

COLLABORATIVE INTELLIGENCE PROJECT

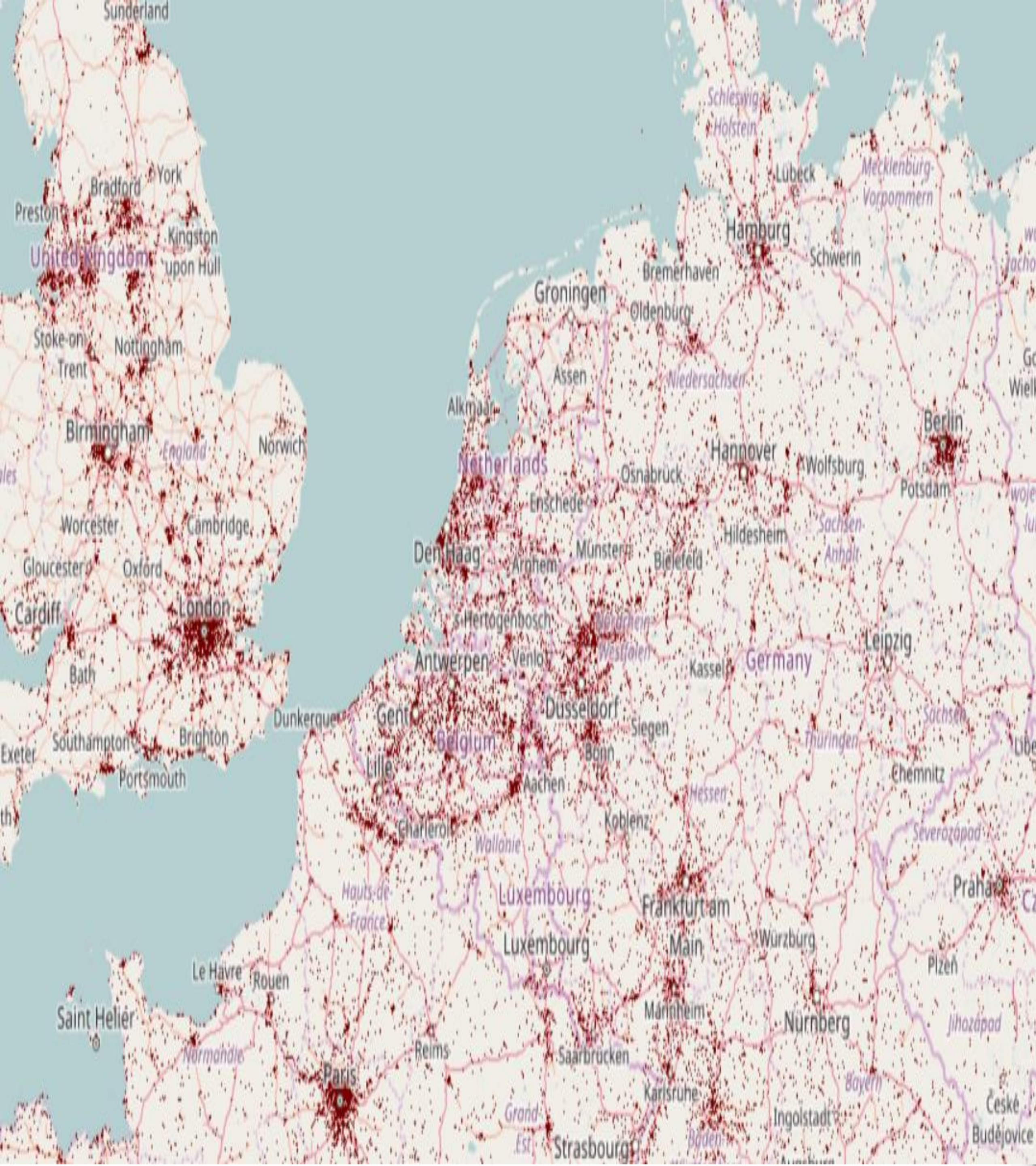
WS-2019/20



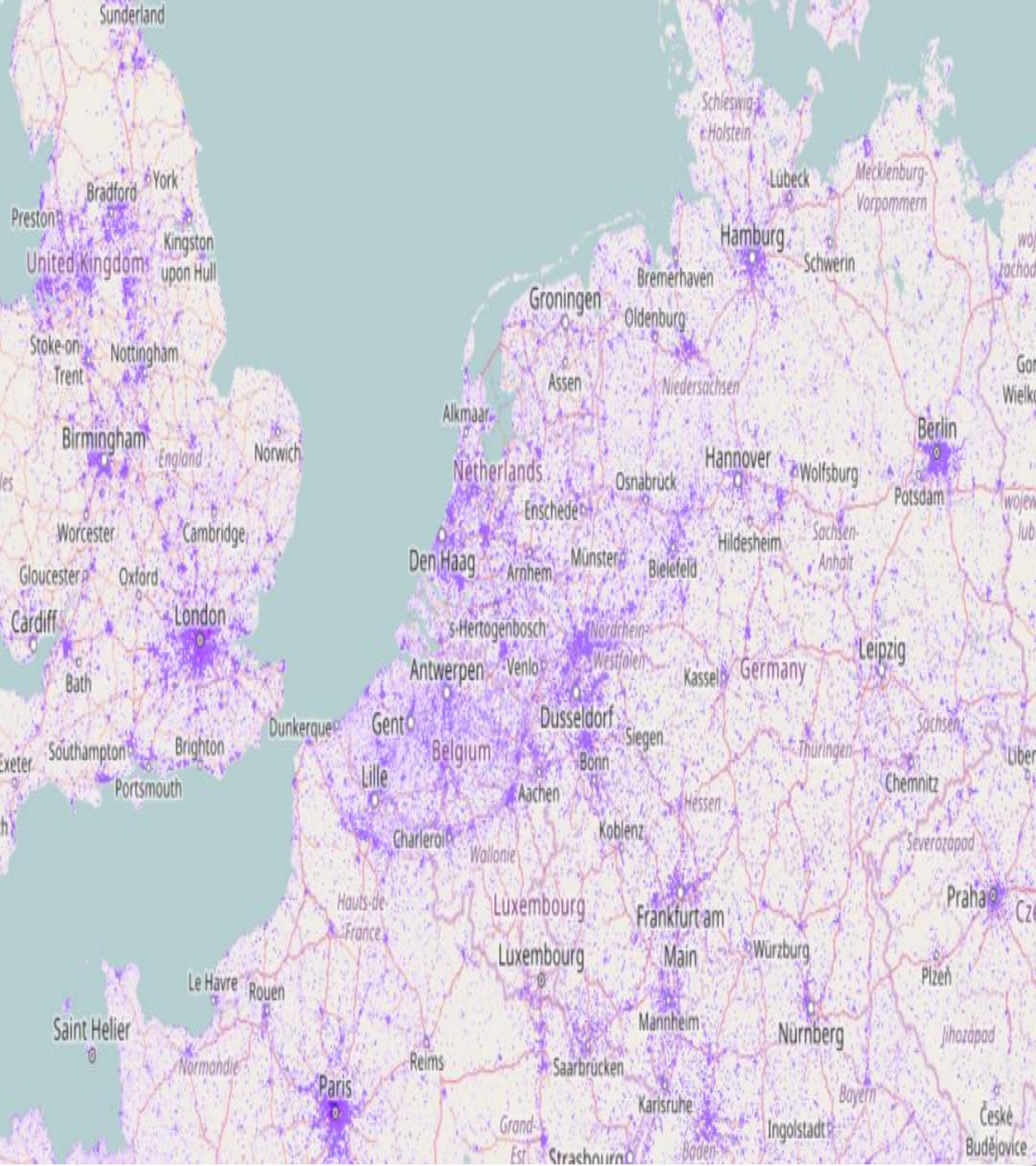
SATELLITE IMAGE ANALYSIS WITH MACHINE LEARNING

INTRODUCTION

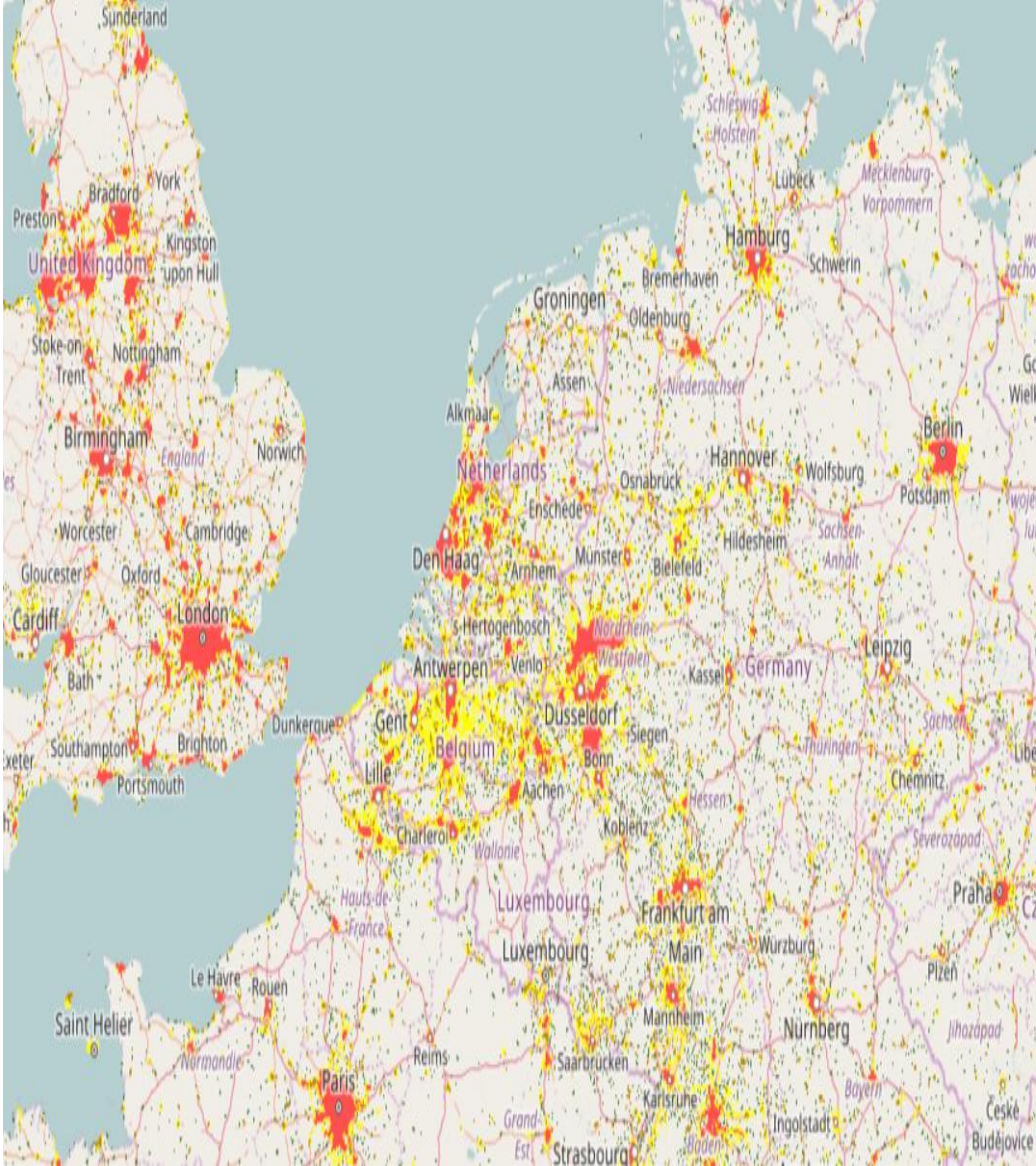
- Global Human Settlement Layer (GHSL) is a tool for assessing the human presence on the planet
- It produces global spatial information in the form of built up maps, population maps and settlement maps
- This information is generated with evidence-based analytics and knowledge using machine learning algorithms
- Earth Observation Satellites, Census data are used to generate this layer
- Pipeline of three products : BUILT-UP -> POP -> SMOD



