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Data Fusion for Multi-Temporal Mapping of Built-Up Areas in Sub-Saharan Africa

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Introduction

Urban remote sensing in Sub-Saharan Africa

→ Lower satellite data availability

→ Tropical climate: high cloud cover

→ Arid climate: spectral confusion between built-up and bare soil

→ Lack of reference datasets

Landsat data availability

→ Landsat 8 : systematic global acquisition

→ Landsat 7 : 12% of the acquisitions over Africa

→ Landsat 5 : 6% of the acquisitions over Africa

→ Many locations in Africa without any Landsat acquisition before 1998.

→ Only 5 scenes with less than 10% cloud cover in Kinshasa

Figure 1. Spectral confusion between bare soil and built-up areas in Gao, Mali: **a)** VHR image of the area of interest, **b)** Near-infrared Landsat band.

Gao, Mali — Johannesburg, South Africa — Katsina, Nigeria

Figure 2. Inter-urban heterogeneity in Sub-Saharan Africa.

Introduction

Windhoek, Namibia

Windhoek, Namibia

Figure 3. Intra-urban heterogeneity in Sub-Saharan Africa.

Urban heterogeneity

→ A method that works for a given urban area in SSA is not guaranteed to work in another.

→ Because of the heterogeneity characterizing the urban mosaic, **supervised learning** is one of the most effective method.

→ Optical sensors are not sufficient to discriminate built-up areas from bare soil.

Proposed methodology

→ Taking advantage of **open-access satellite datasets**, both optical and synthetic aperture radar (SAR): Landsat, ERS-1&2, Envisat, Sentinel-1.

→ Leveraging crowd-sourced geographic databases such as **OpenStreetMap** to support the training of the classification models.

→ Tested in **44 case studies** across Sub-Saharan Africa, and for five different years: 1995, 2000, 2005, 2010 and 2015.

Case Studies

Antananarivo, Madagascar	Bouake, Côte d'Ivoire	Brazzaville, Congo
Bukavu, D.R. Congo	Chimoio, Mozambique	Dakar, Senegal
Dodoma, Tanzania	Freetown, Sierra Leone	Gao, Mali
Ikirun, Nigeria	Iringa, Tanzania	Johannesburg, South Africa
Kabwe, Zambia	Kampala, Uganda	Kaolack, Senegal
Katsina, Nigeria	Kayamandi, South Africa	Kinshasa, D.R. Congo
Kisumu, Kenya	Libreville, Gabon	Lusaka, Zambia
Mbeya, Tanzania	Mekele, Ethiopia	Monrovia, Liberia
Nairobi, Kenya	Ndola, Zambia	Nelspruit, South Africa
Nzerekore, Guinea	Obuasi, Ghana	Okene, Nigeria
Onitsha, Nigeria	Ouagadougou, Burkina Faso	Owo, Nigeria
Pietermaritzburg, South Africa	Pietersburg, South Africa	Saint-Louis, Senegal
San Pedro, Côte d'Ivoire	Shaki, Nigeria	Tamale, Ghana
Toamasina, Madagascar	Tulear, Madagascar	Umuahia, Nigeria
Windhoek, Namibia	Yamoussoukro, Côte d'Ivoire	Ziguinchor, Senegal

