Modelling urban growth and socio-economic and health inequalities in Sub-Saharan African cities

VERY-HIGH RESOLUTION (FINE-SCALE)
Land-cover maps
Land-use maps
Population density maps

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Land cover vs. Land use

MAUPP

- **Land cover**

  'the observed biophysical cover of the earth's surface'

- **Land use**

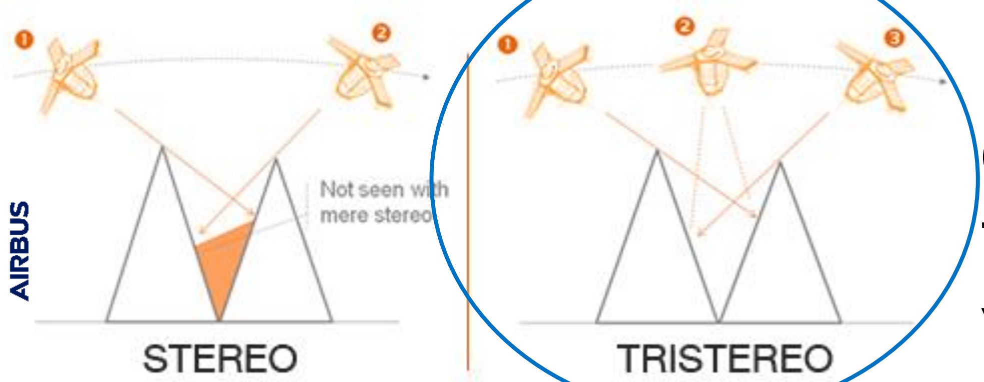
  'the purpose for which an area of land is being used, such as residential, agricultural, commercial, retail, or industrial'

(source: Oxford Reference)

Often mixed but should be mapped apart

Data and processing chain

Very-high resolution remote sensing



Pléiades (Airbus D&S)

0.5 m spatial resolution

Tristereo

VNIR

Dakar

Semi-Automated Processing Chain

MAUPP

- Development of a semi-automated processing chain to produce maps
- Open source
- Python used to chain Grass GIS and R commands

```
else: print "r.object.geometry is already installed on your computer"
```

Set list of raster from which to compute statistics with i.segment.stats

Here after, a list of raster layer on which to compute statistics is saved. Please adapt those layers according to the raster you want to use for object statistics.

```
In [ ]: ## Display the name of rasters available in PERMANENT and CLASSIFICATION mapset
        print grass.list_strings("raster", mapset="PERMANENT", flag='r')
        print grass.list_strings("raster", mapset="CLASSIFICATION", flag='r')
```

```
In [ ]: ## Define the list of raster layers for which statistics will be computed
        inputstats="opt_blue@PERMANENT"
        inputstats+=",opt_green@PERMANENT"
        inputstats+=",opt_nir@PERMANENT"
        inputstats+=",opt_red@PERMANENT"
        inputstats+=",NDVI@PERMANENT"
        inputstats+=",Brightness@PERMANENT"
        inputstats+=",nDSM@CLASSIFICATION"
        print inputstats
```

Compute statistics of segments with i.segment.stats

In the following section, 'i.segment.stats' add-on is used to compute object statistics. Please refer to the official help if you want to modify the parameters. Other raster statistics and morphological features could be used according to your needs.

```
In [ ]: ## Define computational region to match the extention of segmentation raster
        grass.run_command('g.region', overwrite=True, raster="segments@CLASSIFICATION")

        ## Saving current time for processing time management
        print ("Start computing statistics for training segments, using i.segment.stats on " + time.ctime())
        begintime_isegmentstats=time.time()

        ## Compute statistics of objets using i.segment.stats only with .csv output (no vectormap output)
        grass.run_command('i.segment.stats', overwrite=True, map="segments_training@CLASSIFICATION",
                          rasters=inputstats,
                          raster_statistics="min,max,range,mean,stddev,sum,coeff_var,first_quart,median,third_q
                          area_measures="area,perimeter,compact_circle",
                          csvfile="F:\\.....\\Classification\\i.segment.stats\\stats_training_sample.csv")
```

remote sensing

MDPI

Article

An Open-Source Semi-Automated Processing Chain for Urban Object-Based Classification

Taïs Grippa [1,*], Moritz Lennert [1], Benjamin Beaumont [1,2], Sabine Vanhuysse [1], Nathalie Stephenne [2] and Eléonore Wolff [1]

grass gis
Bringing advanced geospatial technologies to the world

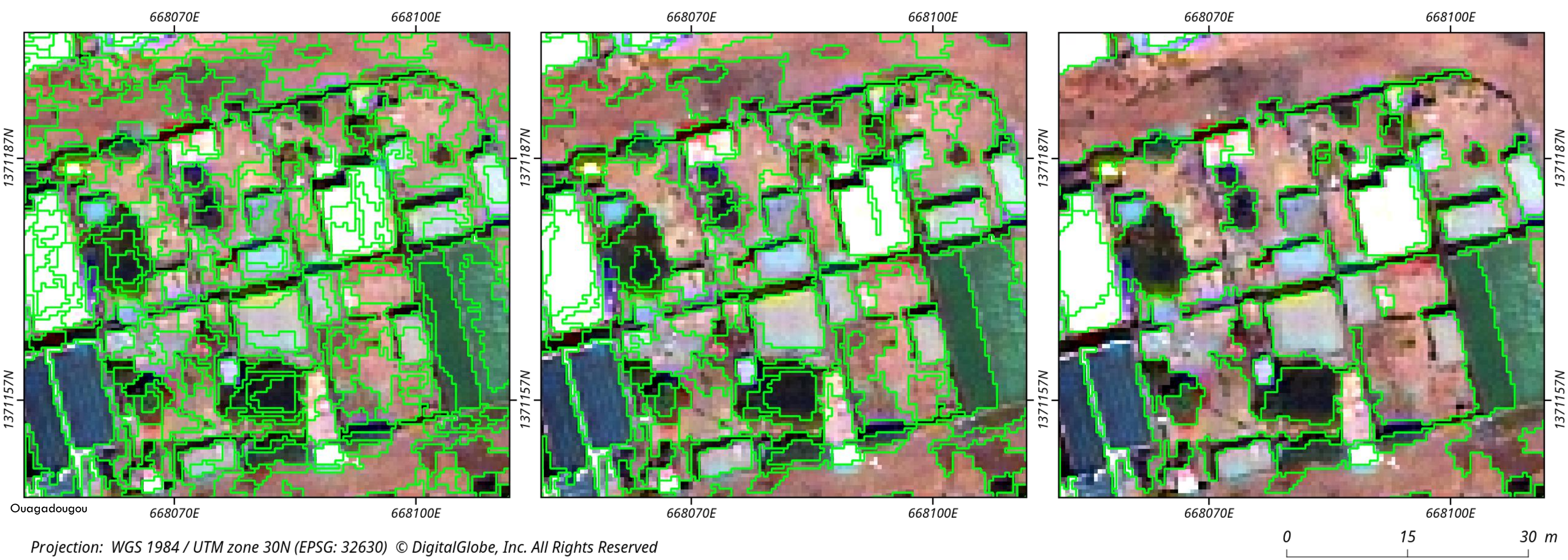
python™

Land cover – step 1

MAUPP

- **Segmentation Parameter optimization**
  - Automated process for optimising the segmentation parameters (local optimisation due to high diversity)
  - Objective: avoid under- or over-segmentation
  - image segmentation into groups of pixels (objects)