GHS-BUILT UP



GHS-POP



GHS-SMOD

MOTIVATION

- Monitoring of human presence on earth is essential to support urban development, policies in economic, social areas on a global scale
- Potential questions:
 1. How much of earth surface is covered by settlements?
 2. How fast are human settlements growing?
- Crisis management relies on answers to these questions
- The more precise the information, the better will be the outcome of decisions made by Government bodies

ALGORITHMS TO GENERATE PRODUCTS :

BUILT-UP, POP, SMOD

Symbolic Machine
Learning
BUILT-UP



Population
Distribution
POP



Settlement Model
SMOD

World Settlement
Footprint
BUILT-UP



Population
Distribution
POP



Settlement Model
SMOD

Convolutional
Neural Network
BUILT-UP



Population
Distribution
POP



Settlement
Model
SMOD

DATA



Sentinel-2 :

- Earth observation satellite operated by European Space Agency(ESA)
- Multi-spectral data with 13 bands
- Spatial resolution : 10m, 20m, 60m

Landsat-8 :

- Earth observation satellite operated by United States Geological Survey(USGS)
- Multi-spectral data with 11 bands
- Spatial resolution : 15m, 30m, 100m

PRODUCT 1

BUILT-UP

GHS BUILT-UP

- **Input** : Multispectral satellite imagery
- **Methodology** : Convolutional Neural Networks, Symbolic Machine Learning, World Settlement Footprint
- **Output** : Built up classification on the image (0=Built up, 1=No built up)
BUILT-UP (0/1) classification and BUILT-UP (confidence 0-100)

Method 1

Symbolic Machine
Learning (SML)

BUILT-UP : SYMBOLIC MACHINE LEARNING (SML)

Step 1 - Data Collection

- X : Collect multi spectral satellite images from Sentinel-2/Landsat-8
- Y : Corine Land Cover(CLC) with land cover labels (Water bodies, Urban region etc.) as categorical reference data

Step 2 - Data Reduction

- Taxonomy : meaning quantization of numerical values
- Sequencing : construct sequences of tuples $X \rightarrow Y$
- Unique sequences : identify unique sequences of $X \rightarrow Y$

Example representation of each pixel : (Band1, Band2, Band3) \rightarrow (Built up)

Contd...

Step 3 – Association Analysis

Interestingness measure:

Evidence-based Normalized Differential Index (*ENDI*) – This measure scores the data sequences in X according to their occurrences in each reference class in Y.

$$ENDI_A = \frac{f_{pos} - f_{neg}}{f_{pos} + f_{neg}}$$

$$ENDI = \frac{ENDI_A + ENDI_B}{2}$$

$$ENDI_B = \frac{p_{pos} - p_{neg}}{p_{pos} + p_{neg}}$$

$$ENDI \text{ range} = [-1, +1]$$

f_{pos} and f_{neg} are the frequencies of joint occurrences among X data instances and the positive and negative reference instances respectively.

p_{pos} and p_{neg} represent the probabilities.

Contd...

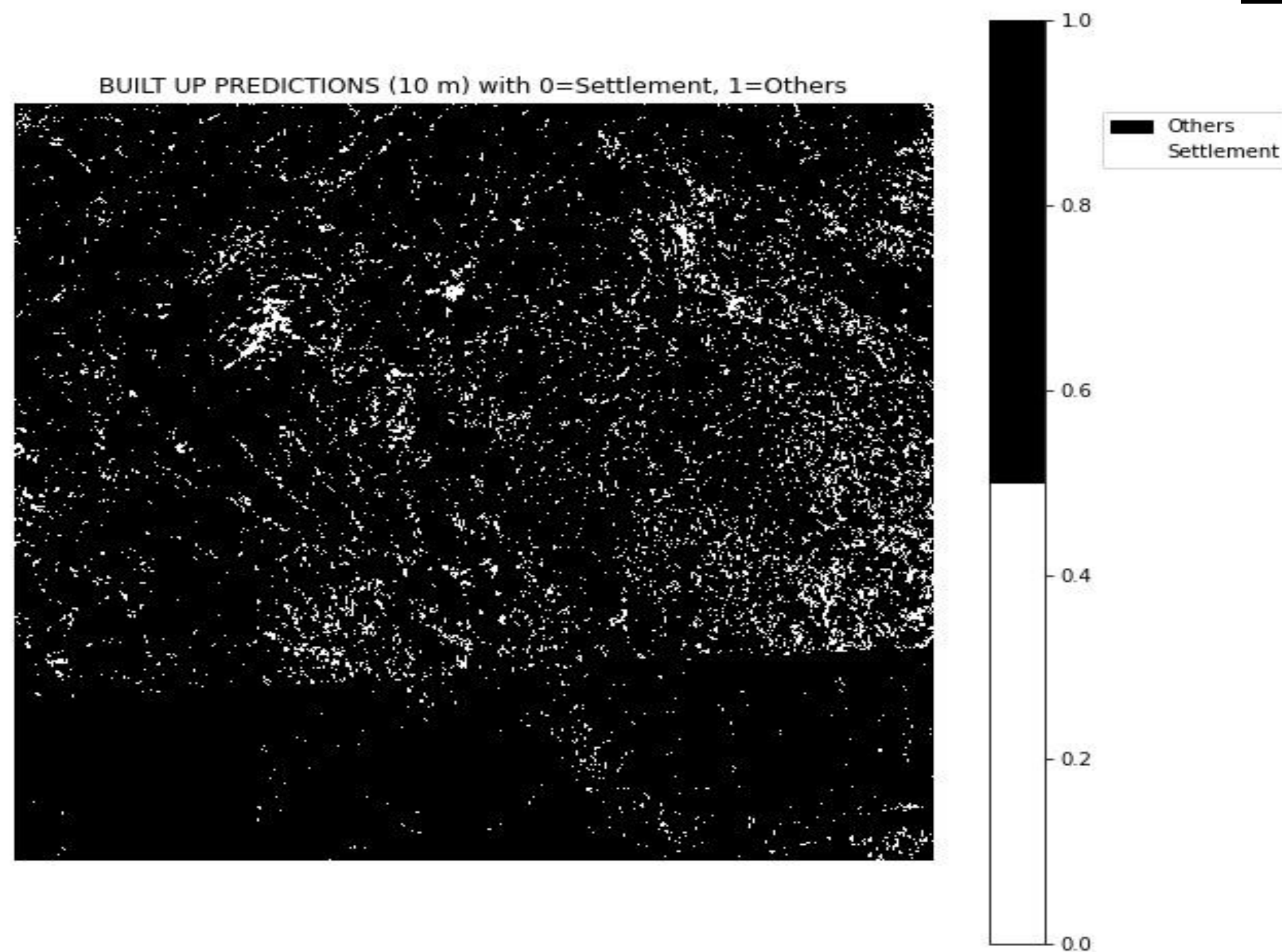
Classification : $\arg \max$ of *ENDI* measures of each class. This results in Built-Up or Non-Built up classification of an individual pixel in an input image.

Accuracy :

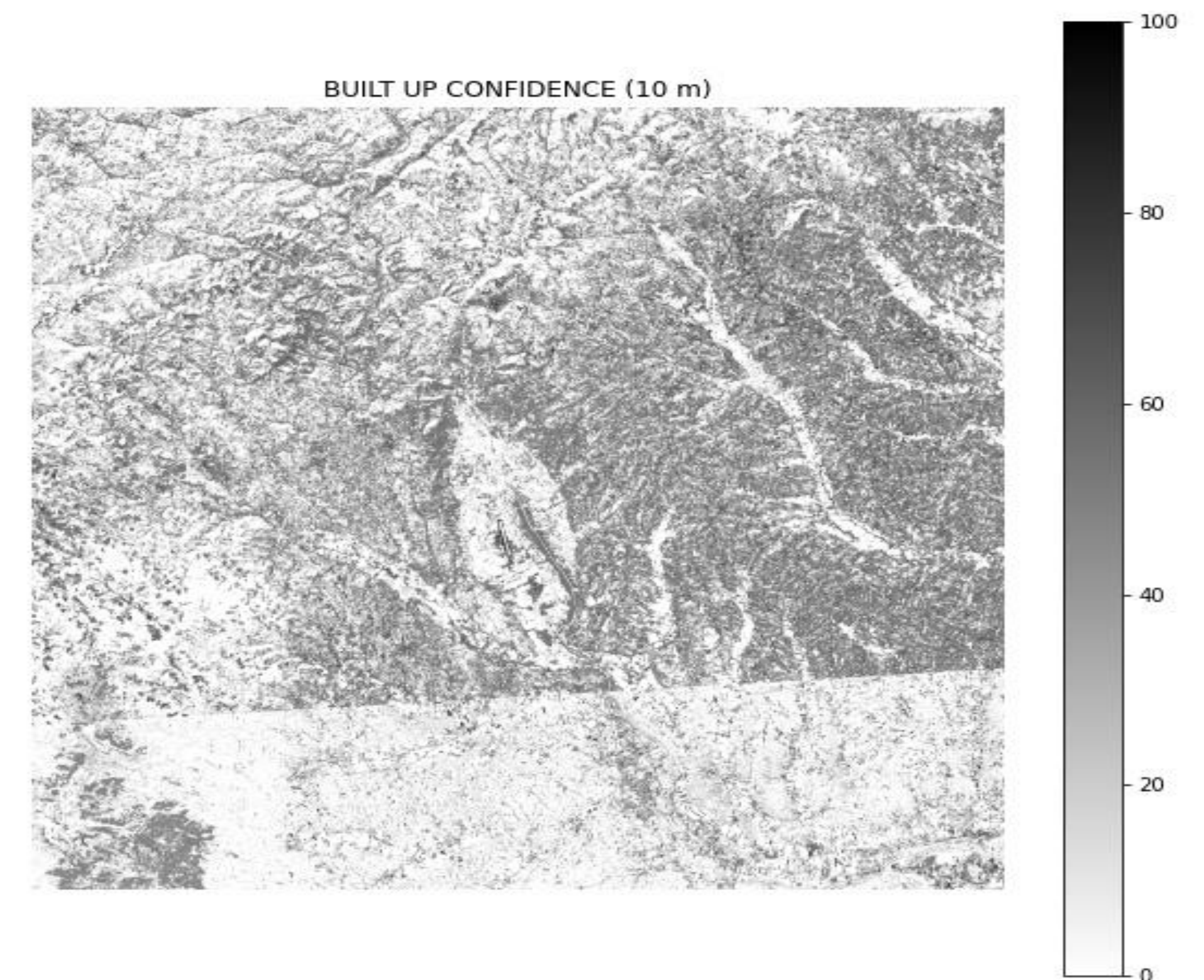
- F1 score
- Precision
- Recall
- MeanIoU
- Macro average

SML RESULTS - (Built up=white, Others=black)