Data Availability

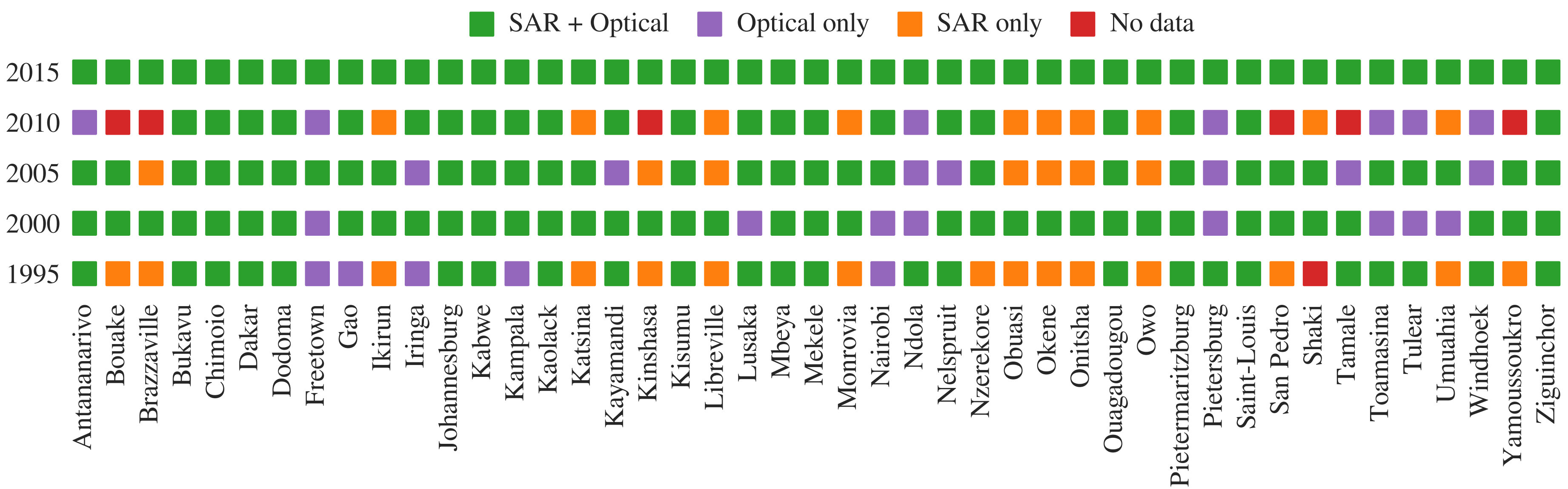


Figure 4. SAR and optical imagery availability for each case study.

SAR & Optical Fusion

Optical

→ Good separation between **vegetation** and **built-up areas**.

→ Confusion between **bare soil** and **built-up areas**.

SAR

→ Good separation between **bare soil** and **built-up areas**.

→ Confusion between **dense vegetation** and **built-up areas**.

