

# **Computer Vision Case Study: Deep Learning for Satellite Imagery and Land Cover Statistical Estimation**

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# Outline

## Goal

Land Cover (LC) statistics and maps represent a critical statistical product, for Official Statistics, for example. Since they require a big effort to be created, the underlying idea is building an automatic and efficient system that processes satellite images in order to generate:

- Automatic Land Cover Maps
- Automatic Land Cover Estimates

## Methodology

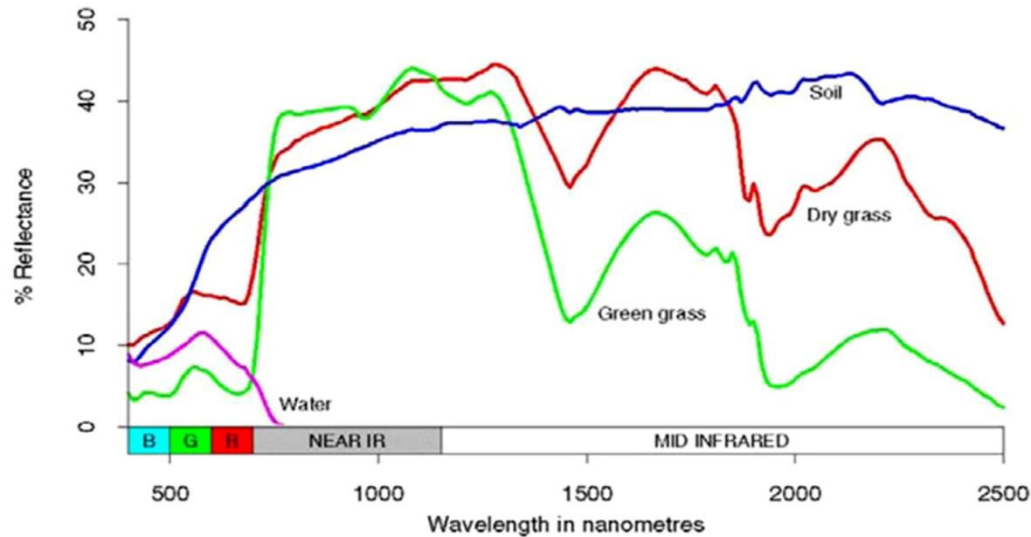
New Approach: using Deep Learning techniques to generate Land Cover maps (classification and segmentation through CNN and U-Net).

## Results

A Deep Learning-based integrated (CNN + U-Net) and automated architecture that gives accurate results for all LC classes

# Deep Learning for Land Cover from Satellite Imagery

## Standard approach: Spectral Signature



### Different LC classes have different reflectance spectra

- Patterns of Reflectance Variation are used to predict LC classes
- A Trained ML algorithm predicts the LC class independently
- Decision on each data point does not depend on neighboring data points

## New approach: Computer Vision (Deep Learning)



### Different LC classes have different spatial/visual patterns

- The Variation of visual/spatial patterns is used to predict LC classes
- Trained ML algo (CNN) predicts the LC class of image pixels based on information from neighboring pixels
- Decision on each pixel depends on the whole sub-image (tile) the pixel belongs to

# Machine Learning for LC from satellite imagery

## TRAINING DATASET

The Training.set affects the classification and prediction accuracy of our machine learning algorithm. We have harnessed the **EuroSAT** dataset features and its EuroSAT Land-Cover classification. EuroSAT is made of satellite imagery which is carefully collected and selected from Sentinel 2 Satellite Copernicus Project.



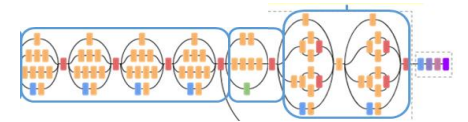
## INPUT

Input images to be processed, must be in excellent agreement with training pictures. That's why we take portions of Italy satellite imagery from Sentinel 2 itself.



## ARCHITECTURE

We chose our Algorithm Architecture accordingly: **Classification Convolutionary Neural Network (CNN) or Segmentation Convolutionary Neural Network (U-Net)**. We built the model by selecting the right hyper-parameters, optimizations and validations.



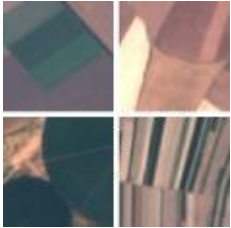
## OUTPUT

The output ground truth is within the training dataset in order to validate the model. Then, the output is yielded by processing the Input dataset in order to perform classifications/predictions.