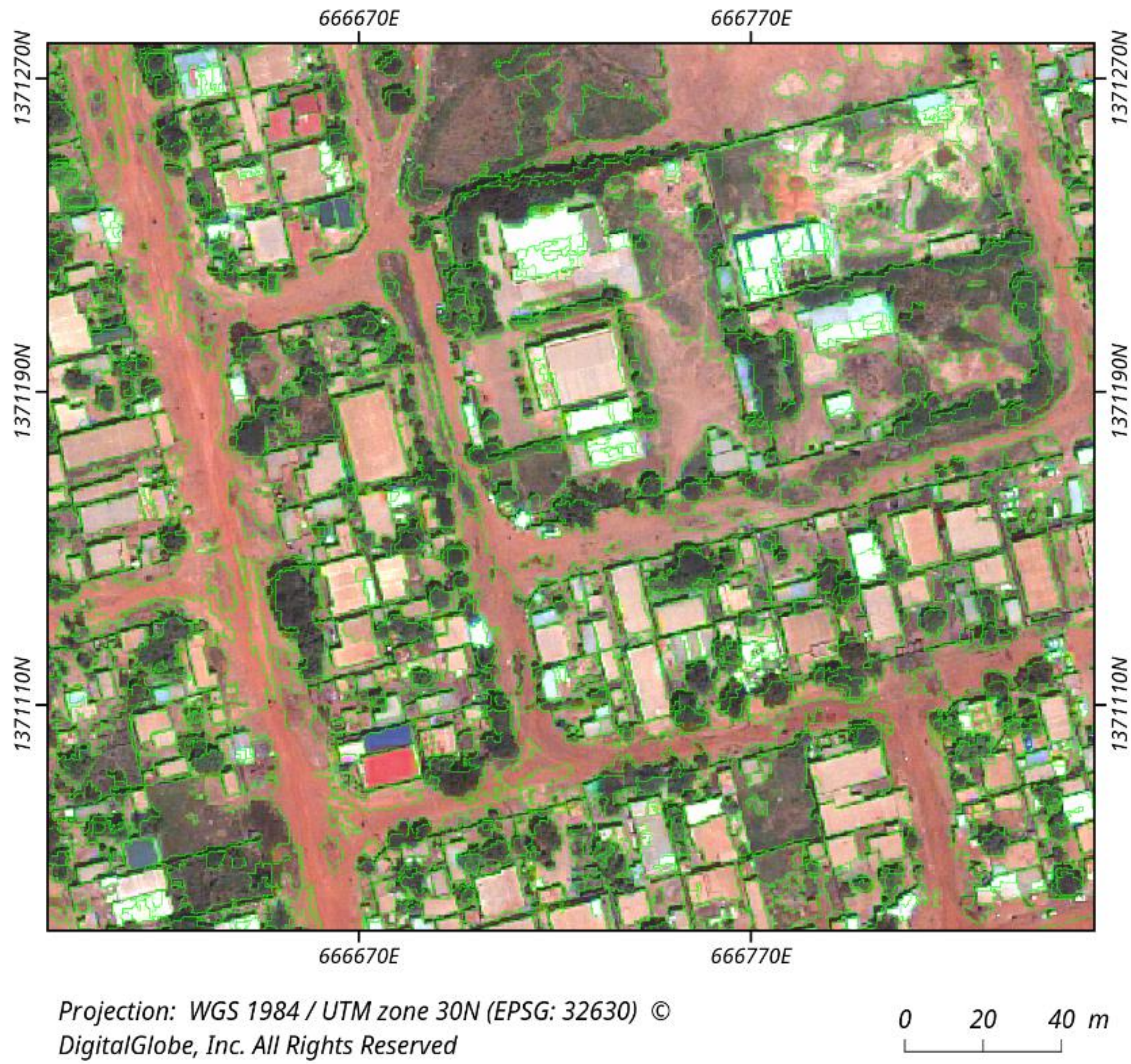
OVER-SEGMENTATION → UNDER-SEGMENTATION



Projection: WGS 1984 / UTM zone 30N (EPSG: 32630) © DigitalGlobe, Inc. All Rights Reserved

Land cover – step 2

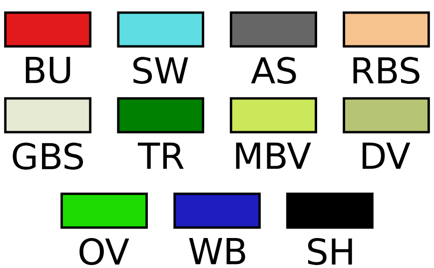
- Segmentation
  - Statistics computed for each object
    - Geometrical (shape, area, compactness)
    - Spectral (VNIR,NDVI)
    - nDSM
    - Textures



Projection: WGS 1984 / UTM zone 30N (EPSG: 32630) © DigitalGlobe, Inc. All Rights Reserved