Graz, Austria

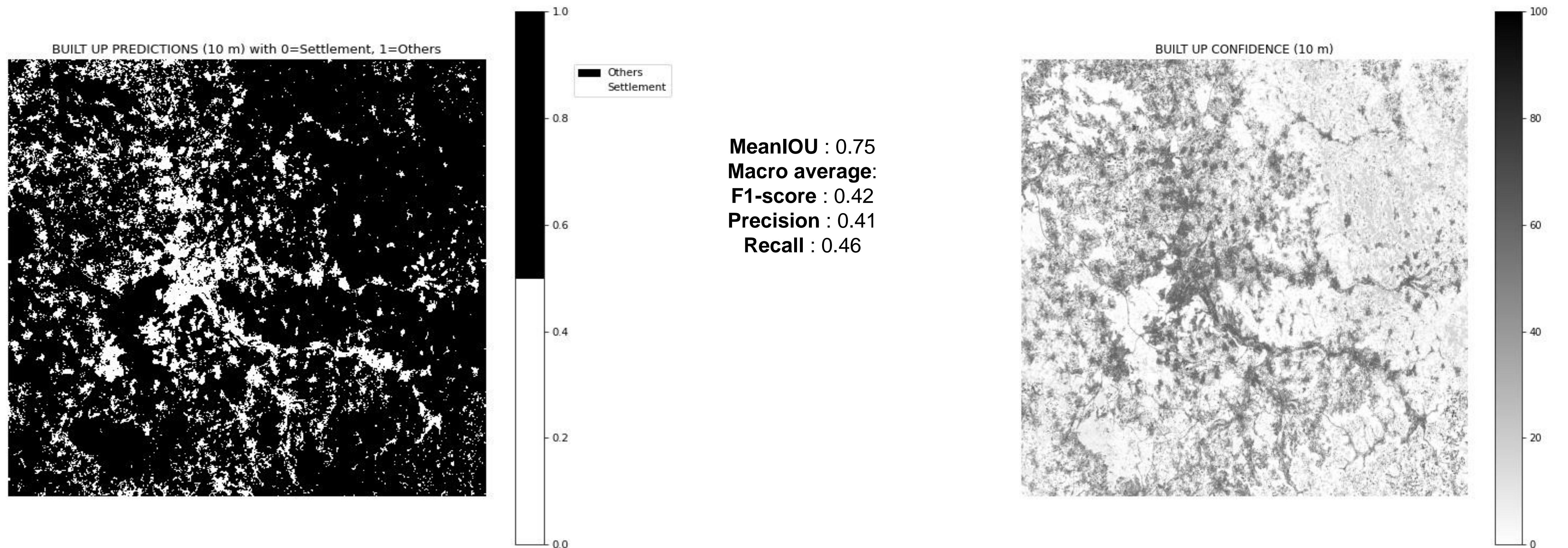


MeanIOU : 0.82
Macro average:
F1-score : 0.31
Precision : 0.33
Recall : 0.33



SML RESULTS - (Built up=white, Others=black)

Stuttgart, Germany



Method 2

World Settlement
Footprint (WSF)

BUILT-UP : WORLD SETTLEMENT FOOTPRINT (WSF)

Step 1 - Data collection

- **Multi temporal scenes** : Collection of different images taken over different time periods on the same region
- **Reference data Y**: Corine Land Cover(CLC) with land cover labels (Water bodies, Urban region etc.) as categorical reference data

Step 2 - Calculate spectral indices

Spectral Index	Formula
Normalized Difference Built-up Index (NDBI)	$(SWIR1 - NIR) / (SWIR1 + NIR)$
Modified Normalized Difference Water Index (MNDWI)	$(Green - NIR) / (Green + NIR)$
Normalized Difference Vegetation Index (NDVI)	$(NIR - Red) / (NIR + Red)$
Normalized Difference Middle Infrared (NDMIR)	$(SWIR1 - SWIR2) / (SWIR1 + SWIR2)$
Normalized Difference Red Blue (NDRB)	$(Red - Blue) / (Red + Blue)$
Normalized Difference Green Blue (NDGB)	$(Green - Blue) / (Green + Blue)$

Contd...

Step 3 - Calculate temporal statistics

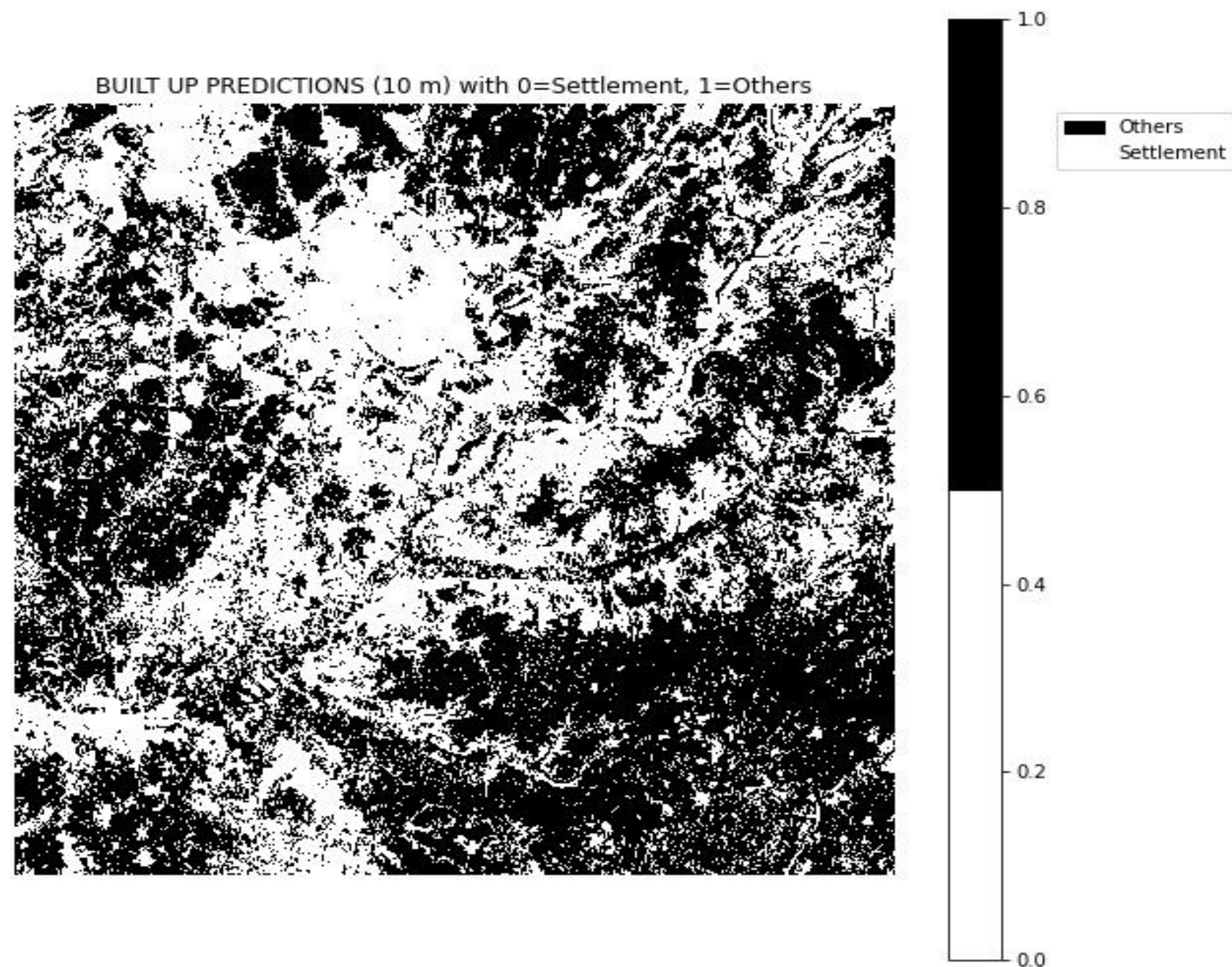
- For each region, calculate temporal statistics (min, max, mean, standard deviation, mean slope) of spectral indices from Step 2.
- X: Spectral indices and temporal statistics from satellite imagery are the features used for training our model.

Step 4 - Training

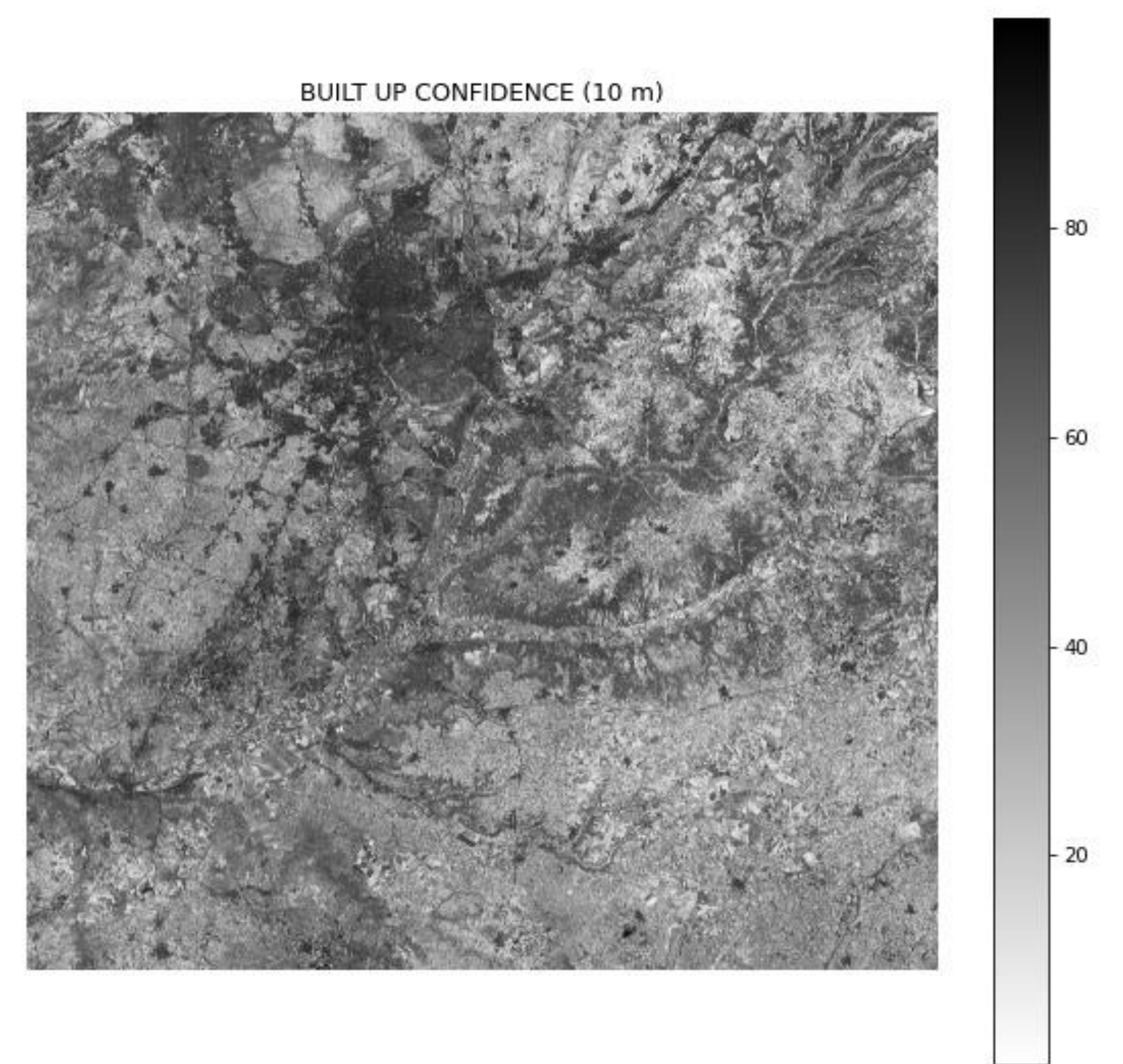
- X as spectral indices and temporal statistics and Y as class labels
- Support Vector Machine (SVM) with RBF kernel

WSF RESULTS - (Built up=white, Others=black)

Madrid, Spain



MeanIOU : 0.53
Macro average:
F1-score : 0.44
Precision : 0.54
Recall : 0.66



Method 3

Convolutional Neural Network (CNN)

