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## A Deep Learning Approach to Land Cover Estimation from Satellite Imagery

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#### Land Cover

Land cover is the observed (bio)physical cover on the earth's surface.

An important **aim** of LC studies is to **estimate** the area (or the percentage) of **land occupied** by a certain **category of entities**: forests, crops, herbaceous vegetation, residential areas, rivers, lakes, etc.





#### **European flagship LC projects:**

- **CORINE** (run by the Copernicus Programme) cartography (i.e. full-coverage) perspective
- LUCAS (managed by Eurostat)

statistical estimation (i.e. sample survey) perspective

- very costly
- very complex production pipelines
- heavy human workload
- low time frequency



Goal: given an input satellite image of an area of interest, we want an automatic system able to:

- classify the territory according to some LC taxonomy
- quantify the area (or proportion) of territory covered by each LC class

Its main benefits can be:

- to returns very **timely** land cover statistics
- to enable land cover estimation for **sub-regional area** level
- to dramatically **reduce production costs**



#### THE EUROPEAN COPERNICUS COSTELLATION PROJECT



Monitoring of planet in many ecosystem

#### **Constellation of 6 families of satellites**

- Sentinel 1: land & water, SAR active radar, Revisit time 12 days
- Sentinel 2: land & water, MSI 13 bands, Revisit time 5 days
- Sentinel 3: water
- Sentinel 4: atmosphere
- Sentinel 5: atmosphere
- Sentinel 6: atmosphere

#### **FULL FREE OPEN ACCESS**



#### Automatic approach to land cover



- Different LC classes have different reflectance spectra
- Variation of reflectance with EM frequency can be used to predict LC class
- Decision on each pixel does not depend on neighboring pixels

#### **Computer Vision /Deep Learning**



- Different LC classes have different visual/spatial patterns
- Trained ML algo predicts LC class of image pixels based on information from neighboring pixels
- Decision on each pixel depends on the whole subimage (tile) the pixel belongs to



#### Automatic approach to land cover (classify and count)





#### **Dataset EuroSAT**



- Available on <u>https://github.com/phelber/eurosat</u>
- Data from Sentinel-2 Multi Spectral Instrument covering 34 European countries
- 27000 geo-referenced labeled images 640x640 meters
- 10 different Land Cover Classes
- 2000-3000 images per class
- Available versions: RGB (10x10 meter of resolution) and multi-spectral (13 spectral bands, 16-bit)



PASTURE

RESIDENTIAL





HERBACEOUS VEGETATION





#### **Overestimate of River e Highway classes**



HIGHWAY



RIVER



- Overestimation of Eurosat *line-shape* classes as Rivers and Highways: giving a label e.g., highway to whole a tile 640m x 640m creates problems of overestimation.
- We apply two U-NET neural networks specialized for segmentation to river and highway classes



#### **U-NET Architecture**





#### **Dataset UNET**

# 1 all

**EuroSAT River** 











- Creation of a dataset suitable for **UNET** training using satellite images of EuroSAT **River** class along with data from **Copernicus High Resolution Layer**.
- The label (mask image) must contain the information about the pixel

0 does not belong to class River (black)1 belongs to the River class (white)

- Our dataset: 1500 validated segmentation masks.
- Building a similar training dataset for the **Highway** class using data from **Open Street Maps**.
- We are ready to publish and share these datasets for river and highway classes segmentation ML tasks





#### Merging of CNN + U-Net outputs





LC map detail of basin of Arno river around Pisa

Land Cover map of Tuscany Region

The final step assigns to each cell the class identified by the U-Net or the class identified by CNN, according to a hierarchy that depends on the degree of confidence we have on each algorithm.

- 1. River/Waterway
- 2. Highways
- 3. Other classes

#### **Regional Estimate of Land Cover**



#### Land Cover map of Tuscany Region

LC CLASS	COVERAGE %
Annual Crop	4.1
Forest	34.1
<u>Herb.</u> Vegetation	27.2
Highway	0.7
Industrial	5.2
Pasture	10.6
Permanent Crop	14.6
<b>Residential</b>	2.4
River	1.6



#### Conclusions

- LC statistics can benefit from machine learning methods and algorithms to achieve a high degree of automation in maps and statistics production.
- This would decrease the effort and costs
- Improve the frequency of the output.
- Classify-and-count generates good estimates for areal LC classes
- U-net approach improves estimates, but needs dataset with specific mask-label
- In the future, we could explore the possibility to assign labels using information from administrative sources, regional technical charts, cadastral maps, and agricultural census to extend U-Net approach to other LC classes
- Use further information such as SAR data from Sentinel 1 or satellite image obtained in different seasons e.g. Crop Classification
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### Thank you

