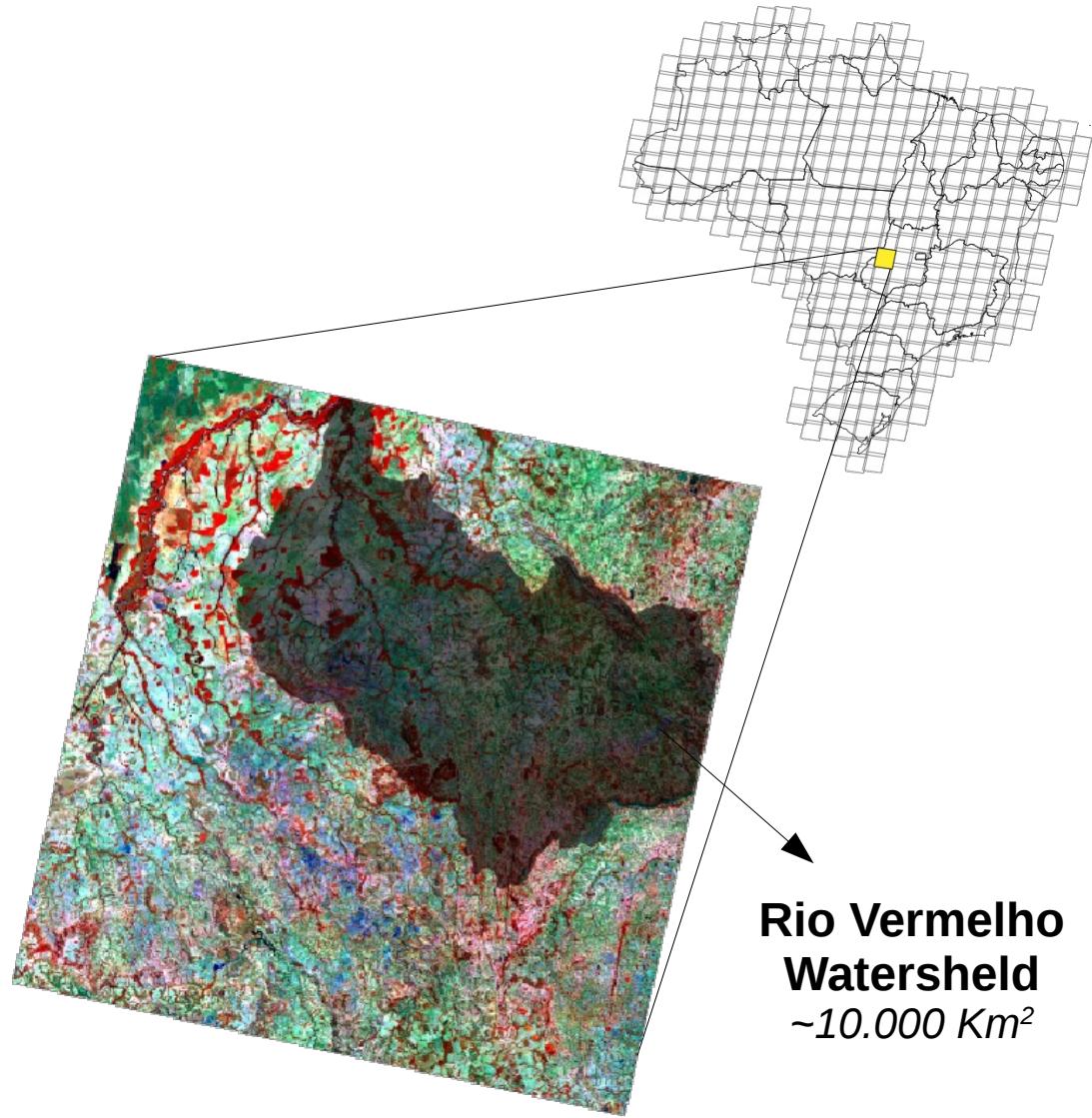
(Final accuracy)