BUILT UP : CNN

Step 1 - Data collection

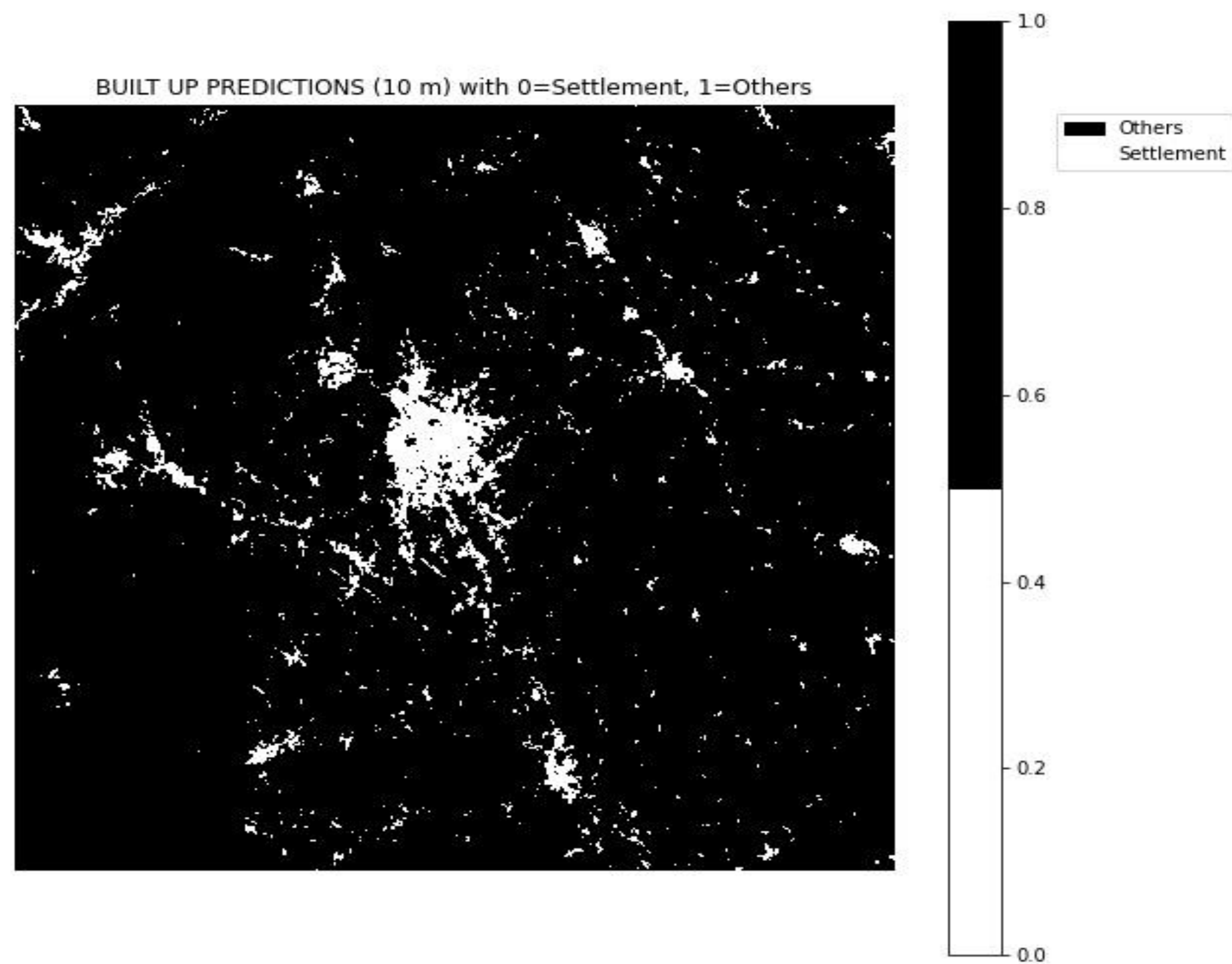
- **Segmented scenes** : Collection of different images with corresponding segmentations of built-up and non-built up.
- **Reference data Y**: Corine Land Cover(CLC) with land cover labels (Water bodies, Urban region etc.) as categorical reference data, Original GHSL products

Step 2 – U-Net, a convolutional neural network

- **Training on MS (Multispectral) images**
- **Training on RGB images**

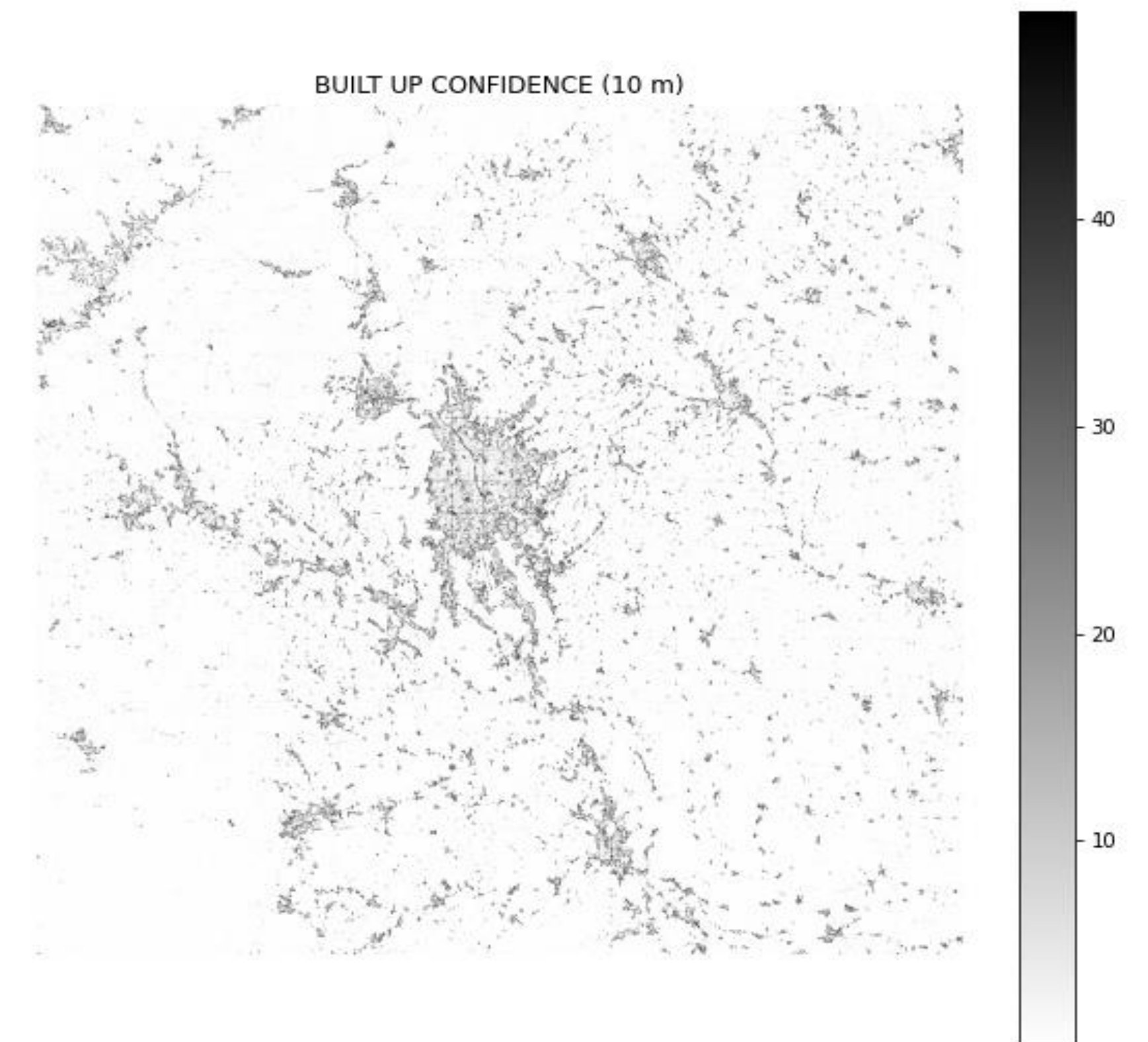
CNN RESULTS

(Built up=white, Others=black)



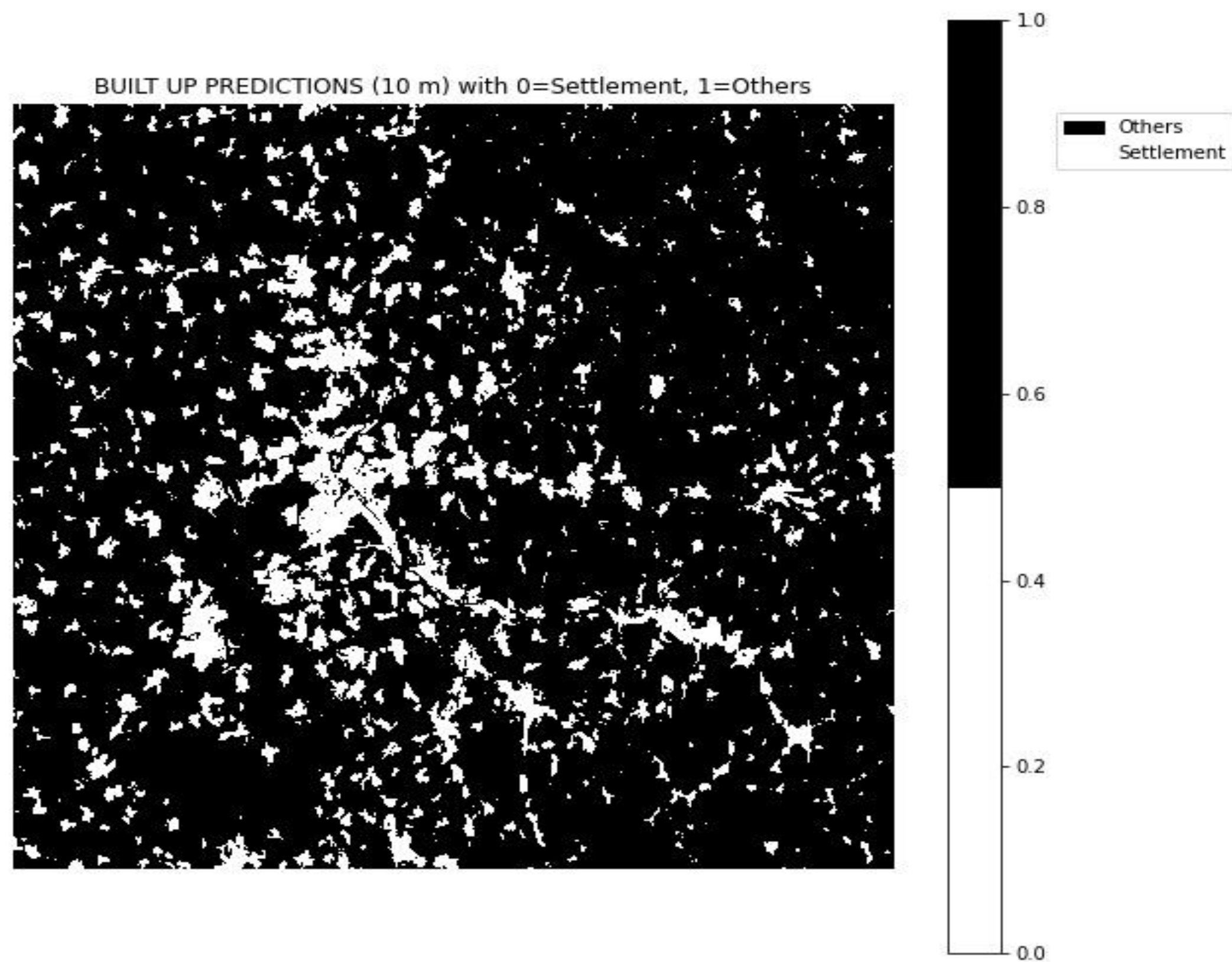
MeanIOU : 0.93
Macro average:
F1-score : 0.60
Precision : 0.58
Recall : 0.64