# CNN: Satellite Imagery Dataset

ANNUAL CROP



RIVER



FOREST



RESIDENTIAL



INDUSTRIAL



HIGHWAY



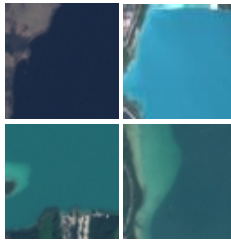
PASTURE



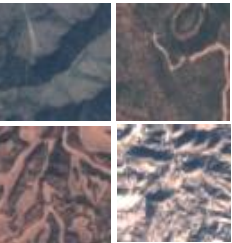
PERMANENT CROP



SEA LAKE



HERBACEOUS VEGETATION



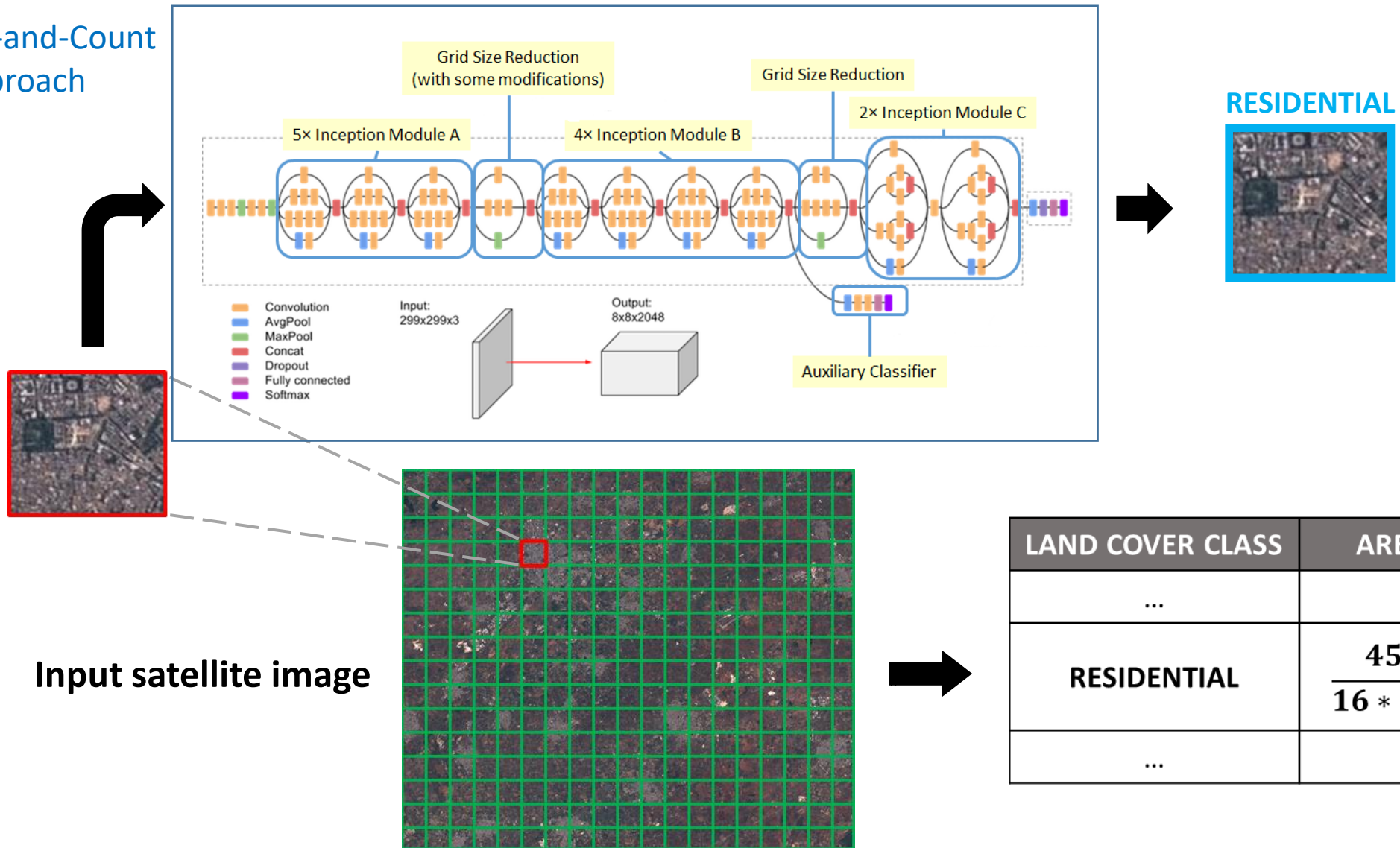
## EuroSAT dataset

(<https://github.com/phelber/eurosat>):

- Based on Sentinel-2 satellite images
- 27000 geo-referenced and labeled image patches (each one of 64x64 pixels)
- 10 different Land Use and Land Cover classes, with 2000-3000 images per class
- RGB (8-bit) and Multi-Spectral (13 spectral bands, 16-bit) versions available

# CNN: Inception-V3 Architecture

Classify-and-Count  
Approach





# GoogleNet – Google (Szegedy, C., et al., 2015)

## Critical Features (Szegedy, C., et al., 2015):

Computationally Effective Deep architecture: 22 layers

Why the name inception, you ask? Because the module represents a network within a network. If you don't get the reference, go watch Christopher Nolan's *“INCEPTION”*, computer scientists are hilarious.