#	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)



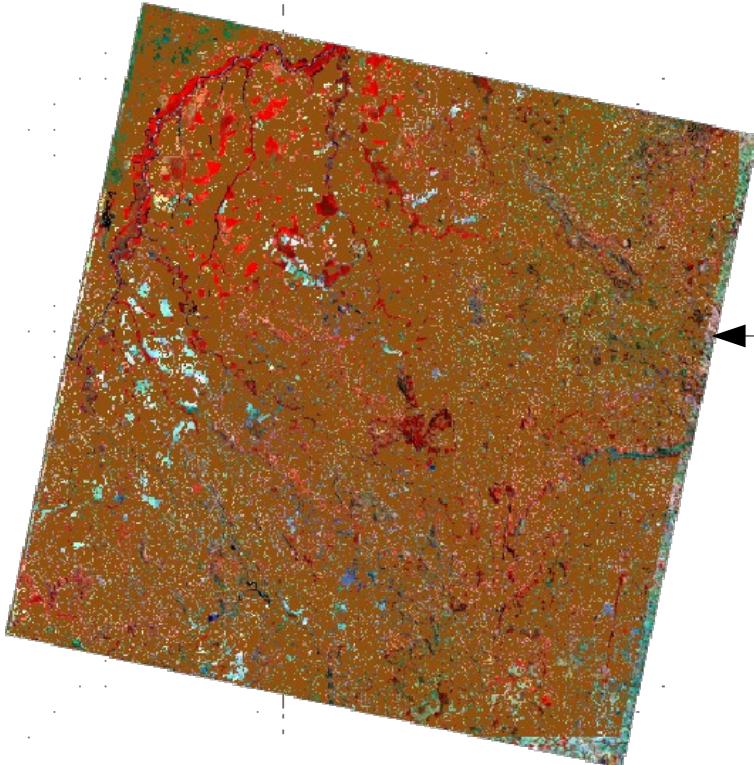
Landsat Sence 223/071  
 $\sim 34.255 \text{ Km}^2$

# Model Predict

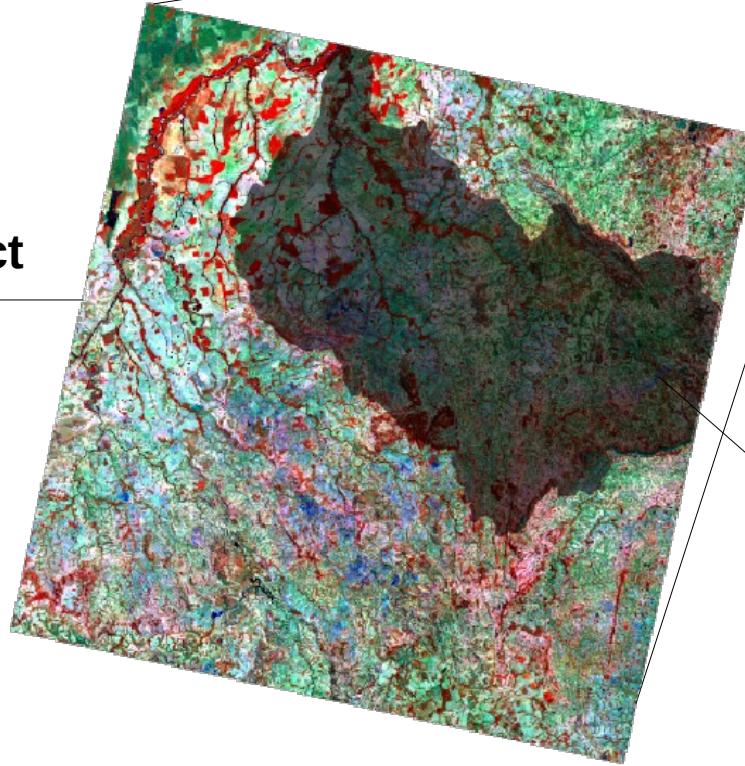
(Classified Map)