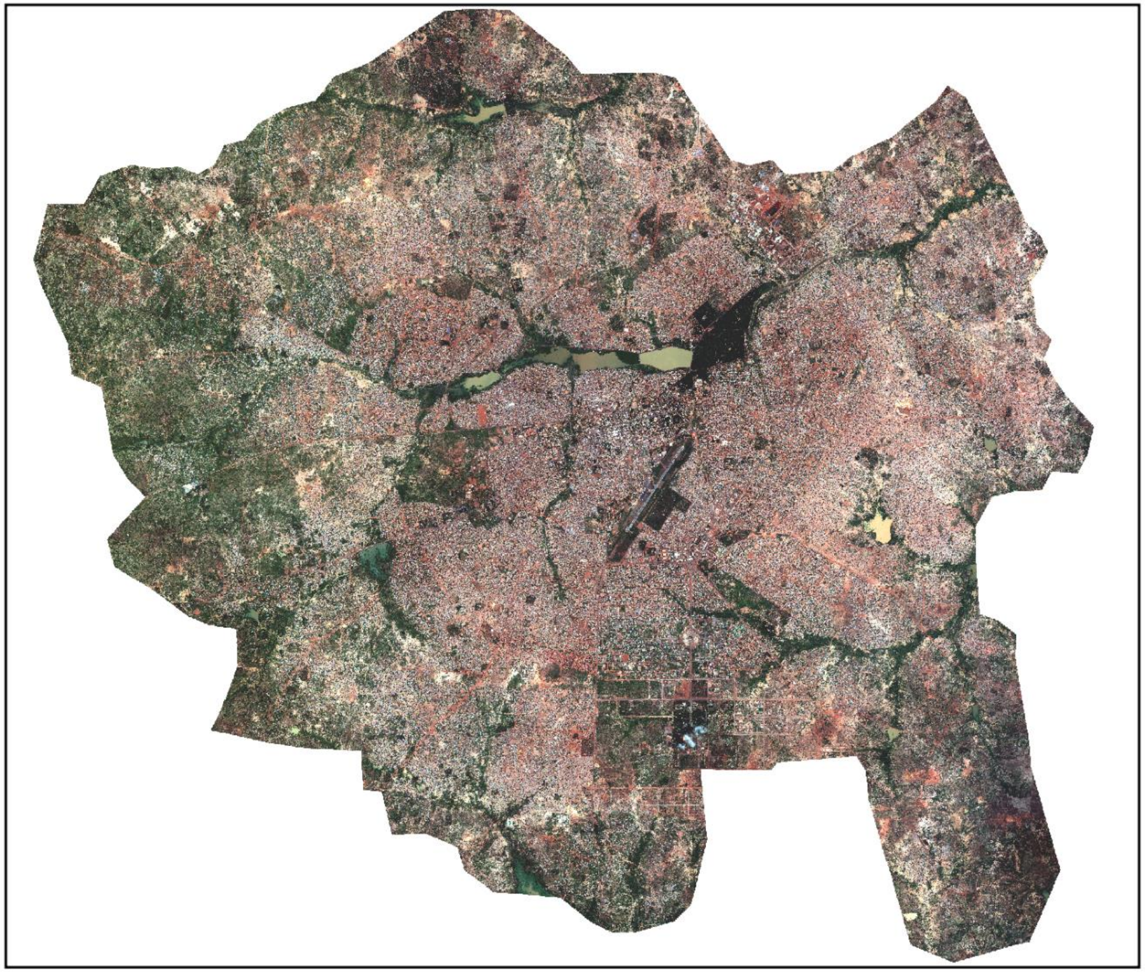
Land cover – step 3

- Classification
  - Random Forest classifier
  - Classification of all the objects



Projection: WGS 1984 / UTM zone 30N (EPSG: 32630)

Land use – step 1 : Partition of the city into blocks



Use of OSM

Lines

- Roads, tracks
- Rivers
- Limits
- …

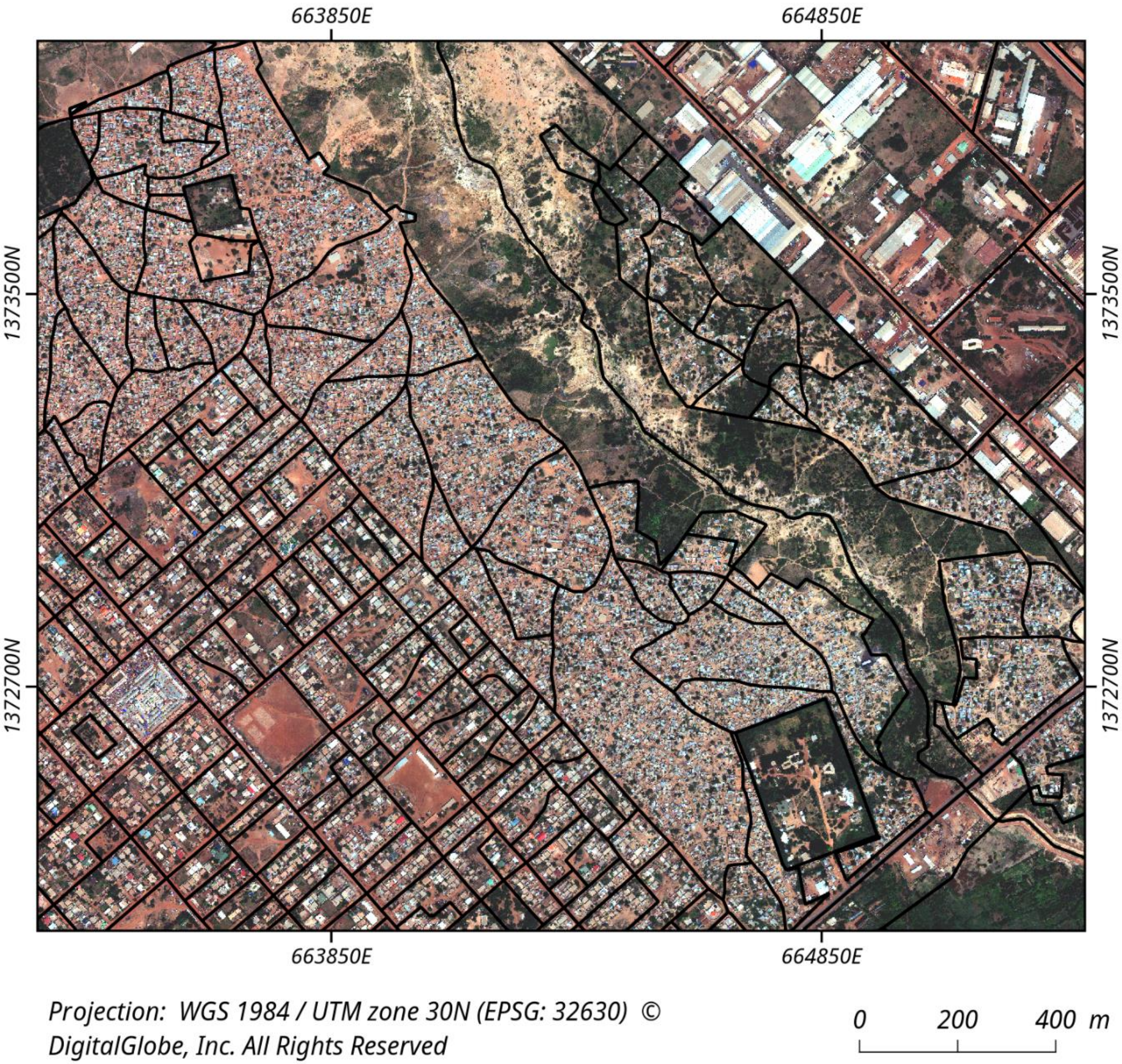
Polygons

- Residential areas
- Parks
- Water bodies
- Cemeteries
- Military camps

Projection: WGS 1984 / UTM zone 30N (EPSG: 32630)