**Inception:** it is basically the parallel combination of  $1\times 1$ ,  $3\times 3$ , and  $5\times 5$  convolutional filters.

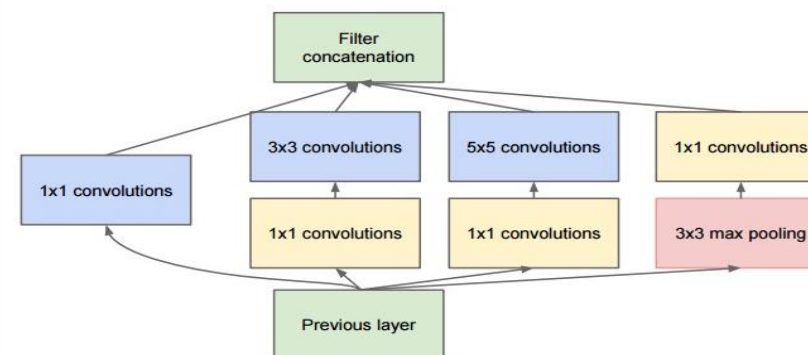
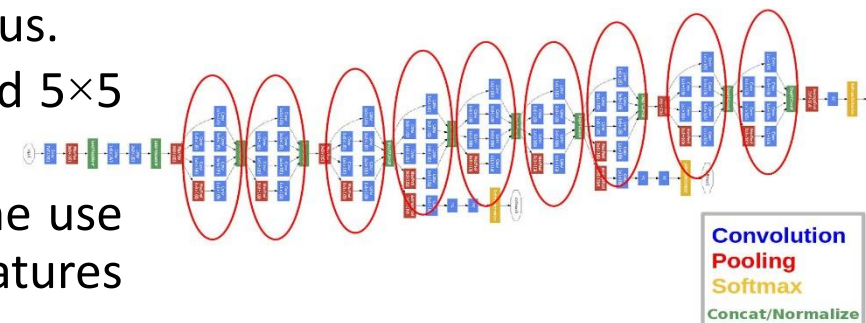
**Bottleneck layer:** The great insight of the inception module is the use of  $1\times 1$  convolutional blocks (NiN) to reduce the number of features before the expensive parallel blocks.

**Upside:** 4 millions parameters!

**Downside:** Not scalable!

## Results:

**7 Models Ensemble : 6.67% Top-5 Error.**



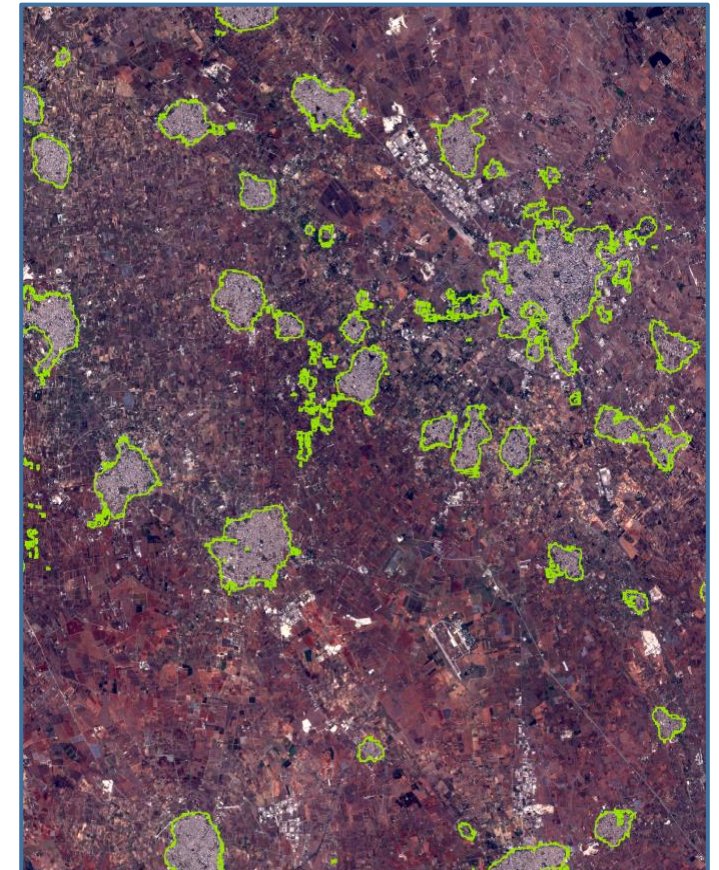
# CNN: Example of Automatic Land-Cover Map