Graz, Austria



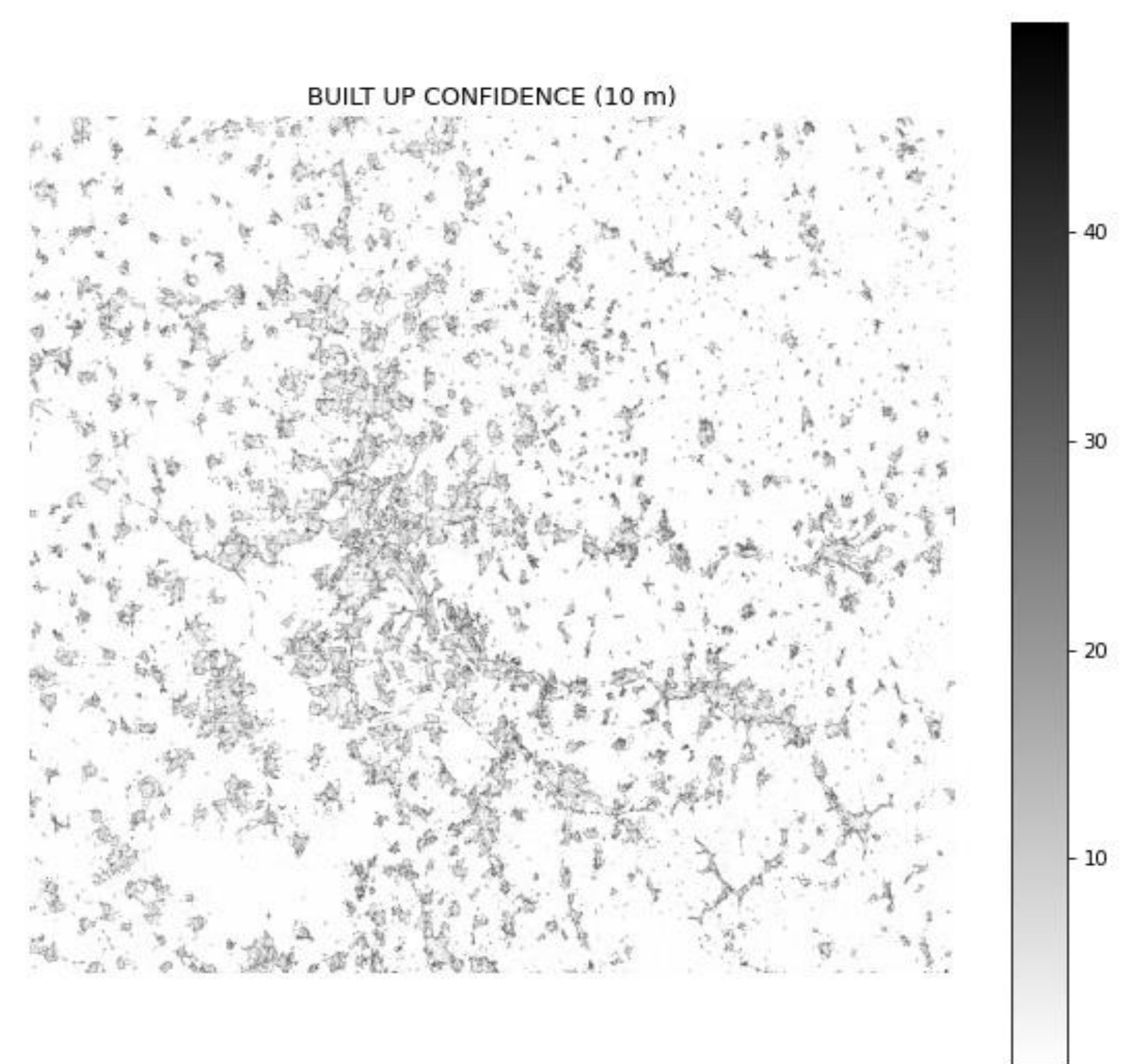
CNN RESULTS

(Built up=white, Others=black)



MeanIOU : 0.85
Macro average:
F1-score : 0.71
Precision : 0.71
Recall : 0.72

Stuttgart, Germany



PRODUCT 2

POP

GHS - POP

- **Input** : Gridded Population of the World (GPW v4). It models the distribution of human population (counts and densities) on a raster surface
+
GHS-BUILT
- **Methodology** : Dasymetric mapping technique
- **Output** : Population Grids that depicts the distribution and density of population expressed as number of people per cell.

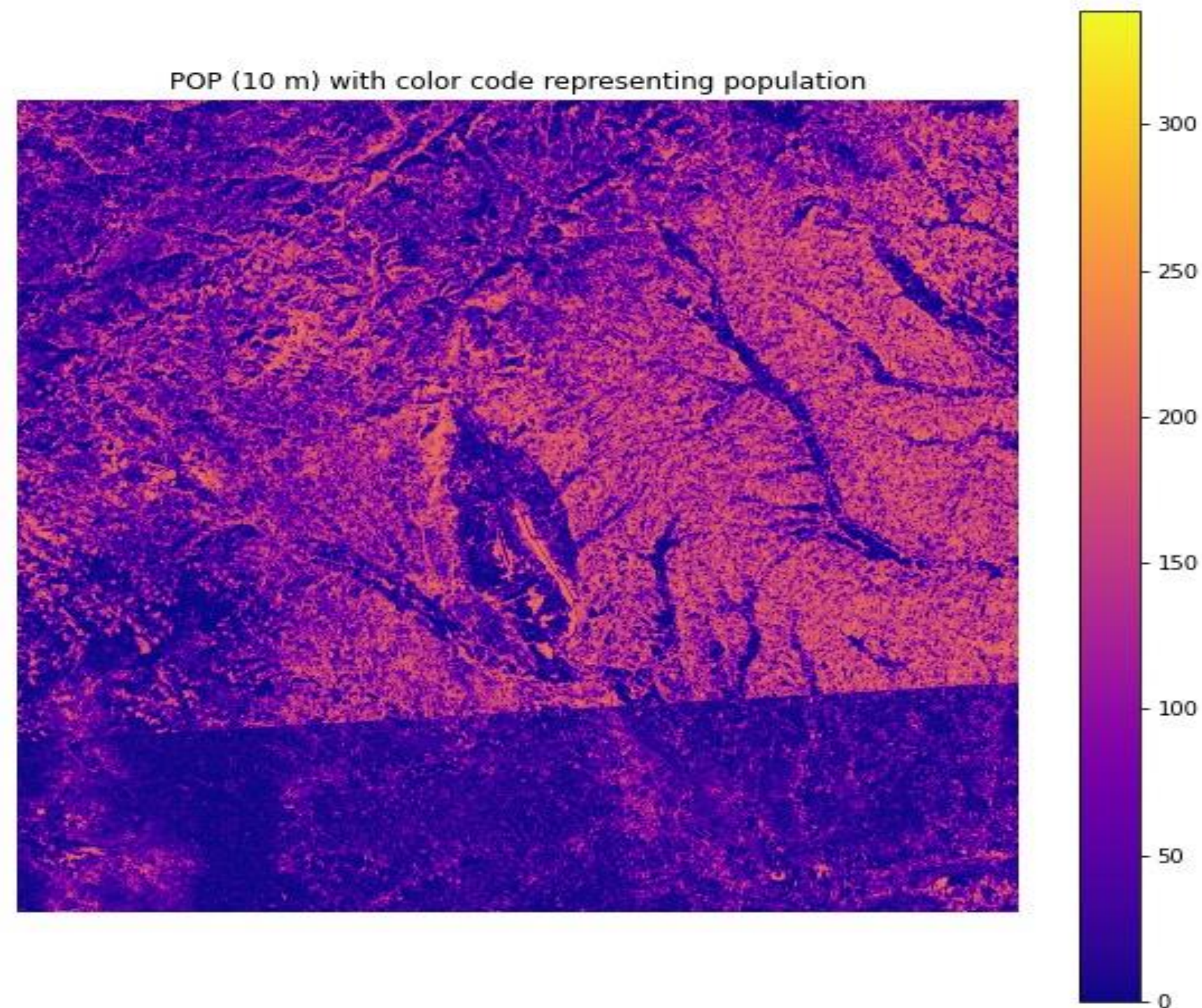
DASYMETRIC MAPPING TECHNIQUE

- **Step 1** - Divide the region into sub-regions with different classes of population (0-6) with 0=*no_population* to 6=*very_high_population*
- **Step 2** - Calculate densities of each types of population
- **Step 3** - Calculate proportions of each population type
- **Step 4** - Assign each region with population based on the evidence of GHS-BUILT, distribute by proportion

SML based BUILT-UP->POP RESULTS

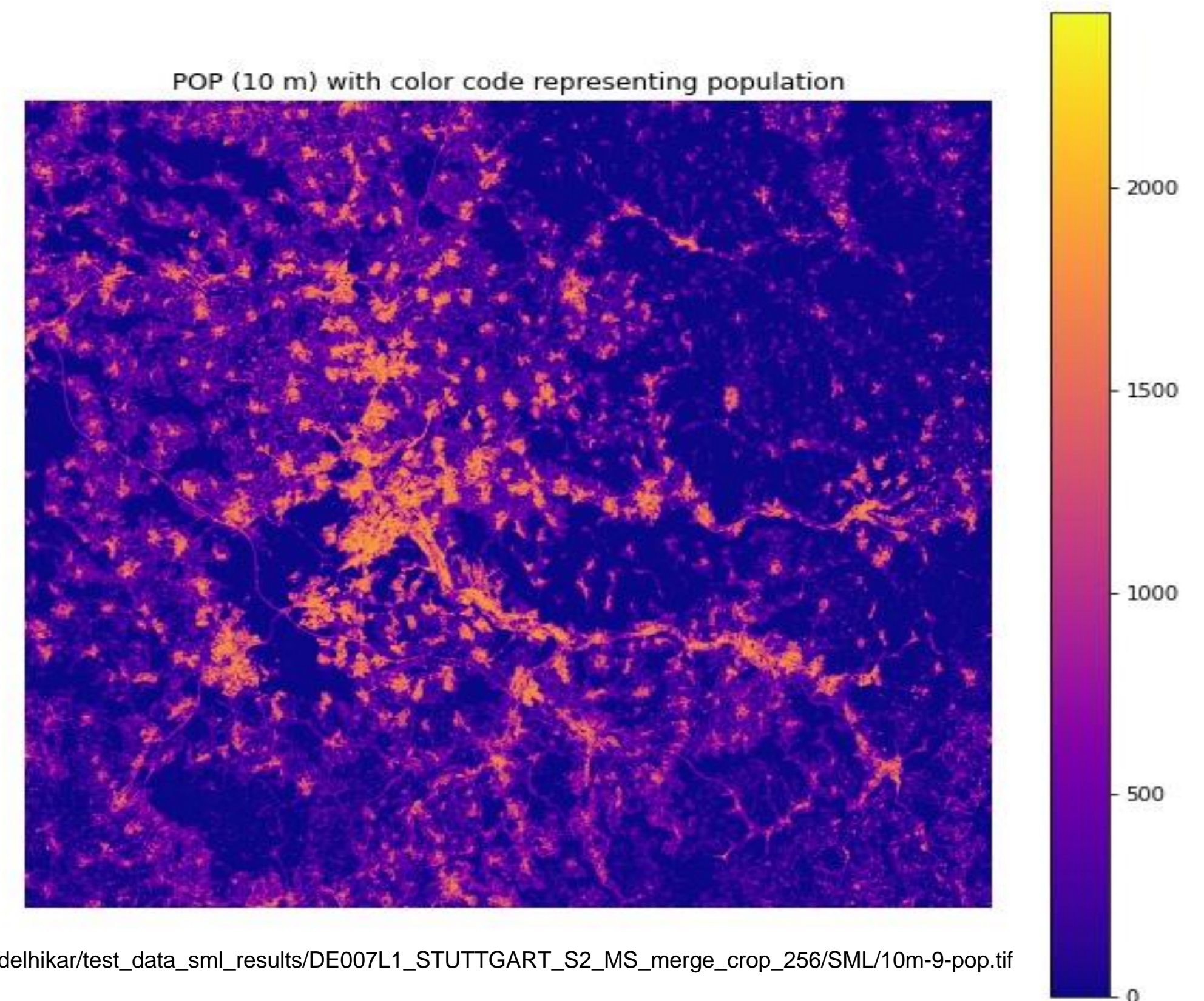
(Yellow=high population, Blue=low population)

Graz, Austria



/netscratch/delhikar/test_data_sml_results/AT002L2_GRAZ_S2_MS_merge_crop_256/SML/10m-9-pop.tif