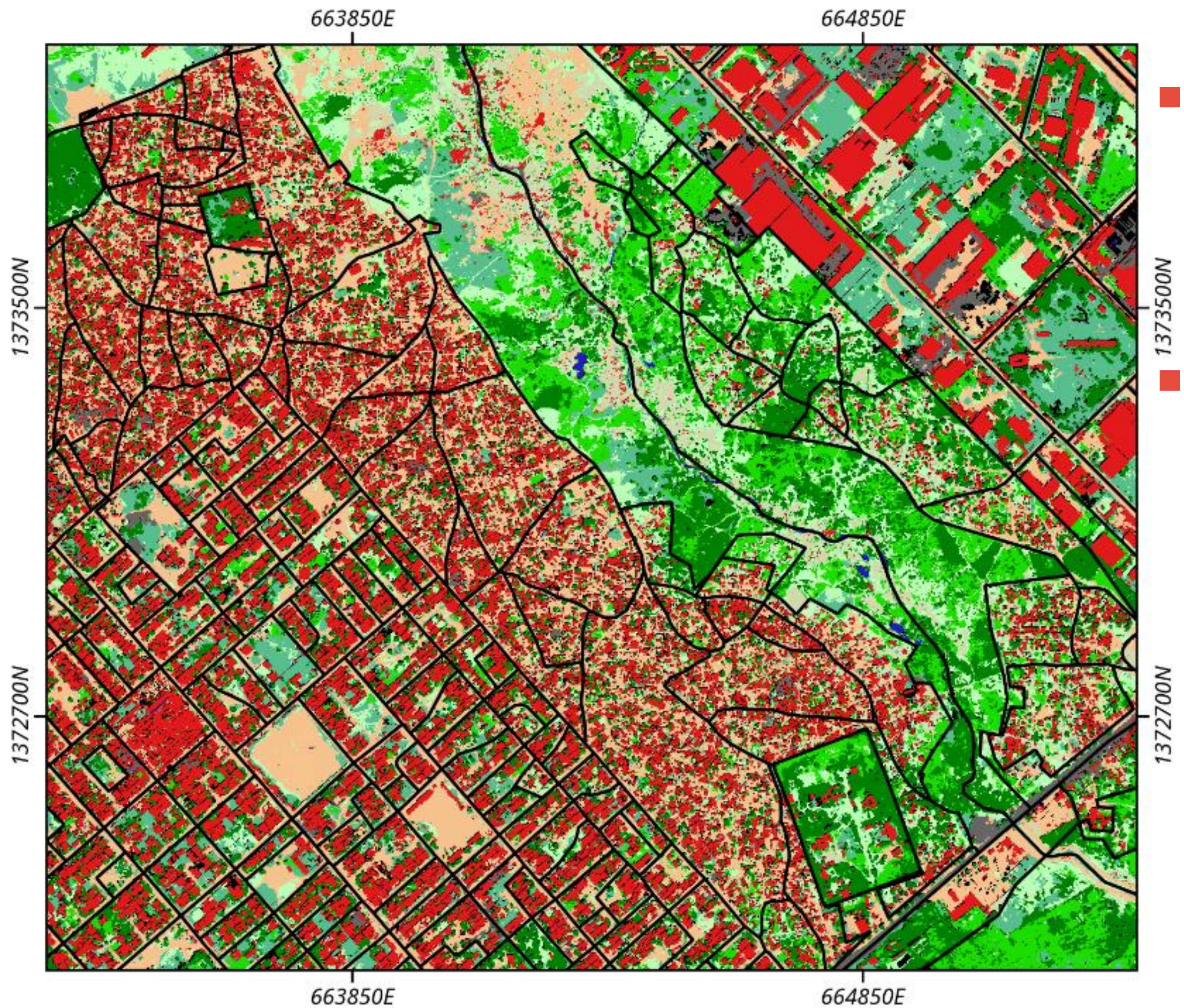
0 2 4 km

Land use – step 1 : Partition of the city into blocks



- Result refined with GIS commands (removing spurious polygons due to overlaps)