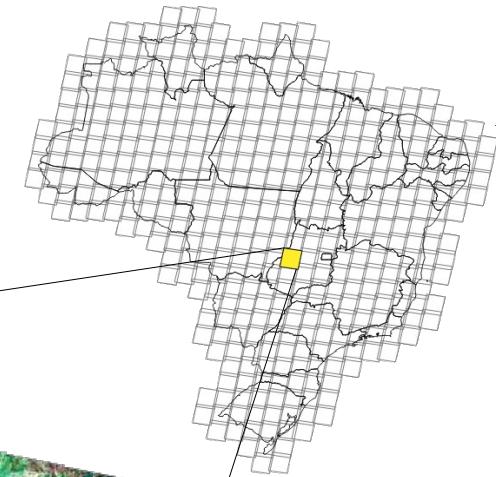
*~1 min runtime*



**Pasture mapping**  
(~38 million of pixels)

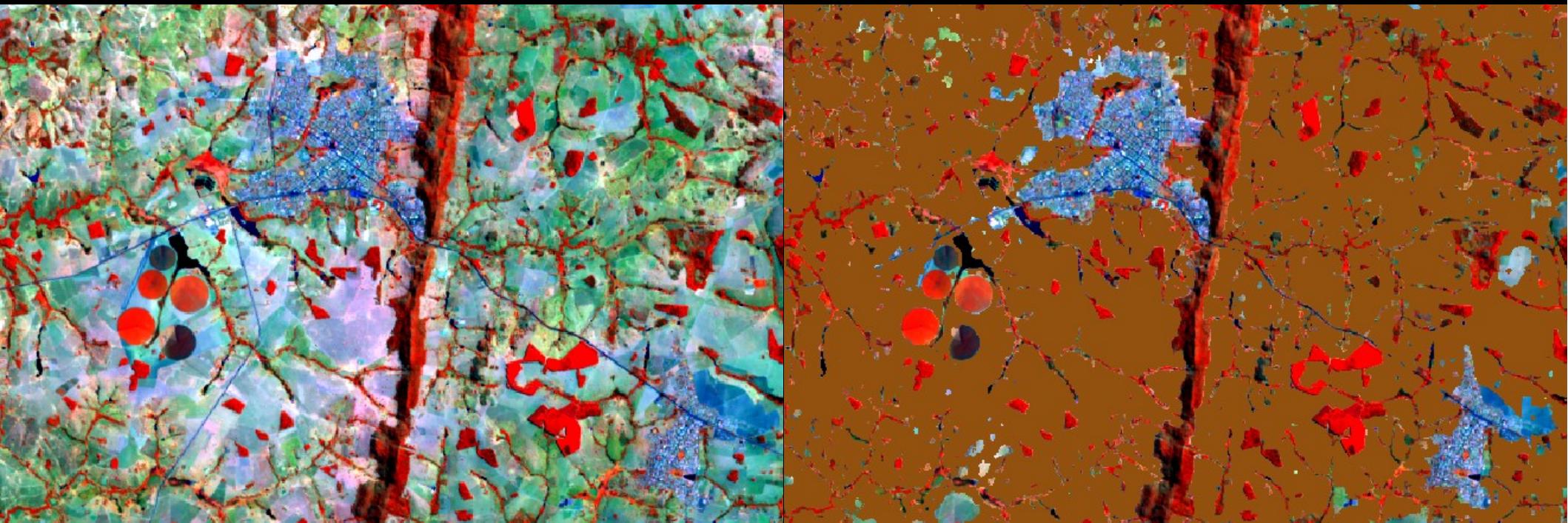


**Landsat Sence 223/071**  
~34.255 Km<sup>2</sup>



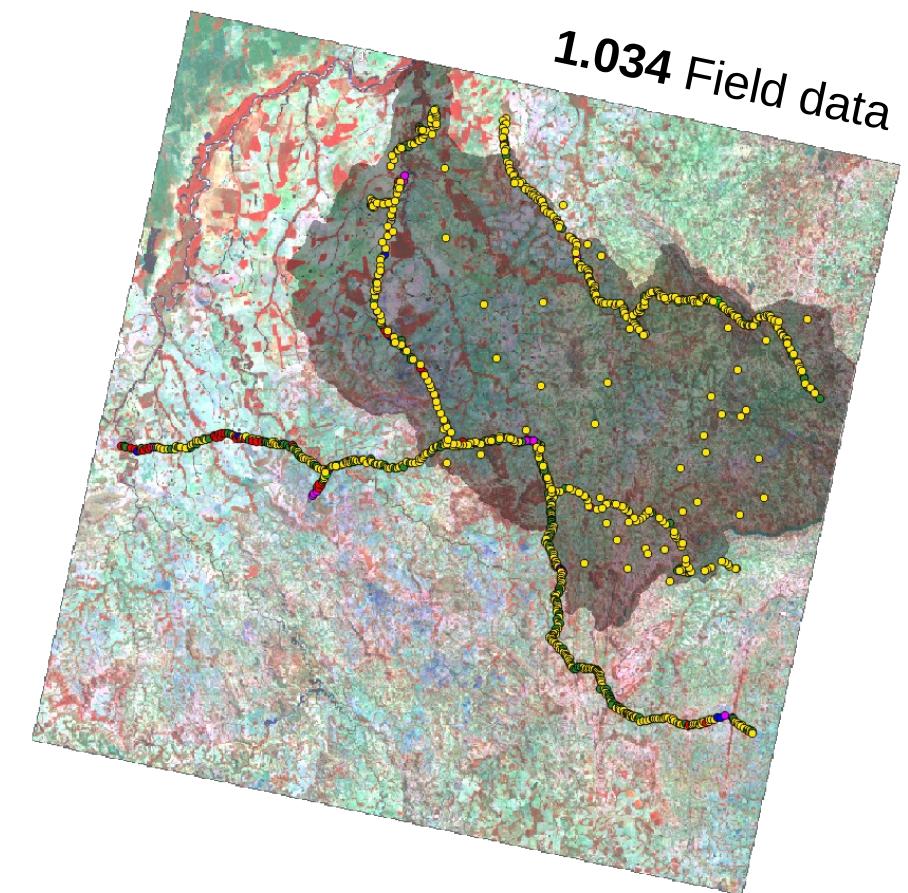
**Rio Vermelho  
Watershed**  
~10.000 Km<sup>2</sup>