Stuttgart, Germany



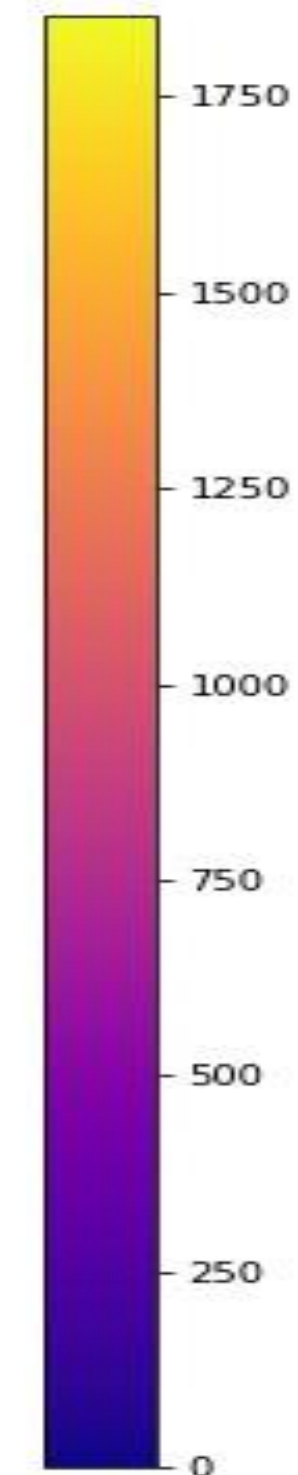
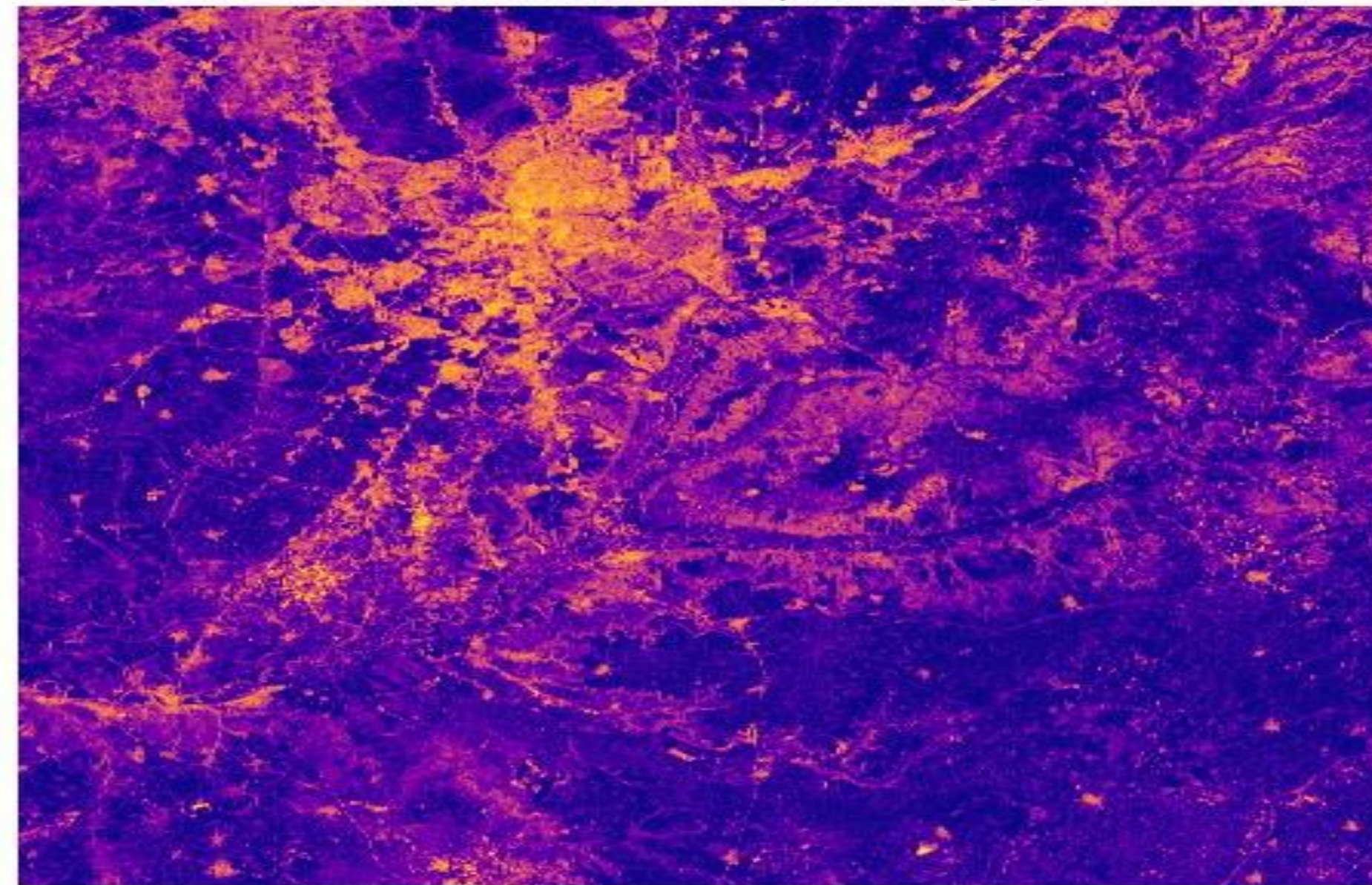
/netscratch/delhikar/test_data_sml_results/DE007L1_STUTTGART_S2_MS_merge_crop_256/SML/10m-9-pop.tif

WSF based BUILT-UP->POP RESULTS

(Yellow=high population, Blue=low population)

Madrid, Spain

POP (10 m) with color code representing population

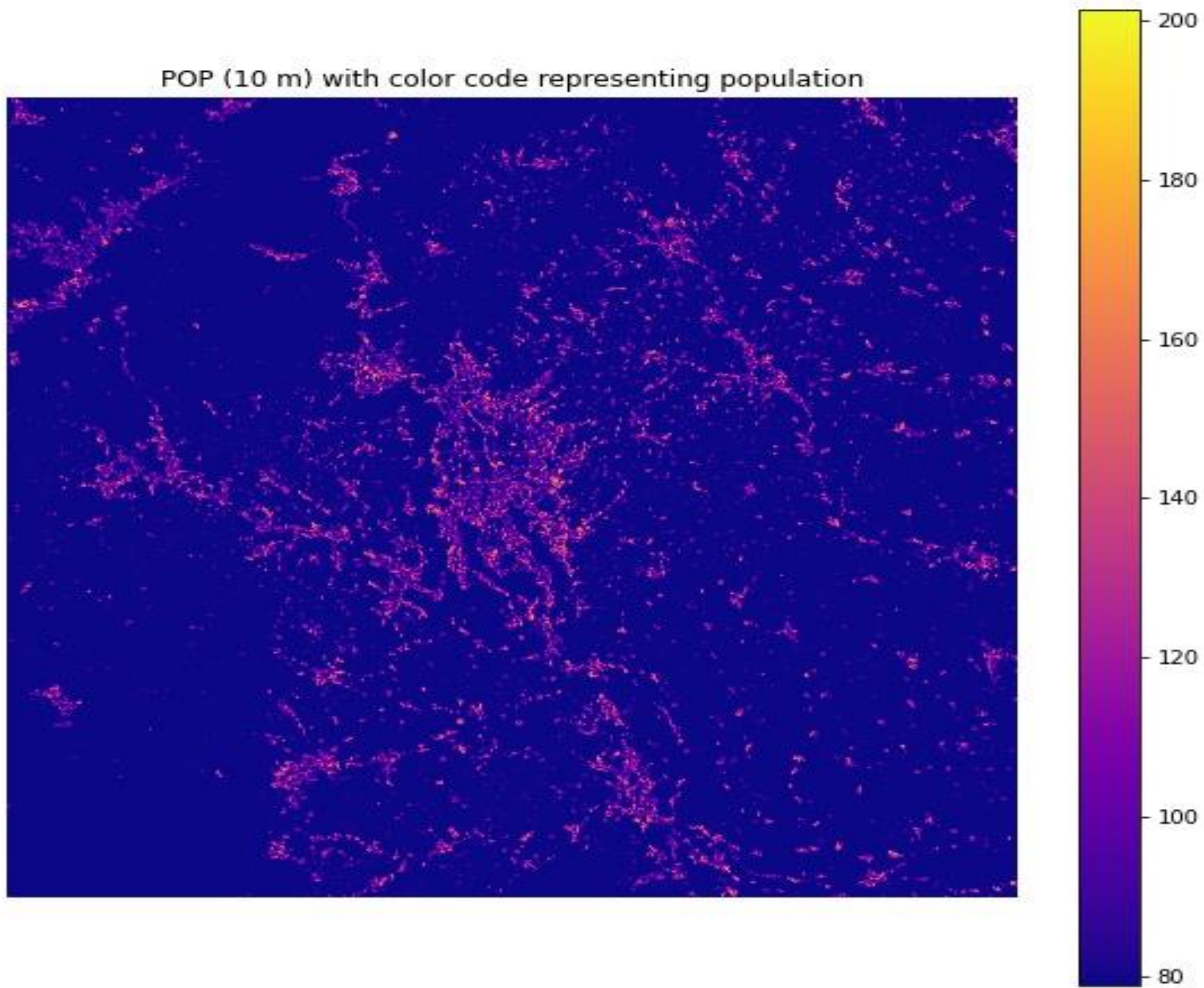


/netscratch/delhikar/WSF/version2/test_data_results_new/madrid/WSF/10m-pop.tif

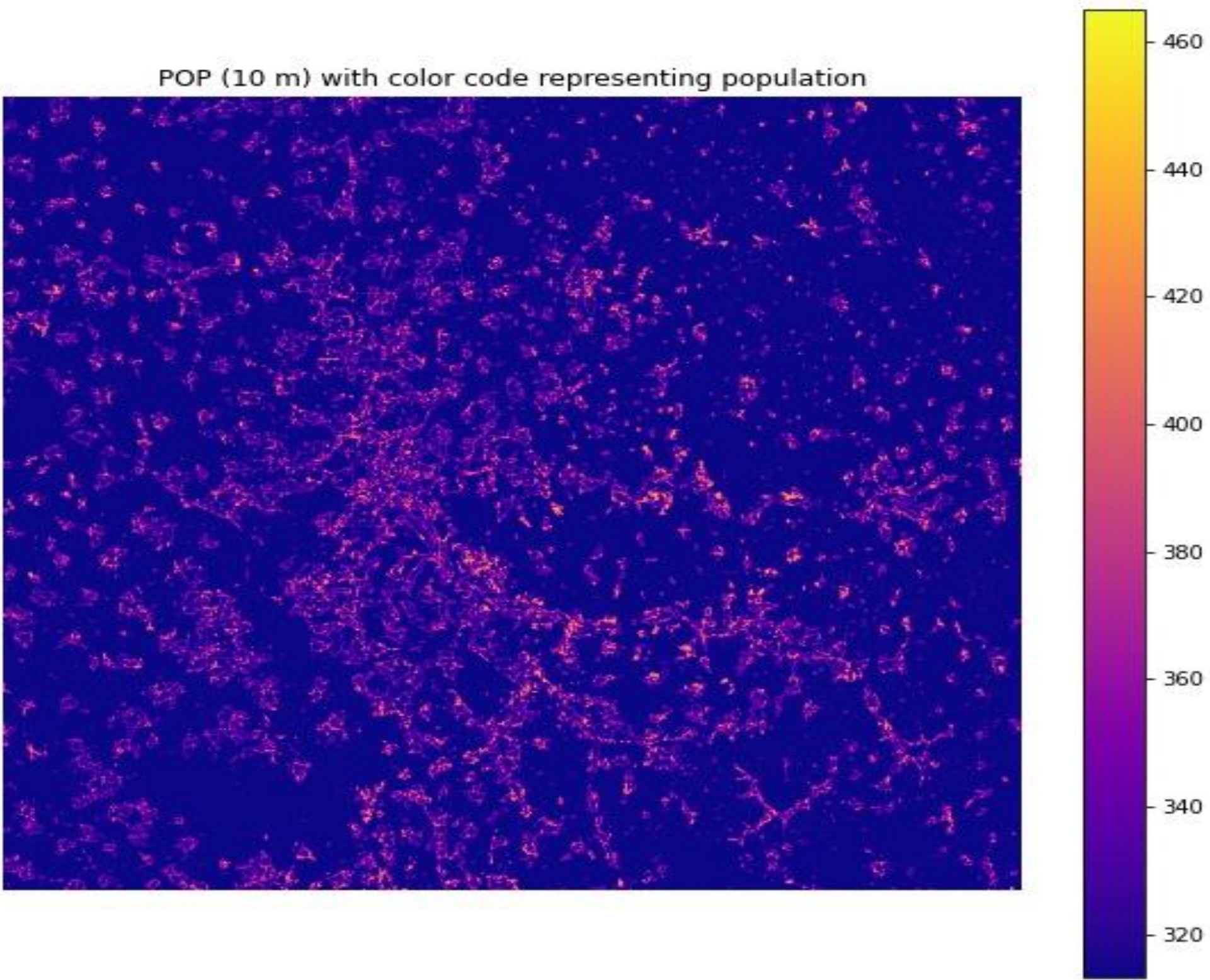
CNN based BUILT-UP->POP RESULTS

(Yellow=high population, Blue=low population)