Land use - Step 2 : Landscape metrics derived from each block

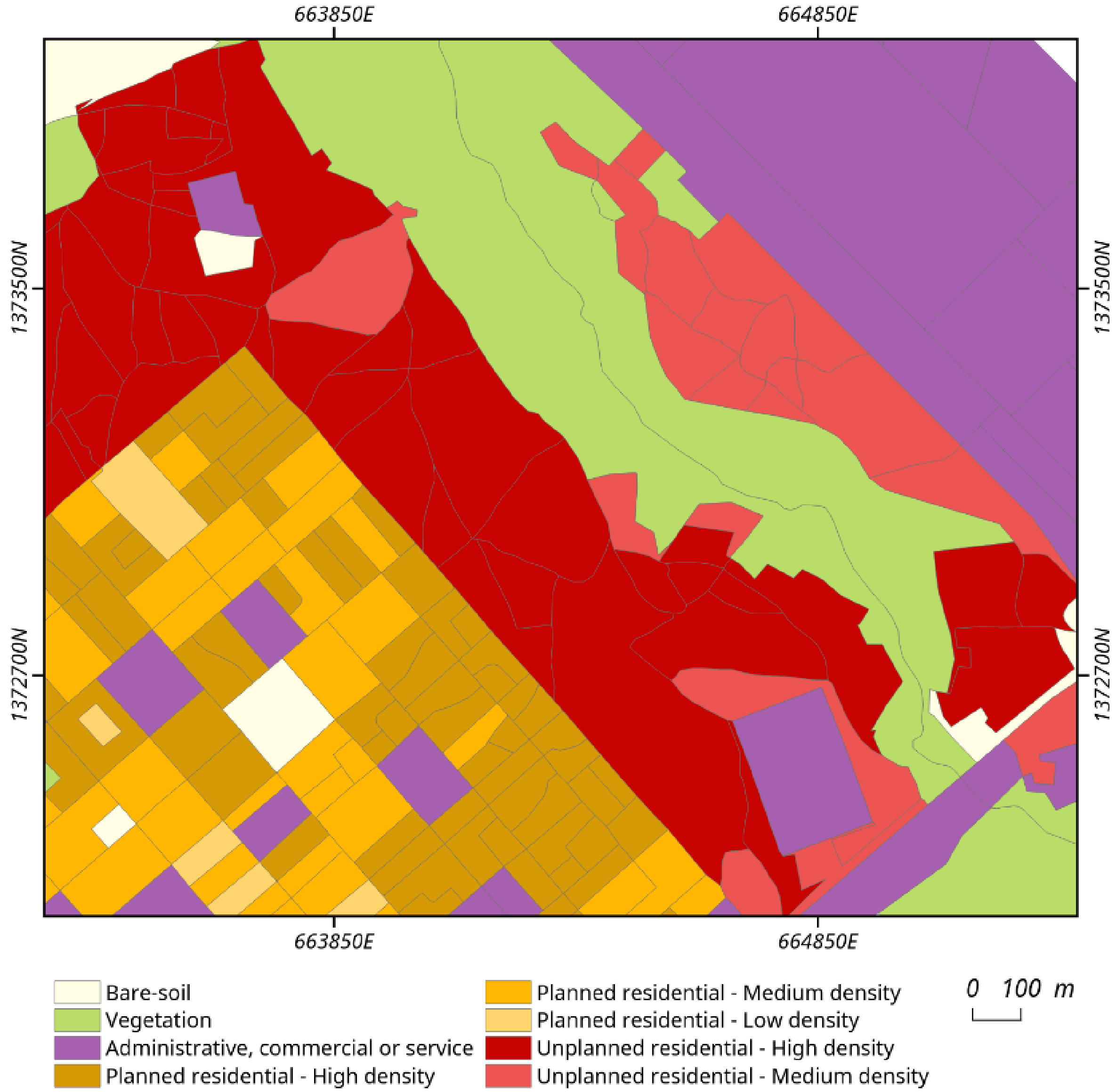


Projection: WGS 1984 / UTM zone 30N (EPSG: 32630) ©

0 200 400 m

- Landscape metrics are calculated for each city block, using the land-cover layer as input
- Different levels
  - Patch metrics (e.g., mean patch size, fractal index)
  - Class metrics (e.g., mean distance between patches of the same class)
  - Landscape metrics (e.g., proportion of each class)

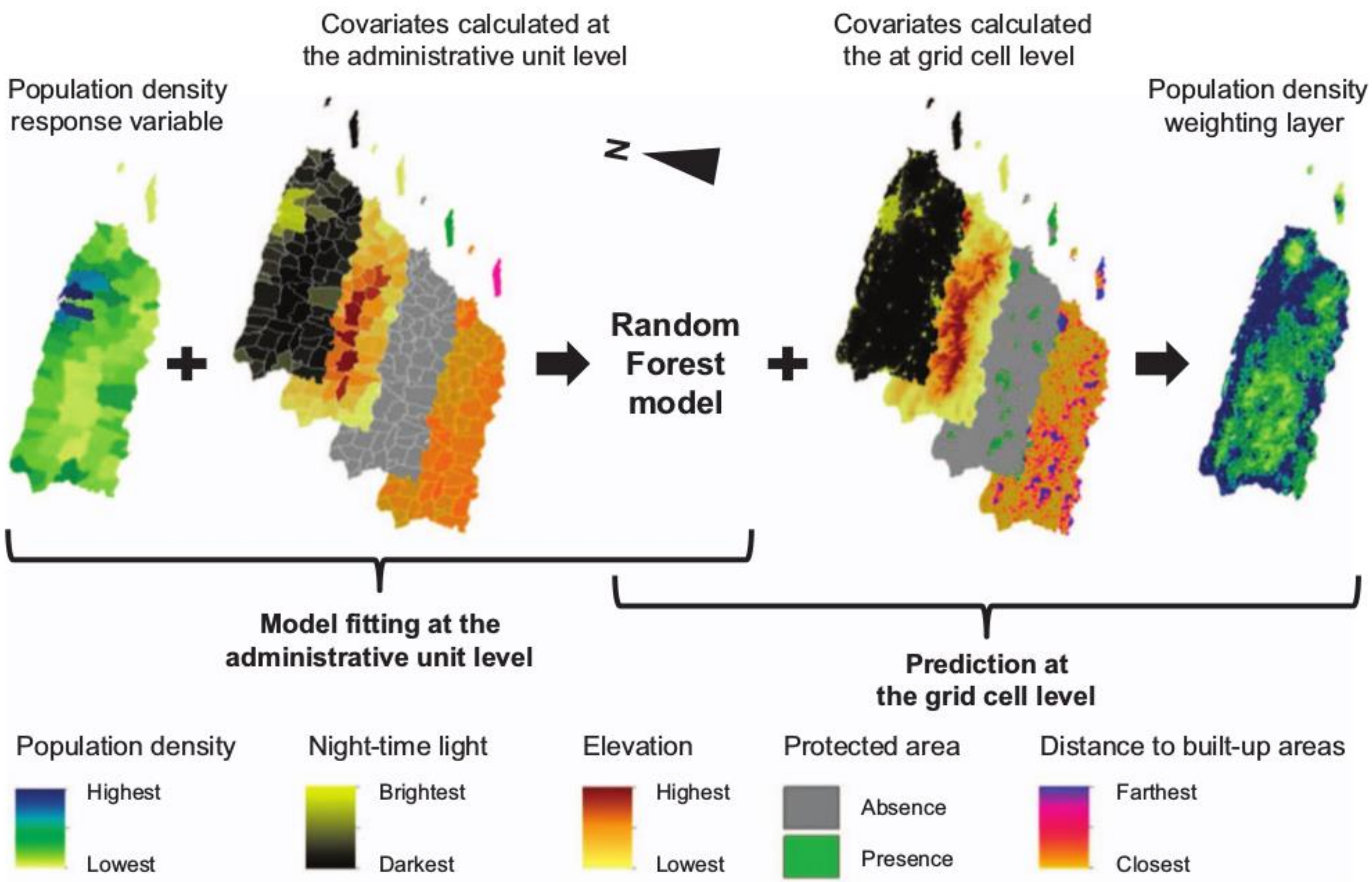
Land use - Step 3 : Classification of the city blocks