[A] Input [Lecce's picture](#)  
(751 km<sup>2</sup>)



[B] Related Lecce LC Map (output)



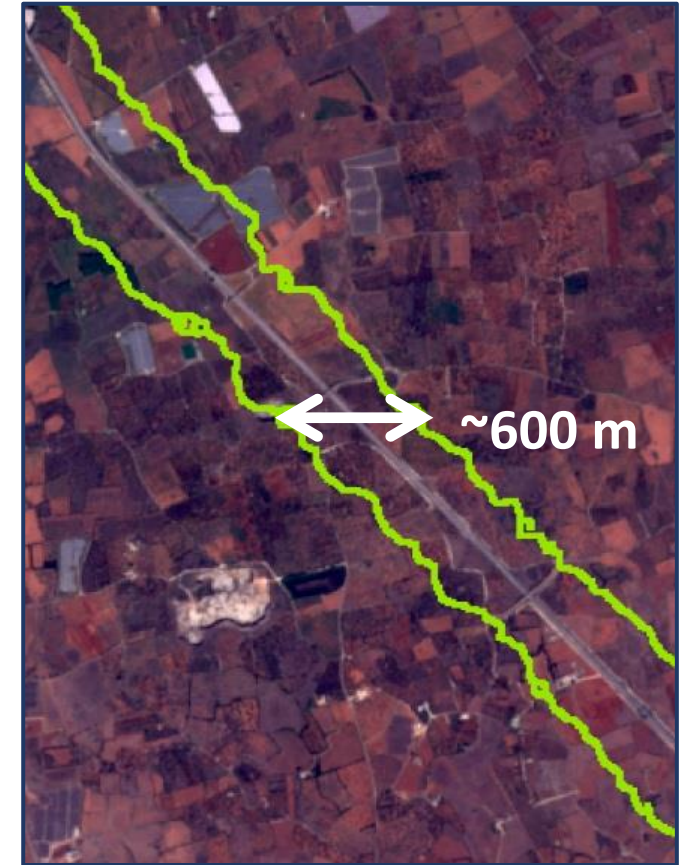
[C] Depiction of the [Residential](#) class  
generated by overlapping [A] and  
[B]



# CNN: Over-estimation effect of *River* and *Highway* classes



[D] Detailed overview of the **Arno River** pathway (**Pisa**, 443 km<sup>2</sup>) on top of a semi-transparent version of the corresponding LC map.



[E] Fragment of Lecce highlighting the border of the *Highway* class predicted by the model. We can see the extent of the over-estimation