# São Luís dos Montes Belos - GO



# Model Predict

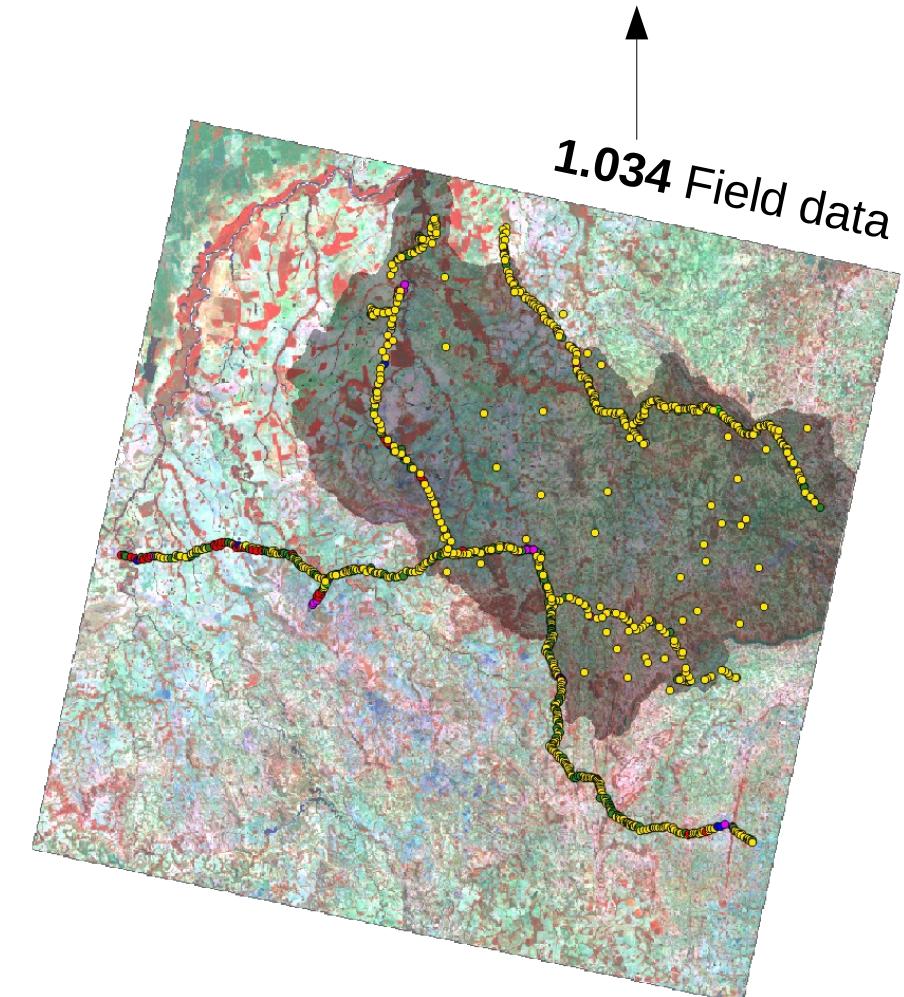
(Classified Map)



# Model Predict

(Classified Map)

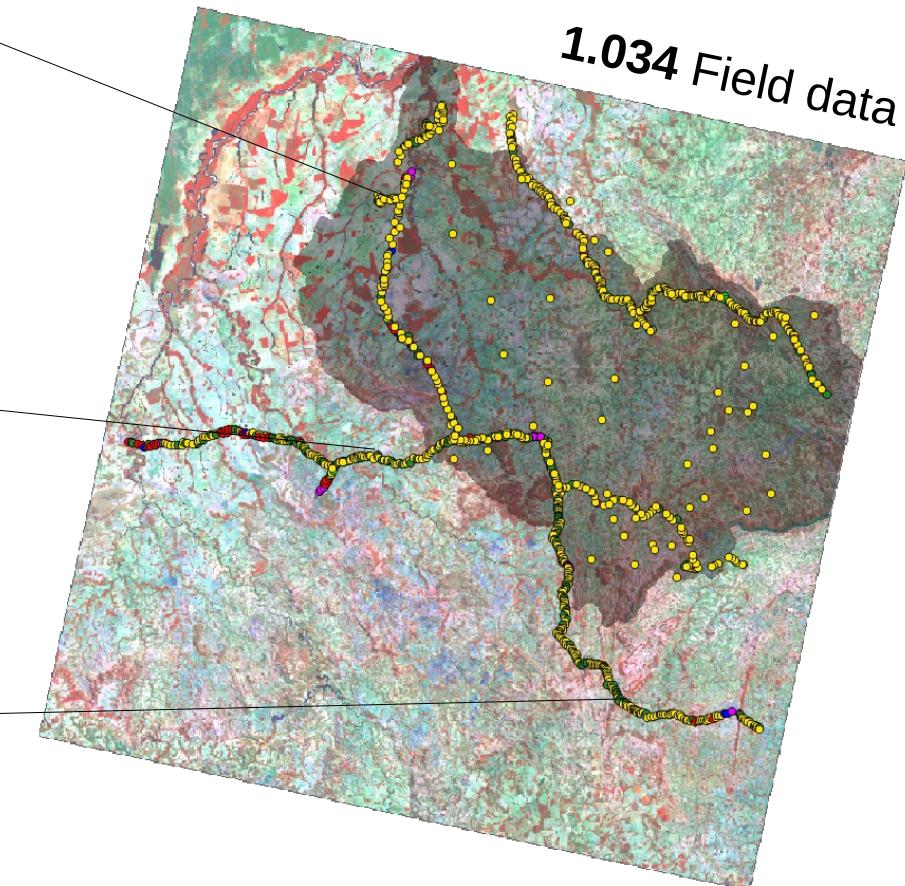
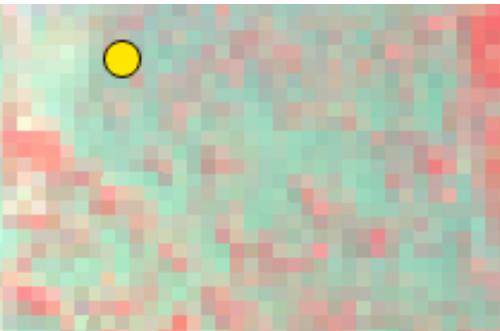
Accuracy	93.91%
Pasture Omission	4.30%
Pasture Comission	13.66%