Graz, Austria



Stuttgart, Germany



PRODUCT 3

SMOD

GHS-SMOD

- **Input** : GHS_BUILT+GHS_POP
- **Methodology** : Divide built up areas into *urban_centre*, *urban_cluster*, *rural_area*, *no_population* based on number of people living per cell
- **Output** : GHS-SMOD

SMOD-RULES

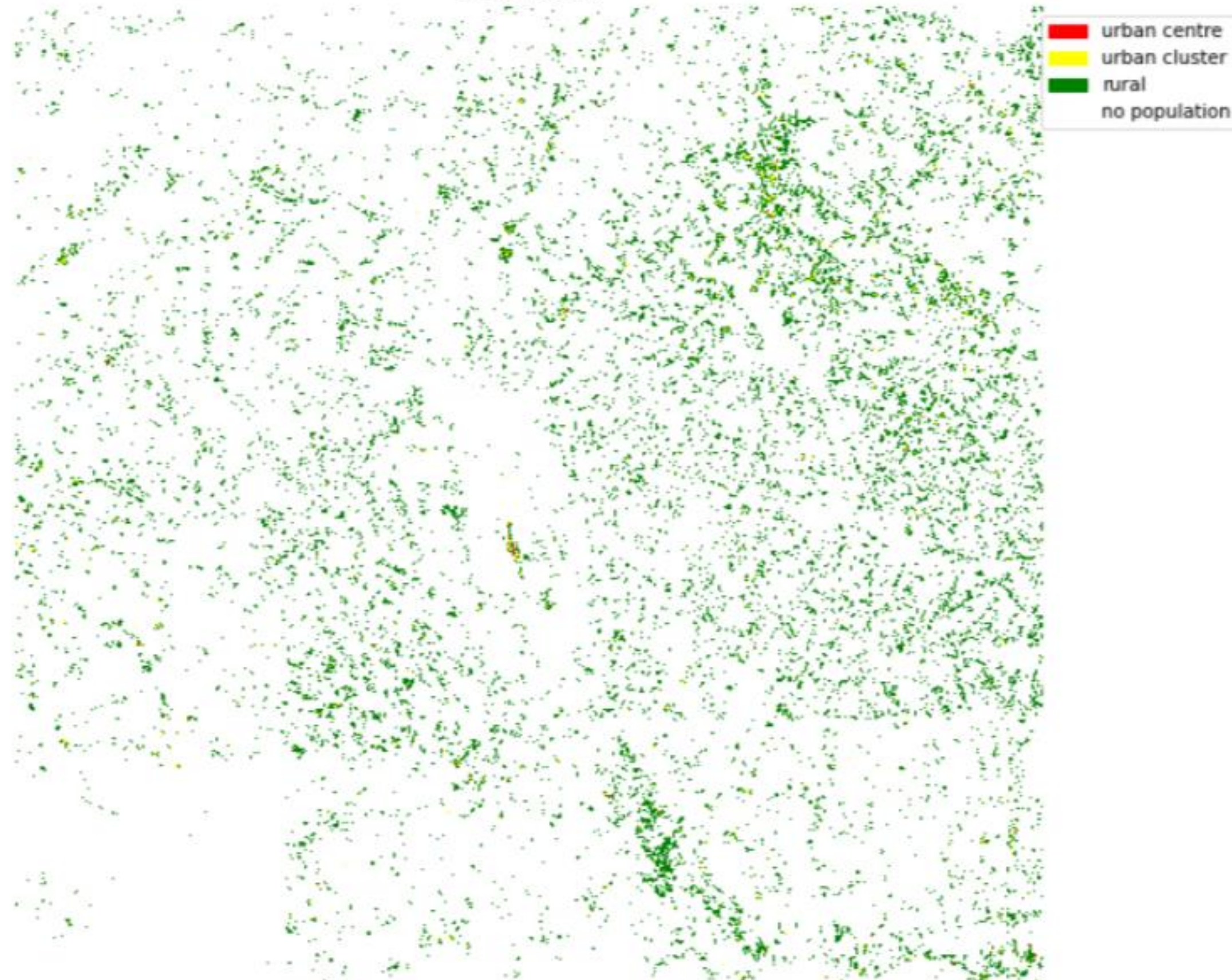
- **Urban center** : If ((GHS-POP>1500) or (GHS-BUILT UP>50%)) and (4 connected cells GHS-POP>50000)
- **Urban cluster** : If ((GHS-POP>300) and (GHS-BUILT UP>3%)) and (4 connected cells GHS-POP>5000)
- **Rural area** : If ((GHS-POP>1) and (single or connected cells GHS-POP<5000))

SML BUILT-UP->POP->SMOD RESULTS

(Red=urban center, Yellow=urban cluster, Green=rural region, White=no population)

Graz, Austria

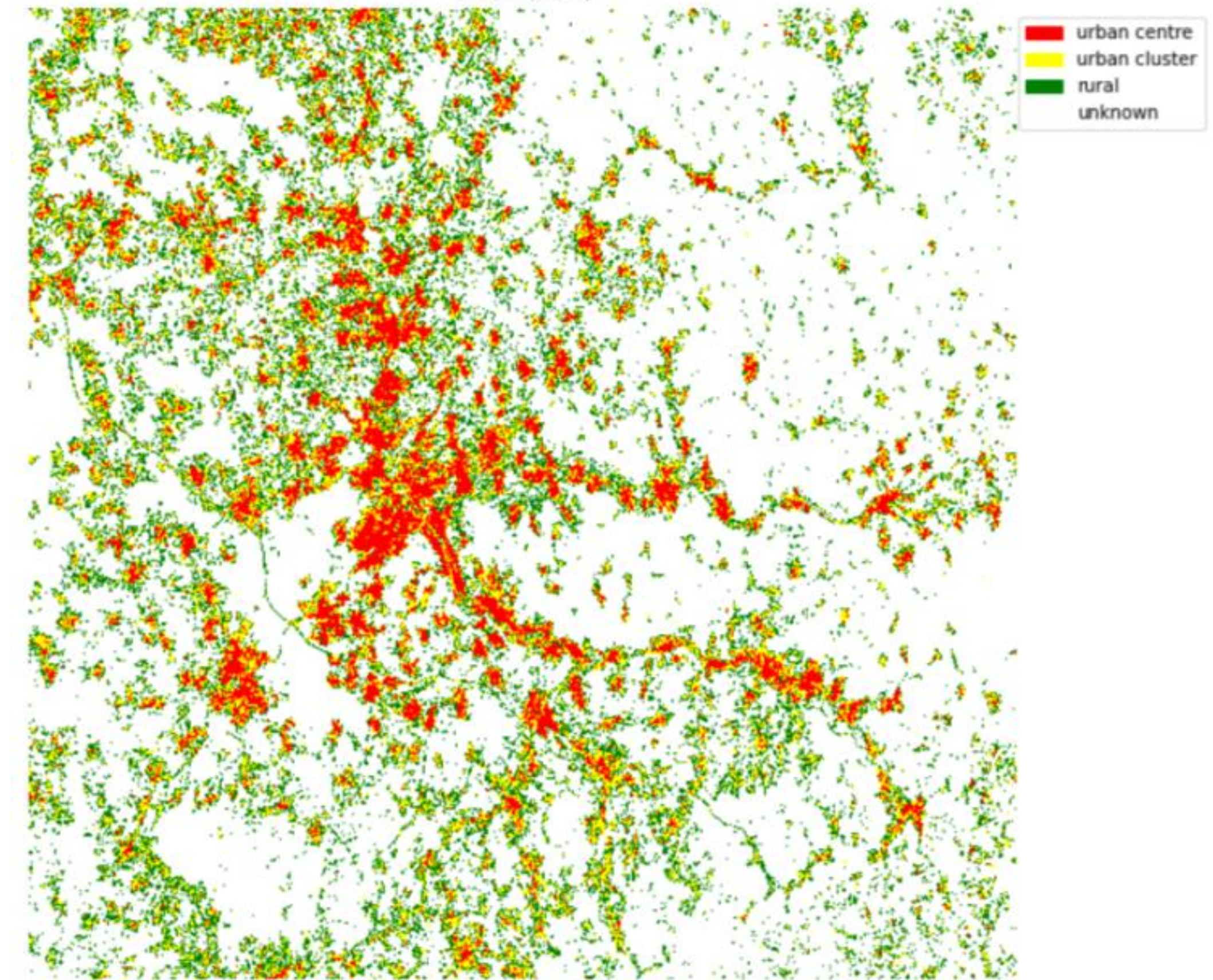
SMOD (10m)



/netscratch/delhikar/test_data_sml_results/AT002L2_GRAZ_S2_MS_merge_crop_256/SML/10m-9-smod.tif

Stuttgart, Germany

SMOD (10m)

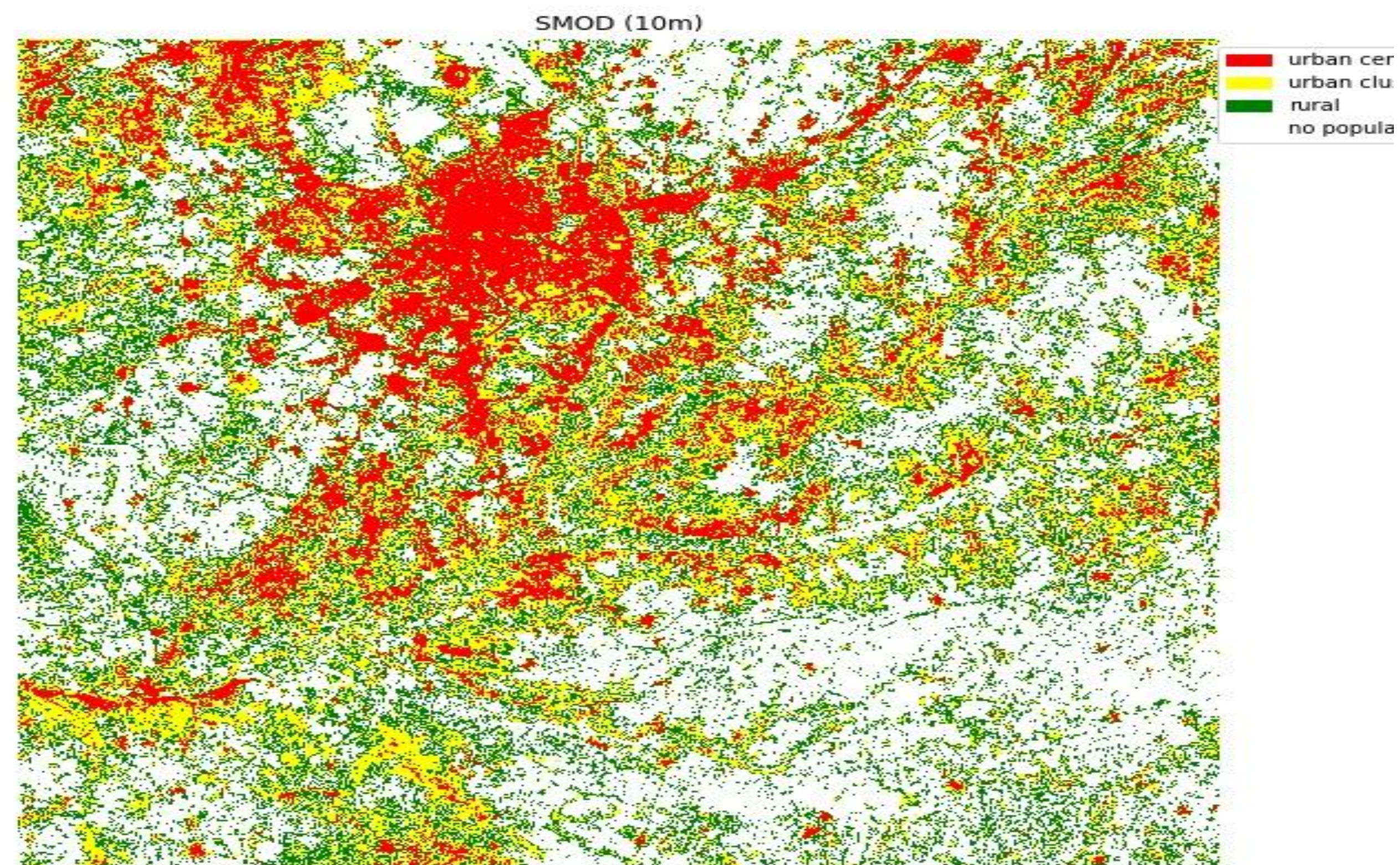


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WSF BUILT-UP->POP->SMOD RESULTS