# U-Net: Dataset creation

EuroSAT Imagery  
*River*

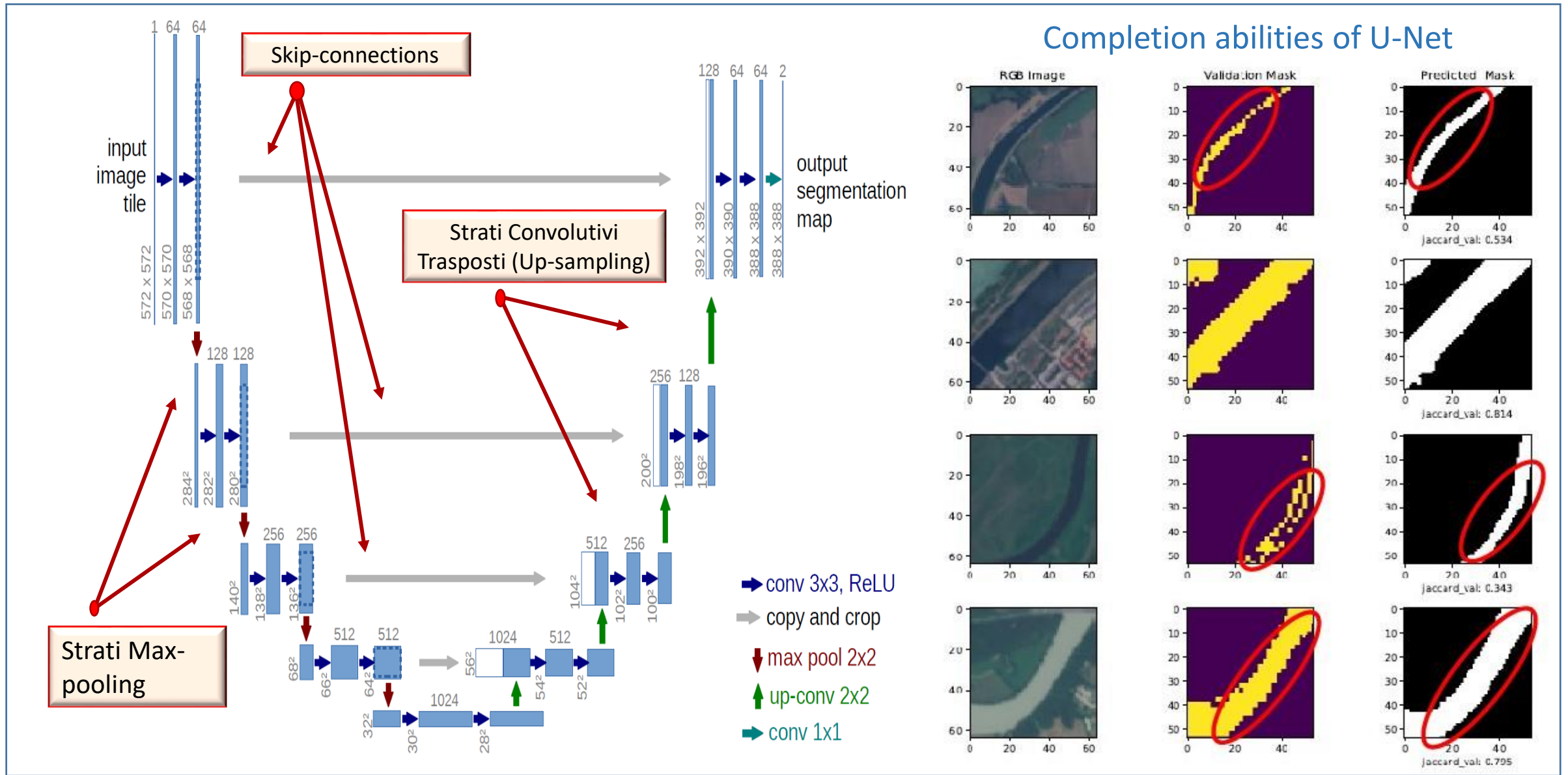


Segmentation Masks  
*River*



- The dataset creation to train the **U-Net** segmentation model was performed by exploiting satellite pictures from *River* class by **EuroSAT** and data from the *Copernicus High Resolution Layer*.
- For each image we determined a label consisting in a **mask** keeping track of the class information for every pixel:  
**0** means the pixel belongs to *River* class (**black**)  
**1** means the pixel does not belong to *River* class (**white**)
- Main difference with the Standard (Classification) CNN Dataset: in classification, the class label refers to the whole image and not to each single pixel such as in segmentation stage.
- Final dataset: 1500 segmentation masks validated.
- Implementation of a similar training dataset for *Highway* thanks to **Open Street Maps** data.