- Classification of the blocks using a machine learning (Random Forest) or rule-based approach

Population density – method

Same method as for high resolution remote sensing data

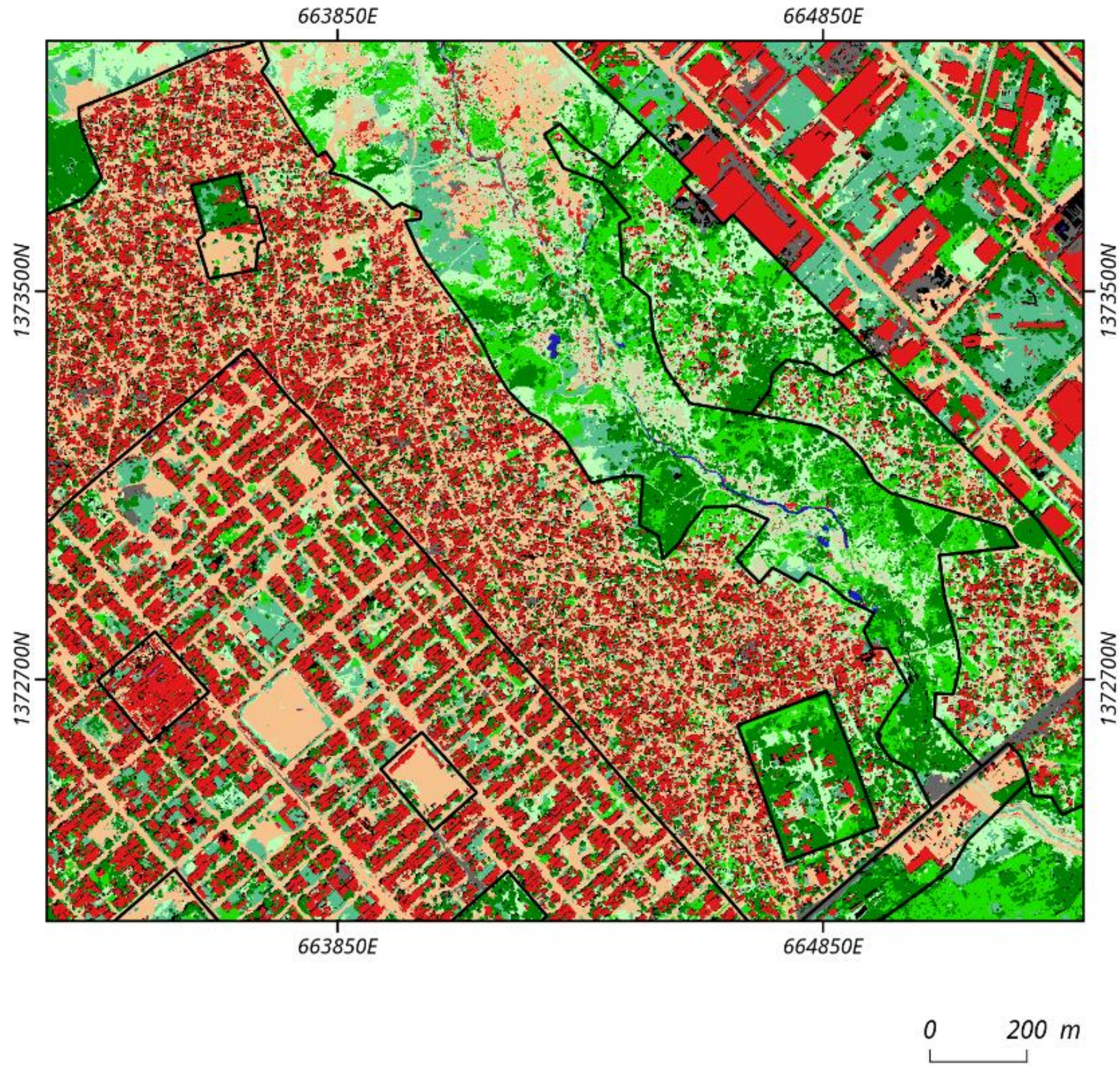


Source: Sorichetta, Alessandro, Graeme M. Hornby, Forrest R. Stevens, Andrea E. Gaughan, Catherine Linard, and Andrew J. Tatem. 2015. "High-Resolution Gridded Population Datasets for Latin America and the Caribbean in 2010, 2015, and 2020." *Scientific Data* 2 (September): 150045. doi:10.1038/sdata.2015.45.