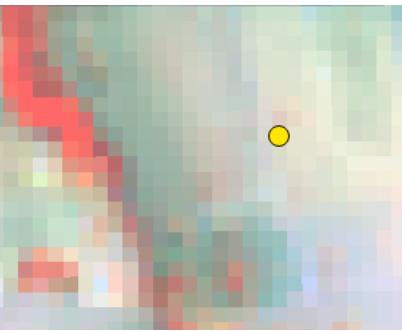
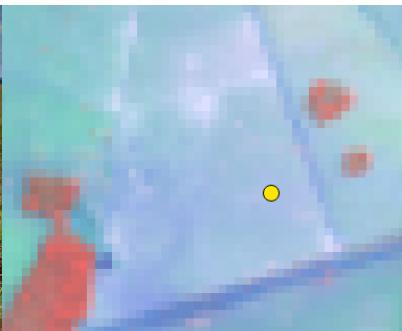
# Model Predict

(Classified Map)

Accuracy	93.91%
Pasture Omission	4.30%
Pasture Comission	13.66%

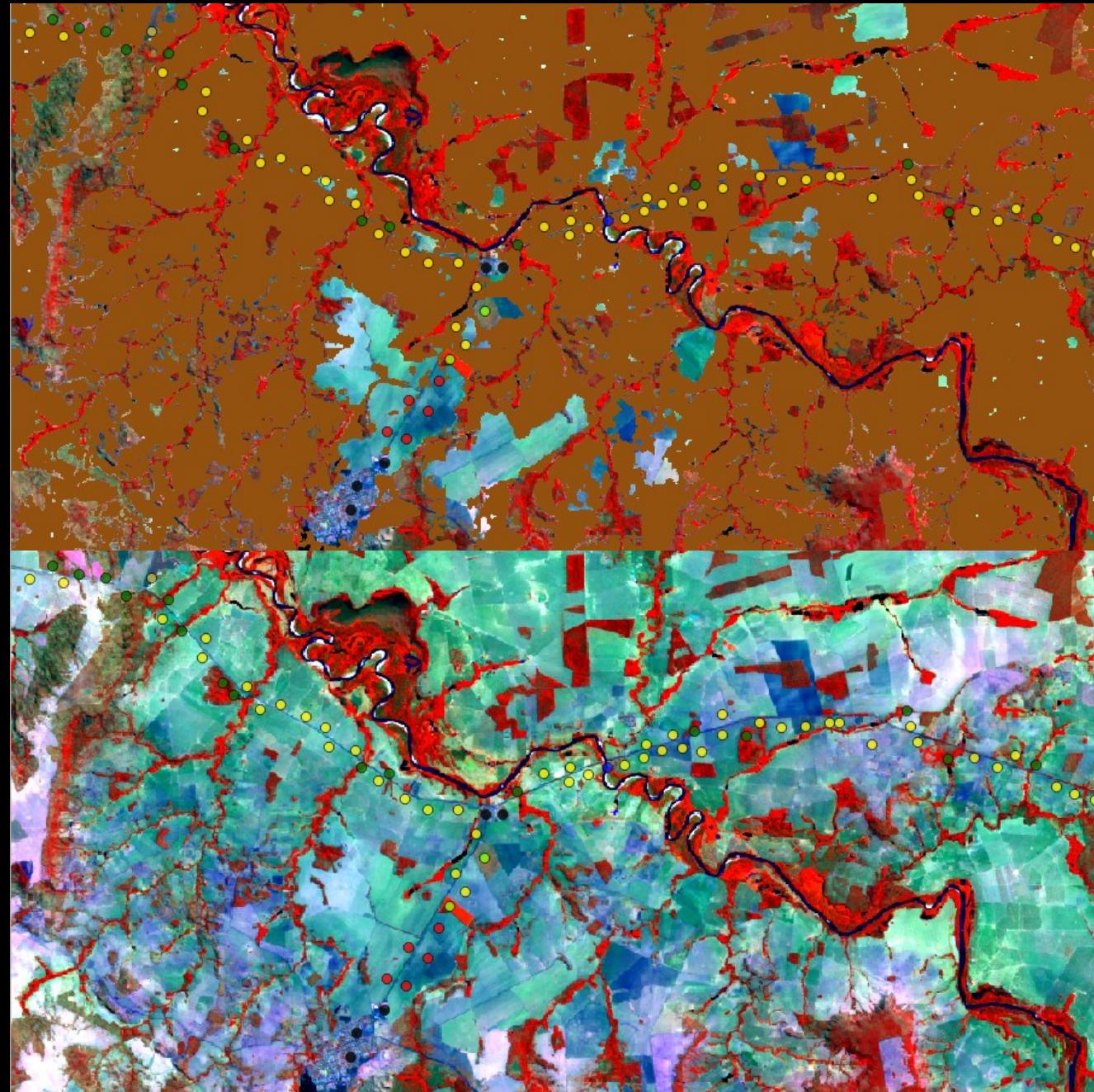


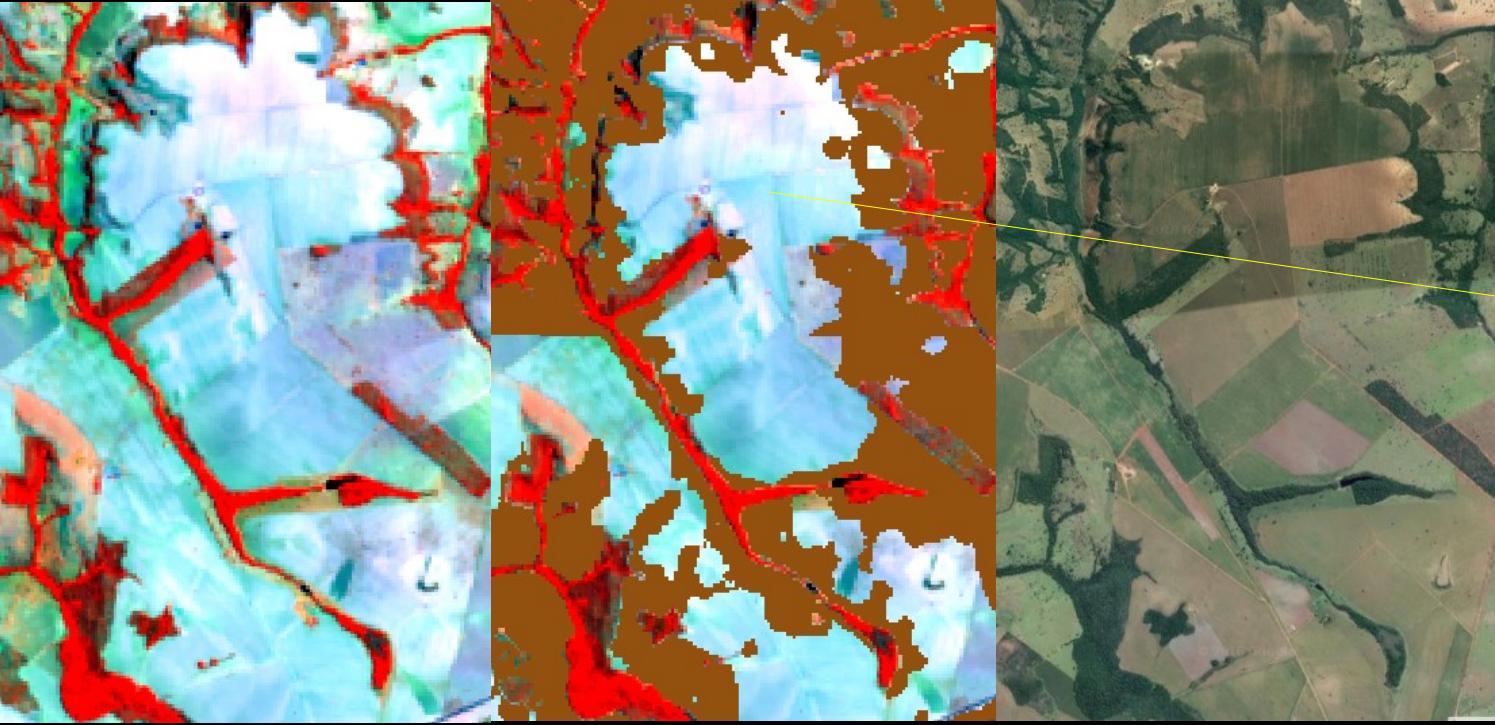
1.034 Field data



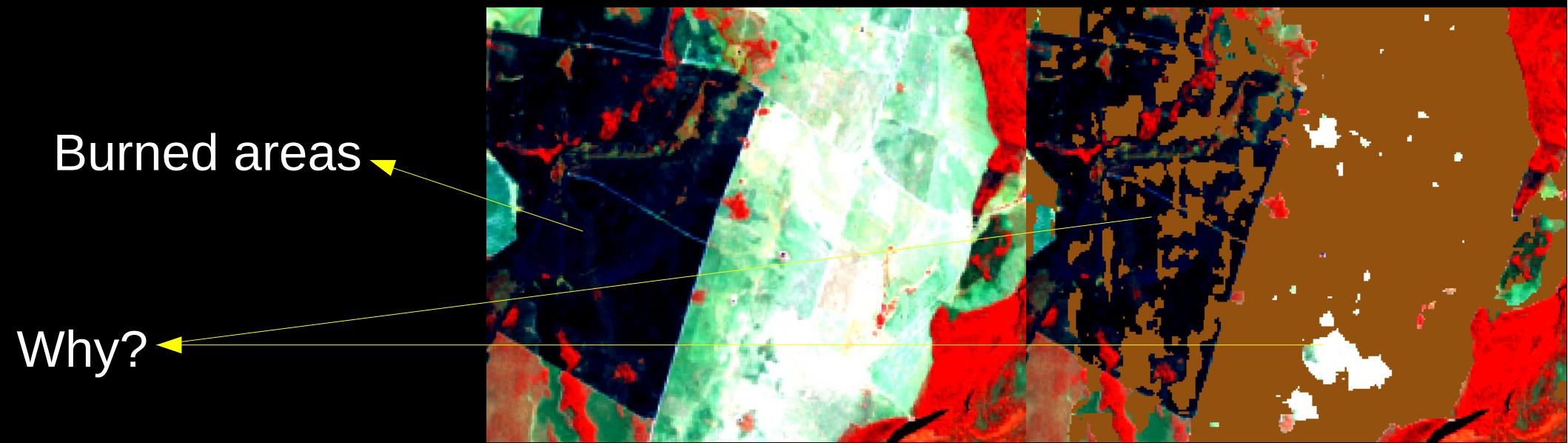