# U-Net: Architecture

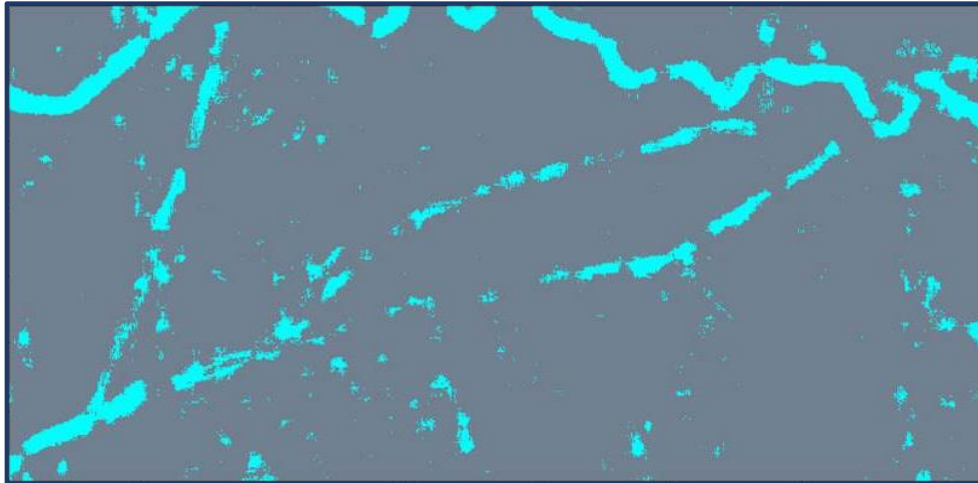




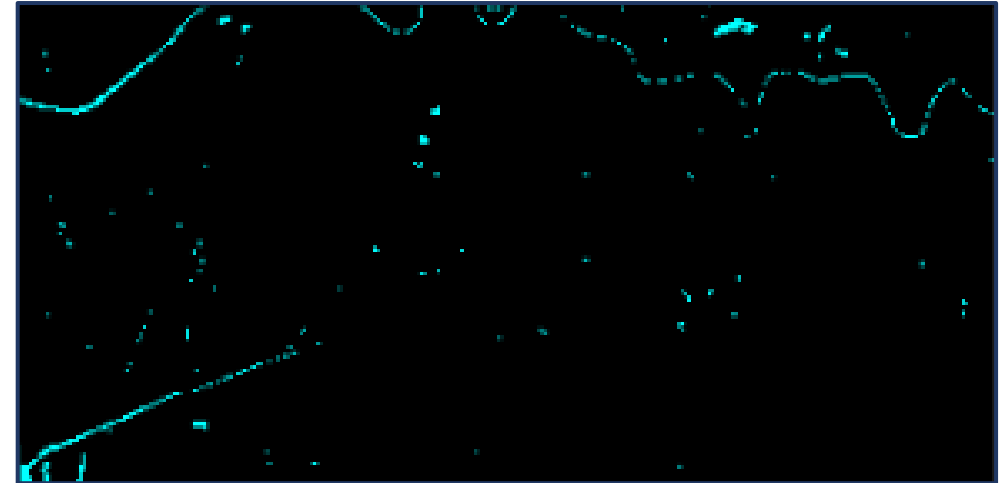
# U-Net: adjustment of the over-estimation issue in “thread-like” classes such as *River*