Population density – prediction

Land Cover

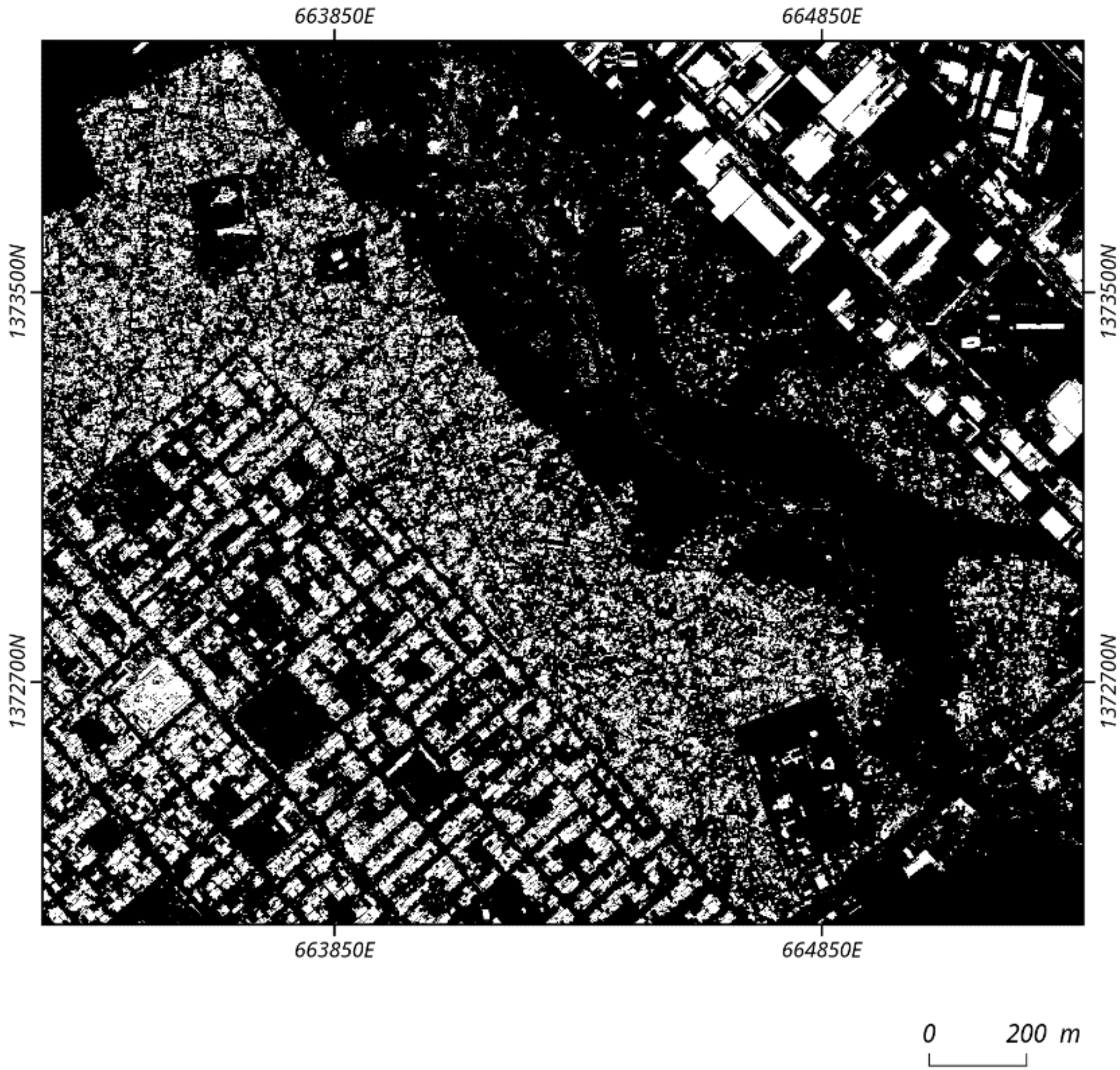
0.5m resolution



Population density – prediction

Binary map

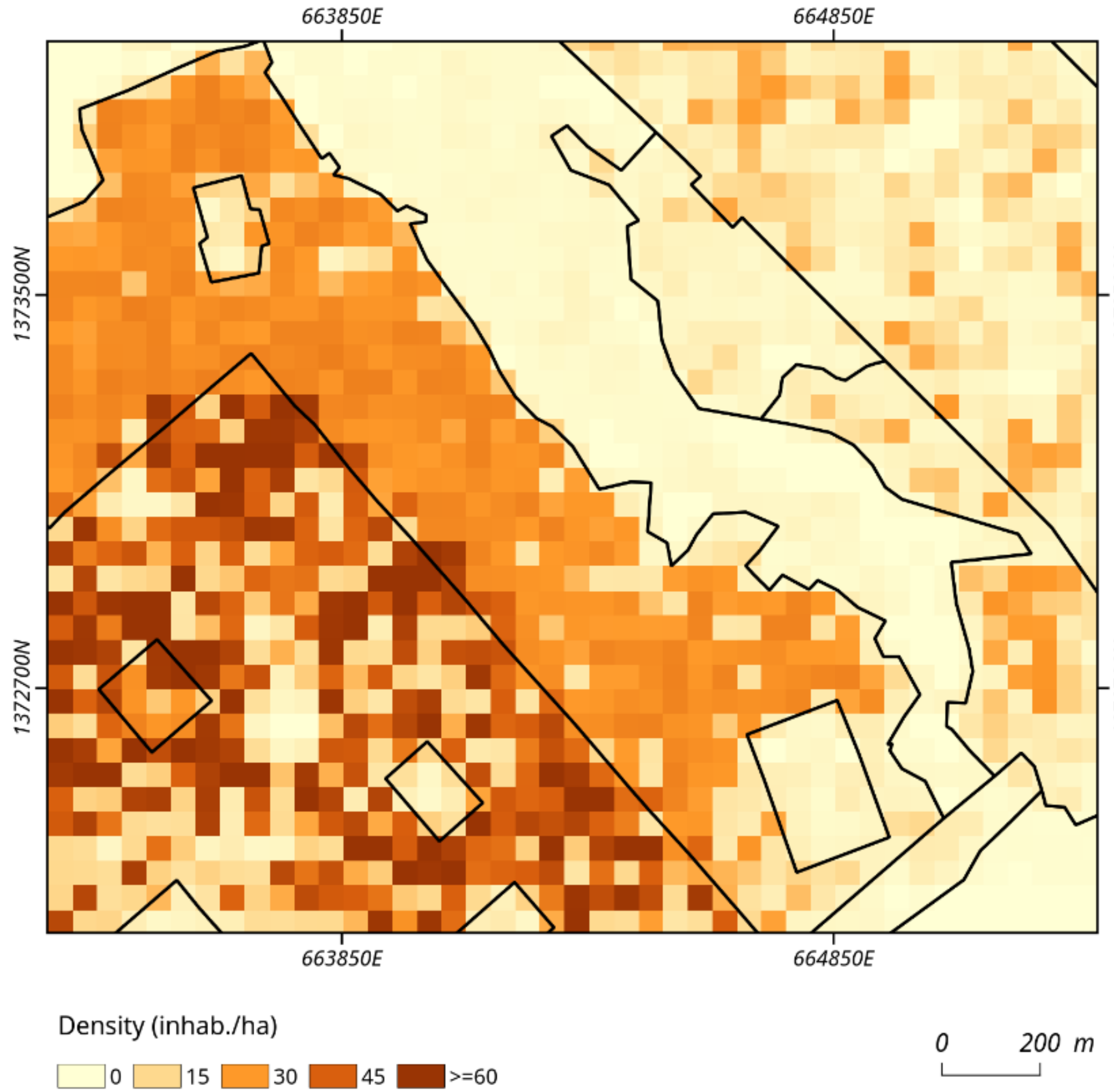
Presence of Built-up



Population density – prediction

First results

Grid cells
50m * 50m



REACT

Poverty and Malaria Mapping in SSA cities

- There is an important gap to fill in the study of poverty and disease in an intra-urban context
- Several RS covariates can help in addressing this task