(Red=urban center, Yellow=urban cluster, Green=rural region, White=no population)

Madrid, Spain



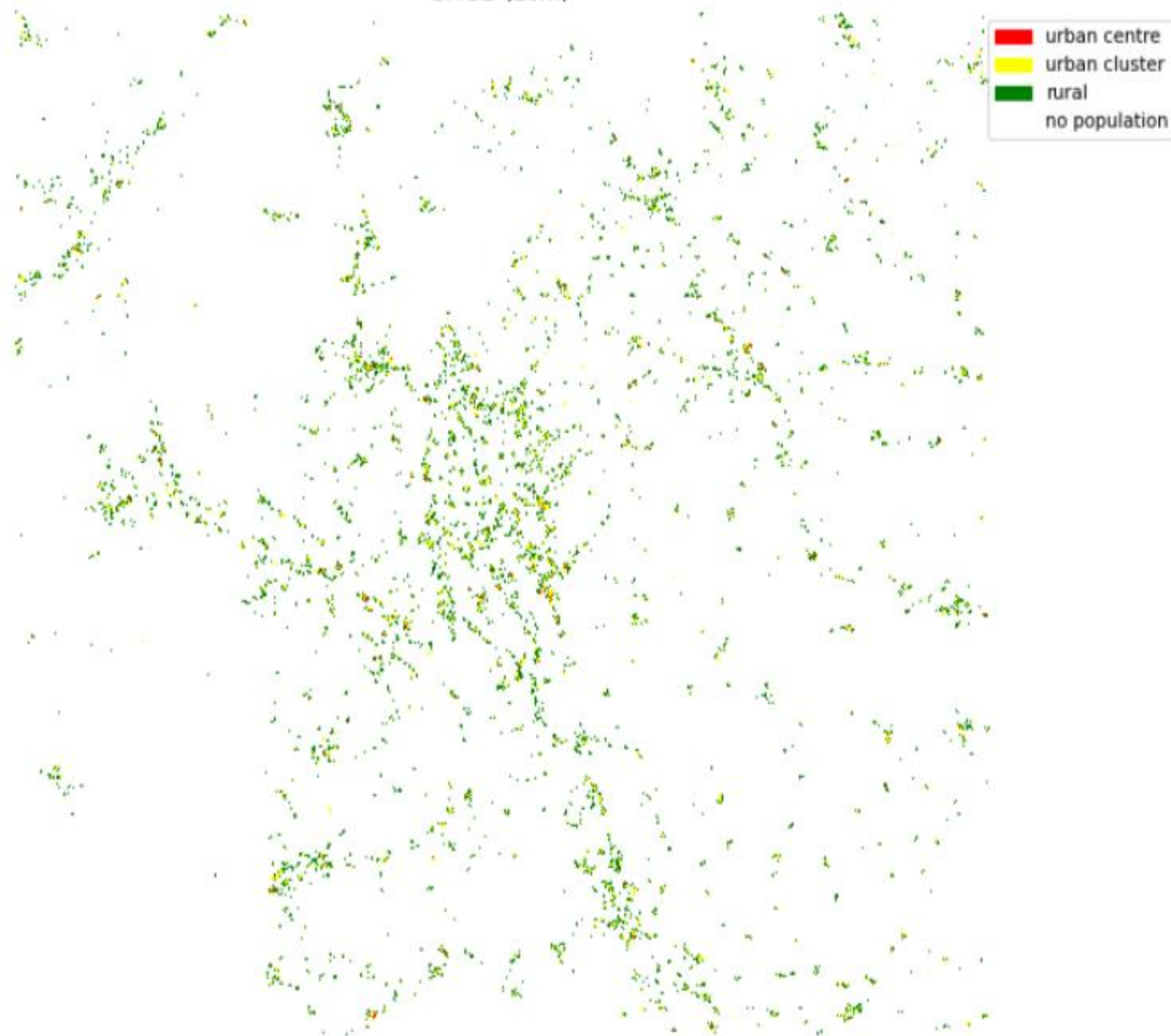
/netscratch/delhikar/WSF/version2/test_data_results_new/madrid/WSF/10m-smod.tif

CNN BUILT-UP->POP->SMOD RESULTS

(Red=urban center, Yellow=urban cluster, Green=rural region, White=no population)

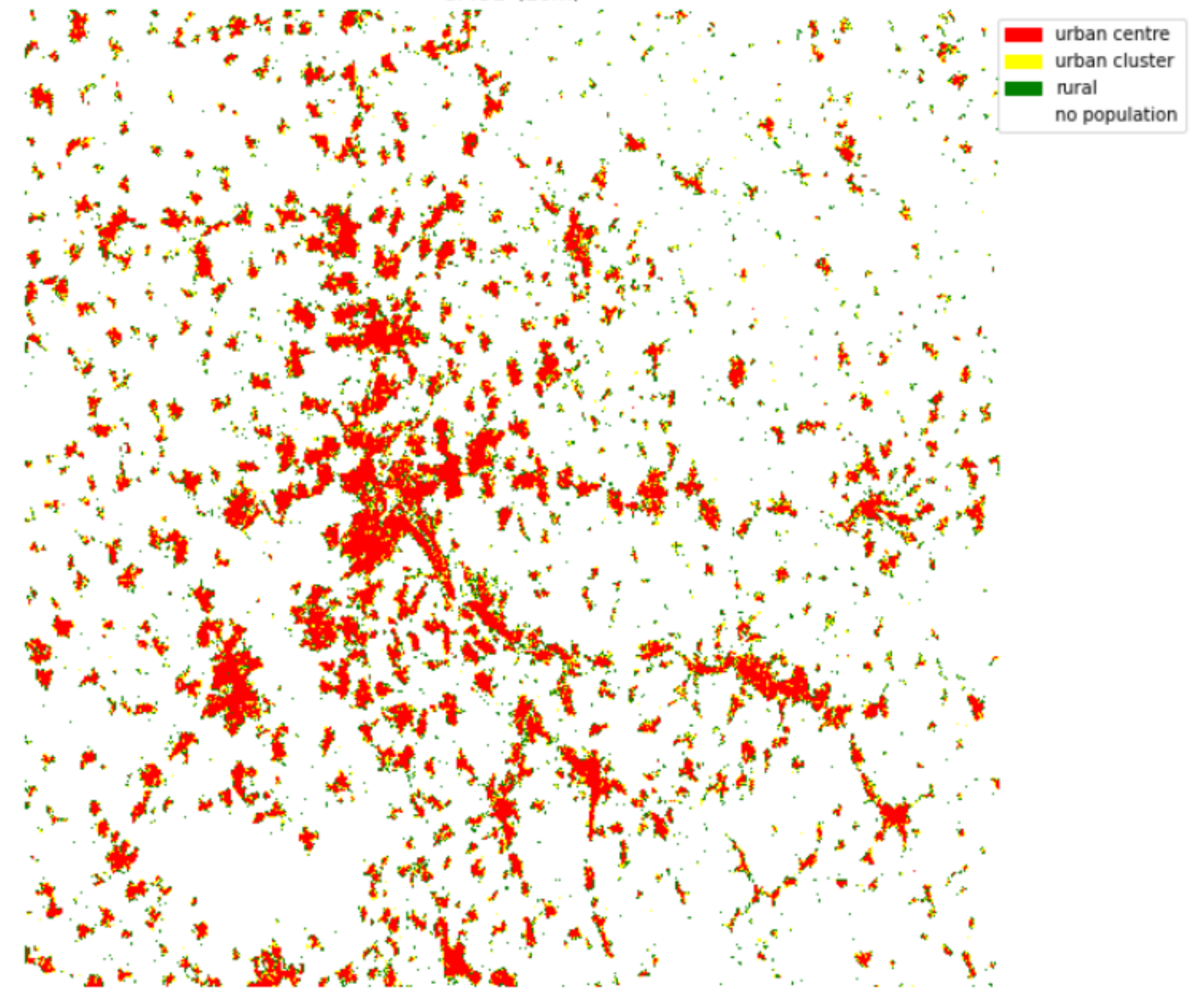
Graz, Austria

SMOD (10m)



Stuttgart, Germany

SMOD (10m)



EXPERIMENTS AND CHALLENGES

BUILT-UP

- In SML method, there is a tradeoff between threshold value of built up confidence and accuracy
- In WSF method, selecting time gap between each of the temporal image can lead to different results

POP

- Setting different thresholds for distribution of population can lead to different results
- Density and Count based POP generation do not work well with the same dasymmetric mapping technique.
- Experimented to generate high resolution (10m) POP layer
- Results are influenced by BUILT-UP

SMOD

- Categorizing areas into urban centre, cluster and rural work differently in pixels around water, mountains etc.
- Experimented to generate high resolution (10m) SMOD layer
- Results are influenced by BUILT-UP, POP

CONCLUSION

- High quality of BUILT-UP is crucial to generate accurate human settlement maps.
- High quality of BUILT-UP influences the generation of POP and SMOD products significantly
- CNN based algorithms yield better results than SML and WSF.
- Future prospect is to explore different algorithms to generate POP, apart from enhancing dasymmetric method to generate very high resolution classification.
- Project location : <https://git.opendfki.de/tanmay.delhikar/satellite-image-analysis>

REFERENCES

BUILT-UP:

- Assessment of the Added-Value of Sentinel-2 for Detecting Built-up Areas: <https://www.mdpi.com/2072-4292/8/4/299>
- Operating procedure for the production of the Global Human Settlement Layer from Landsat data of the epochs 1975, 1990, 2000, and 2014: https://publications.jrc.ec.europa.eu/repository/bitstream/JRC97705/landsatghs_report_2016_final_online.pdf
- A New Method for Earth Observation Data Analytics Based on Symbolic Machine Learning: : <https://www.mdpi.com/2072-4292/8/5/399/html>
- Benchmarking of the Symbolic Machine Learning classifier with state of the art image classification methods: https://publications.jrc.ec.europa.eu/repository/bitstream/JRC97964/aamethod_tech_report_final5.pdf

POP:

- Development of new open and free multi-temporal global population grids at 250 m resolution : https://www.researchgate.net/publication/304625387_Development_of_new_open_and_free_multi-temporal_global_population_grids_at_250_m_resolution
- Generating Surface Models of Population Using Dasymetric Mapping : https://astro.temple.edu/~jmennis/pubs/mennis_pg03.pdf
- Combining GHSL and GPW to improve global population mapping: <https://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=7326329>

SMOD:

- *GHSL basic concept*: <https://ghsl.jrc.ec.europa.eu/data.php?sl=2#GHSLBasics>

WSF:

- *Outlining where humans live-the world settlement footprint 2015*: <https://arxiv.org/ftp/arxiv/papers/1910/1910.12707.pdf>



THANK YOU