Classification by  
means of CNN

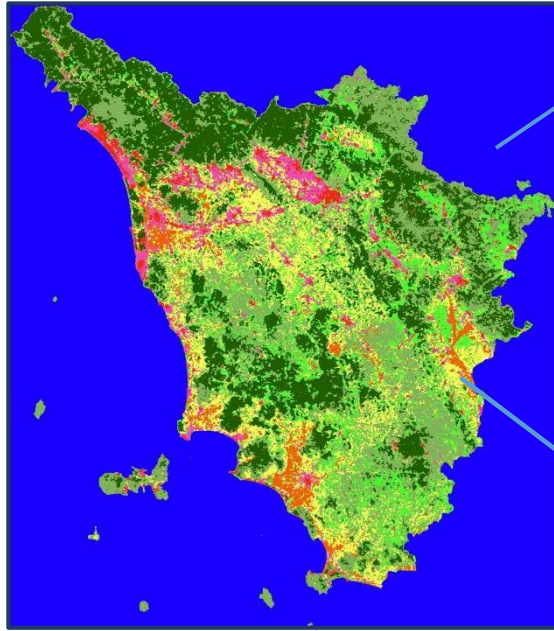


U-Net  
Segmentation

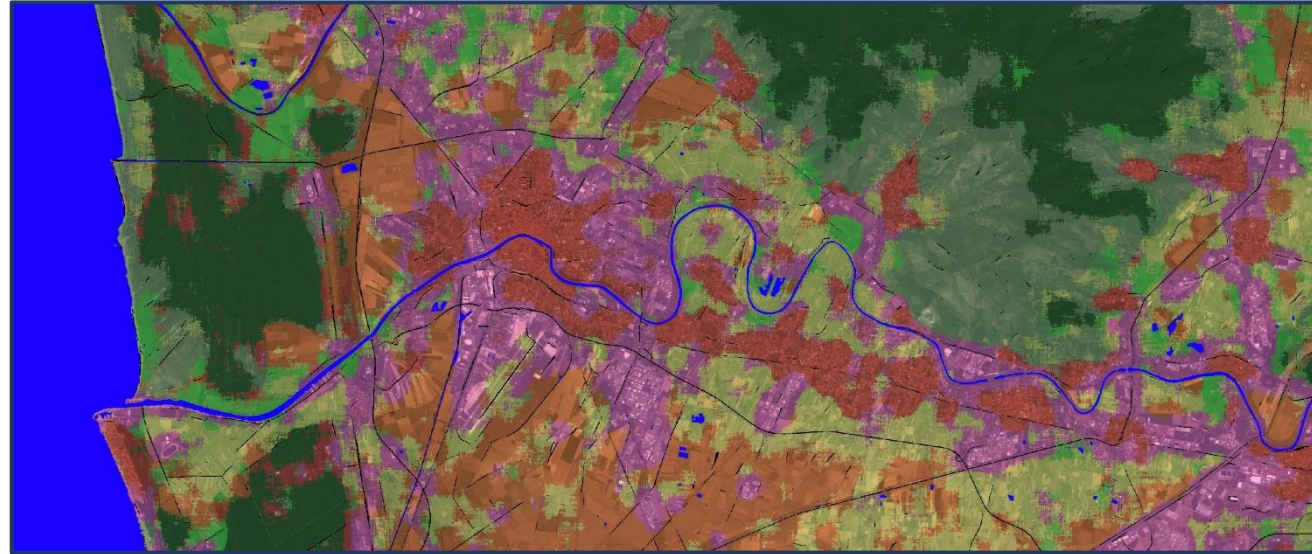




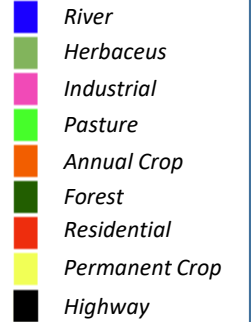
# Integrated Map CNN + U-Net



Tuscany LC Map



Detail of Arno river view (Pisa, 443 km<sup>2</sup>) overlapped to a semi-transparent version of the corresponding map coming from the CNN and U-Net integration process. Different colours refer to different LC classes.

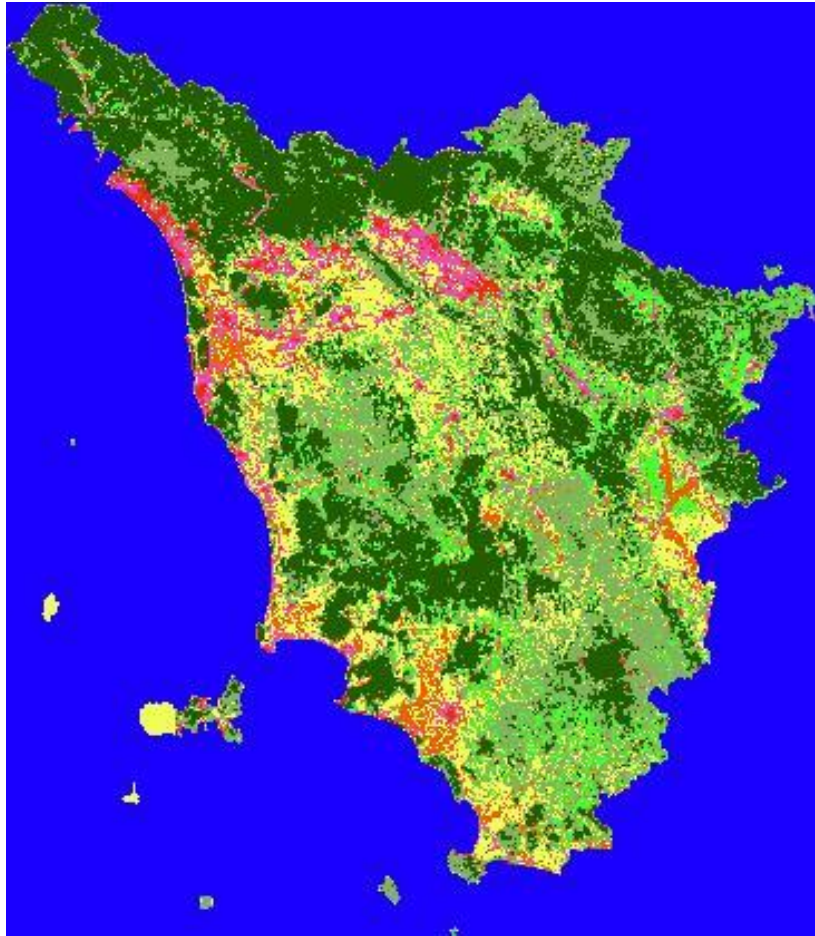


**Integrated system (CNN + U-Net) works perfectly with all the LC classes**

- U-Net predicts *River* and *Highway*.
- Whereas CNN classifies the other classes with are left over.










# Example of integrated (CNN+U-Net) LC map and statistics

CNN + U-Net:

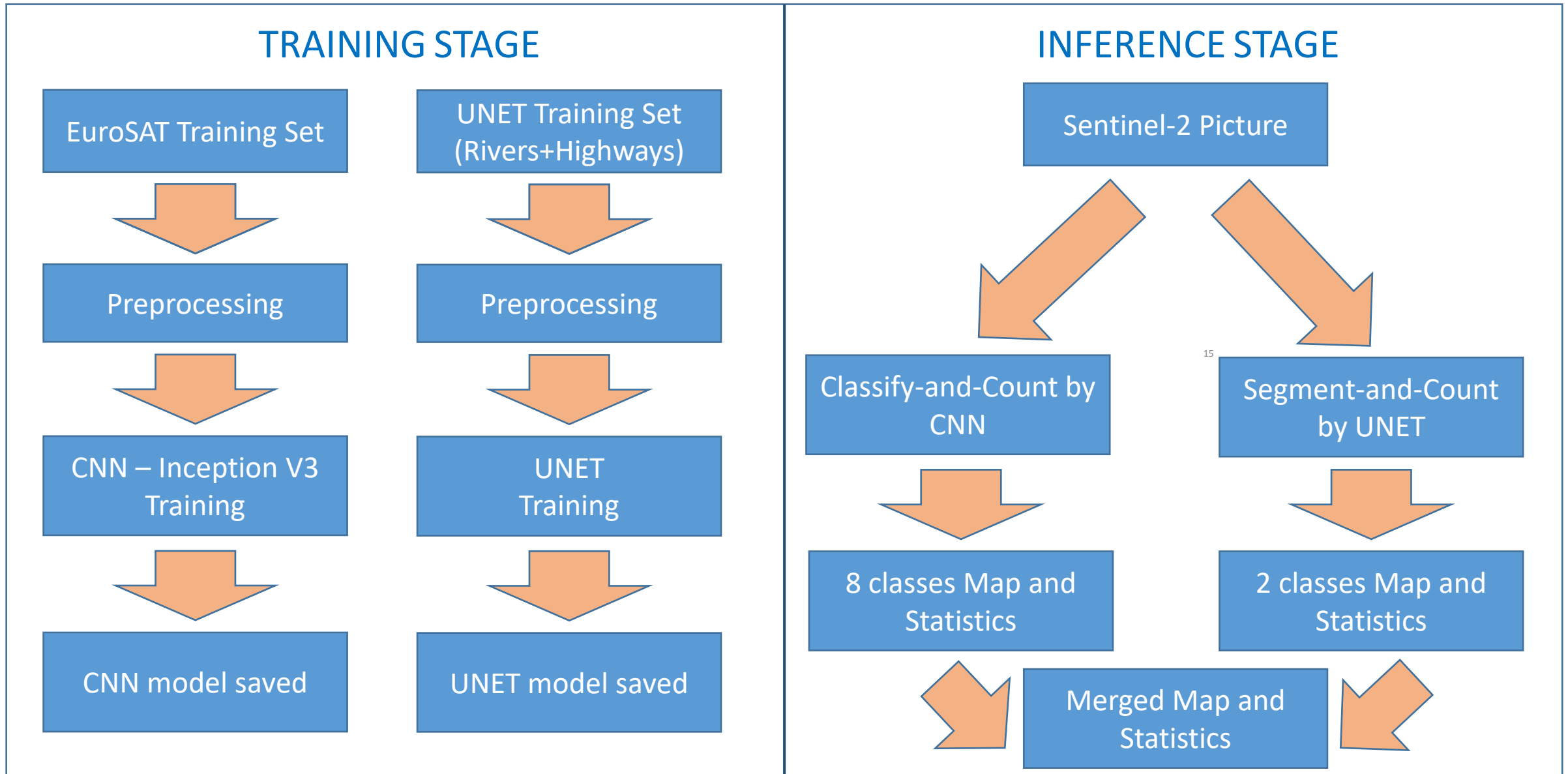


Land Cover map of Tuscany



| LC CLASS  |                  | COVERAGE % |
|---|------------------|------------|
|    | Annual Crop      | 4.1        |
|    | Forest           | 34.1       |
|    | Herb. Vegetation | 27.2       |
|    | Highway          | 0.7        |
|    | Industrial       | 5.2        |
|    | Pasture          | 10.6       |
|    | Permanent Crop   | 14.6       |
|   | Residential      | 2.4        |
|  | River            | 1.6        |

# Land Cover System – Pipeline Architecture

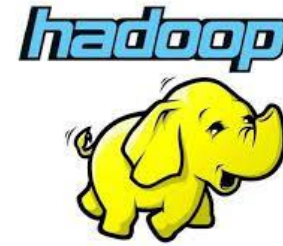


# References



# Azure Wishlist

1) **Hadoop** and **Spark** to fasten pre-processing and post-processing with different cloud nodes



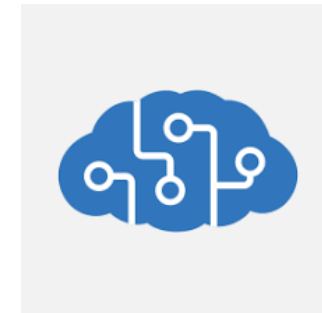
2) More **GPUs** like **Tesla V100** or better to optimize **Deep Neural Networks** parallelization and speed up **Training** and **Testing**



3) **Backup** systems to save data, models and code



4) **Cognitive services** for Computer Vision and NLP tasks



Thank you for your attention  
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