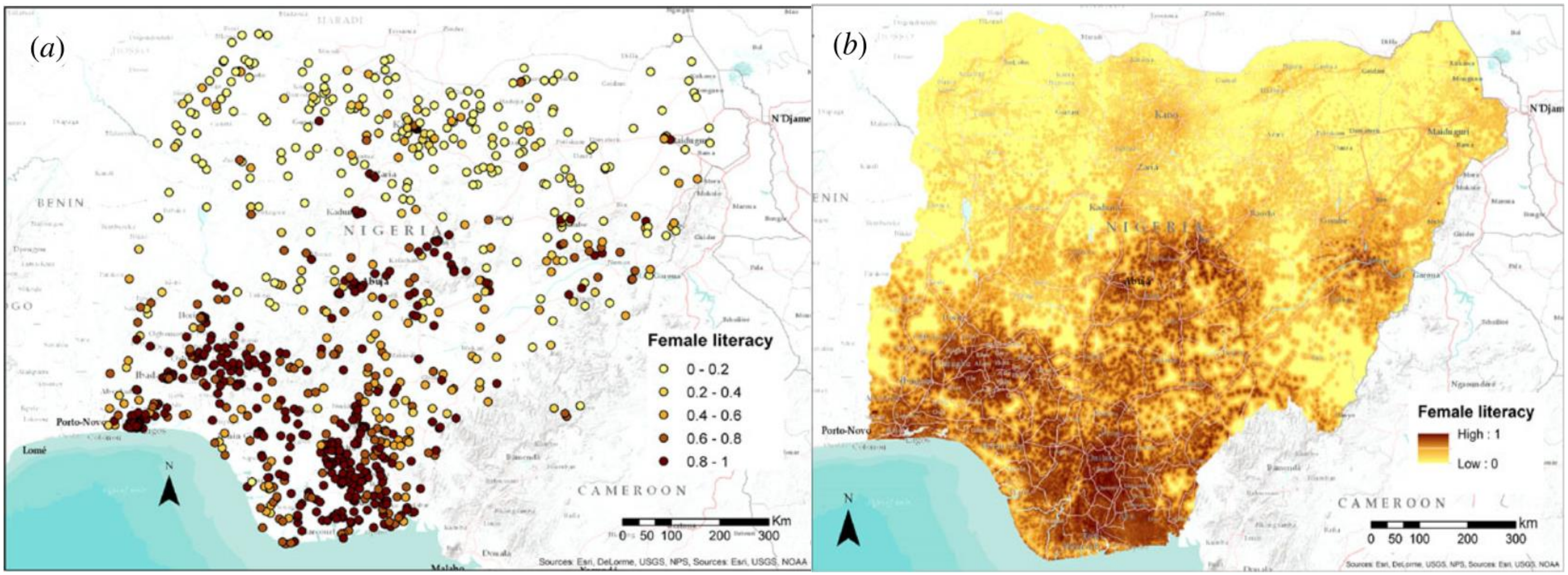
Very-High Resolution -Pleiades

↓

Elevation, Land cover, Land use, Ratios, Indices (vegetation, wetness), Density, Distance, Landscape metrics…

Poverty Mapping

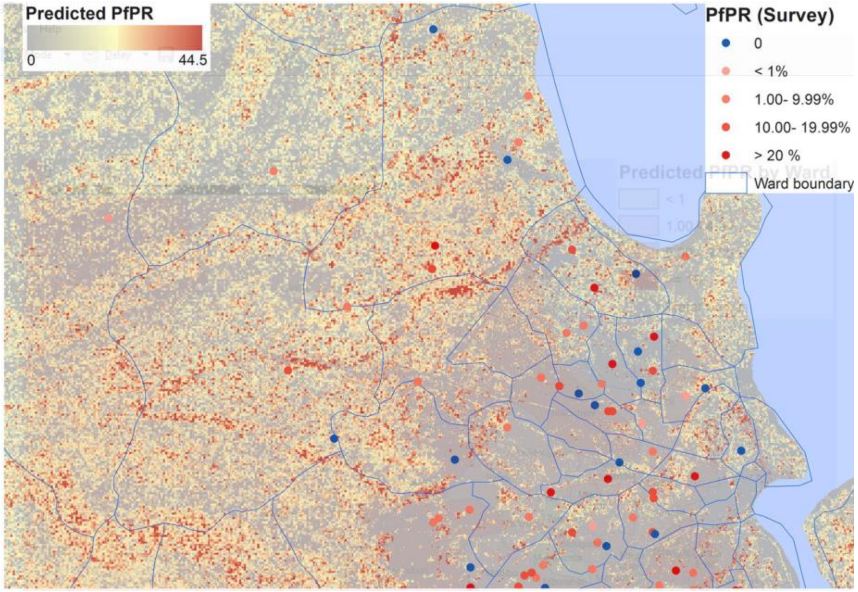
- Demographic Indicators predicted at the national level from Demographic and Health Surveys (DHS)
- Mainly moderate to low RS covariates used (i.e. MODIS LC and EVI, nightlights, aridity

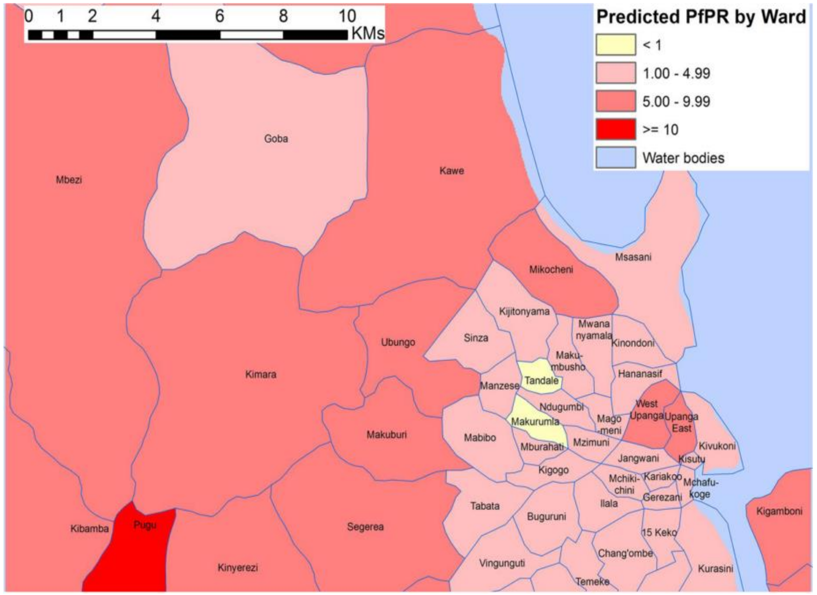


In **REACT** aiming for modelling intra-urban variations through VHR covariates and DHS surveys

Intra-Urban Malaria Mapping

- Intra-urban Malaria Prevalence in Dar es Salaam (Kabaria et al. 2016)
- Land Cover ratios as input with high-resolution RS products





VHR covariates can push beyond the state of the art further improving malaria predictions (Grippa et al. 2017)

References

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