# Field data

- Crop
- Sugarcane
- Water
- Urban areas
- Pasture
- Silviculture
- Native Vegetation





Crop borders  
problems ?

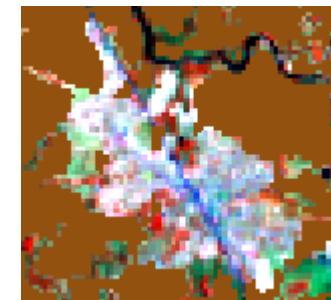


Burned areas

Why?

# Model Predict

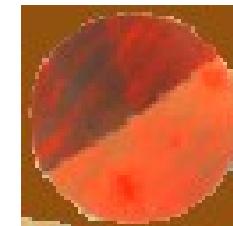
(Classified Map)



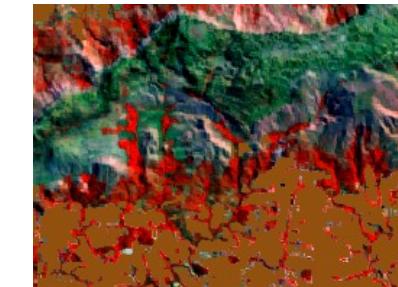
Urban Areas  
(*Faina*)



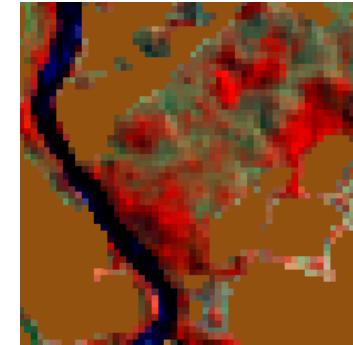
Silviculture



Pivots



Hillshade areas  
(Serra dourada)



Native vegetation  
and water

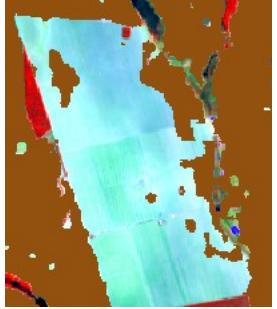


# Model Predict

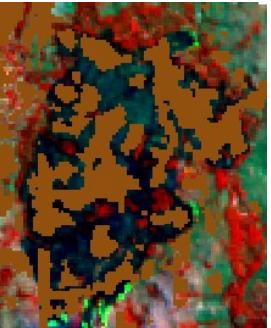
(Classified Map)



Rangelands



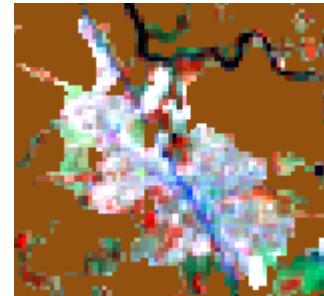
Crop areas



Burned  
areas



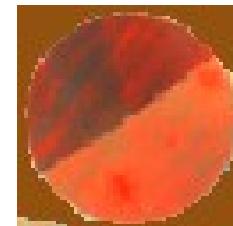
Native vegetation  
and water



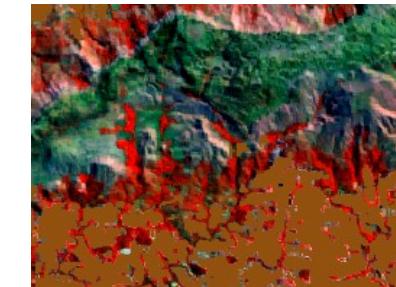
Urban Areas  
(Faina)



Silviculture



Pivots



Hillshade areas  
(Serra dourada)



## **Consider temporal domain:**

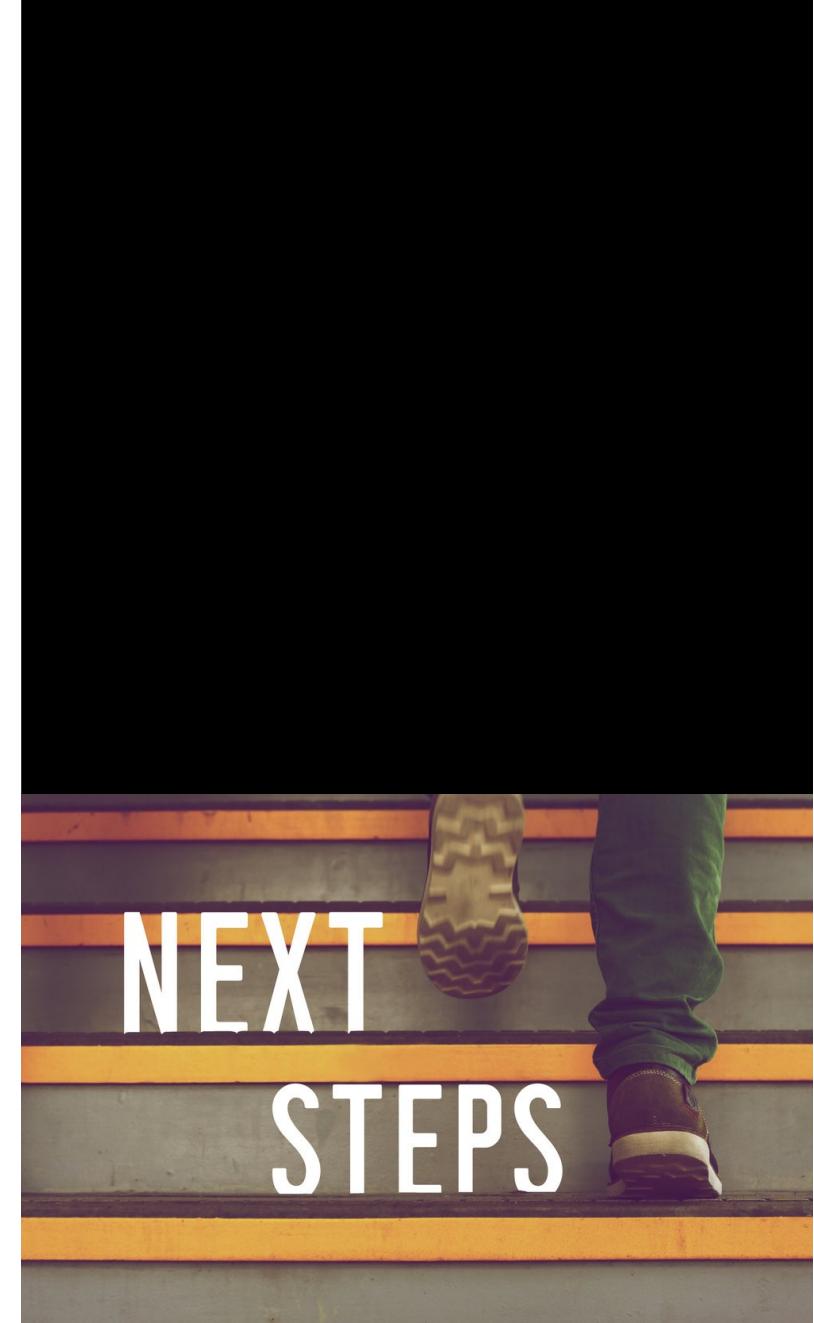
- Multiple images
- Cloud screening
- Time series analysis
- Encode-decoder (LSTM/GRU)

## **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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