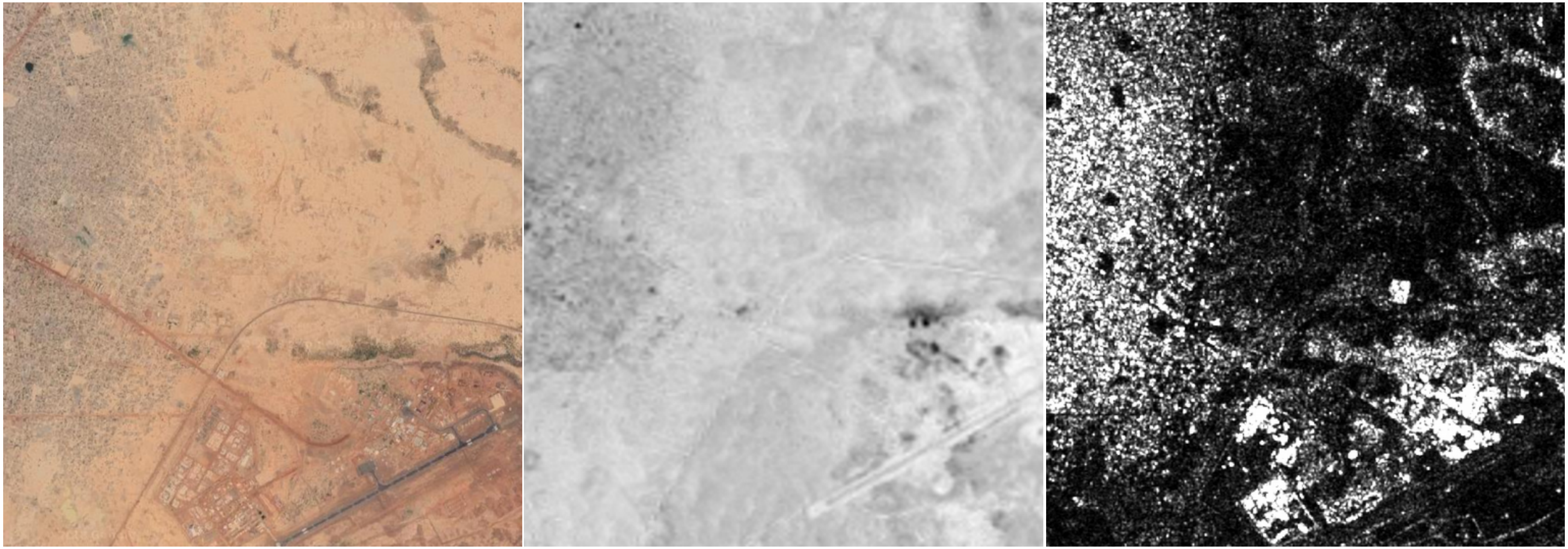
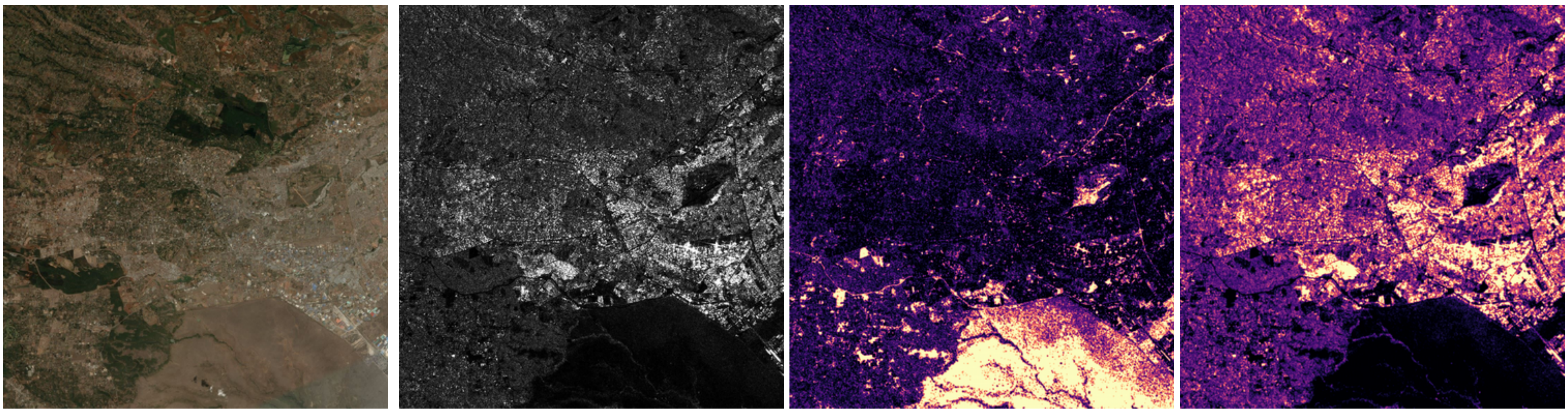


Figure 5. Detection of built-up areas in Gao, Mali:
a) VHR image of the area of interest, courtesy of Google Earth,
b) Normalized Difference Built-Up Index (NDBI) computed from Landsat 8 data,
c) Sentinel-1 VH backscattering

SAR & OPTICAL FUSION



Area of Interest | SAR Backscattering | Energy Texture | Mean Texture

Figure 5. GLCM textures in Nairobi, Kenya.

Supervised learning

→ Random Forest **pixel-level supervised classification**

→ Features: **Landsat** bands, **SAR** textures

→ Training samples extracted from **OpenStreetMap**

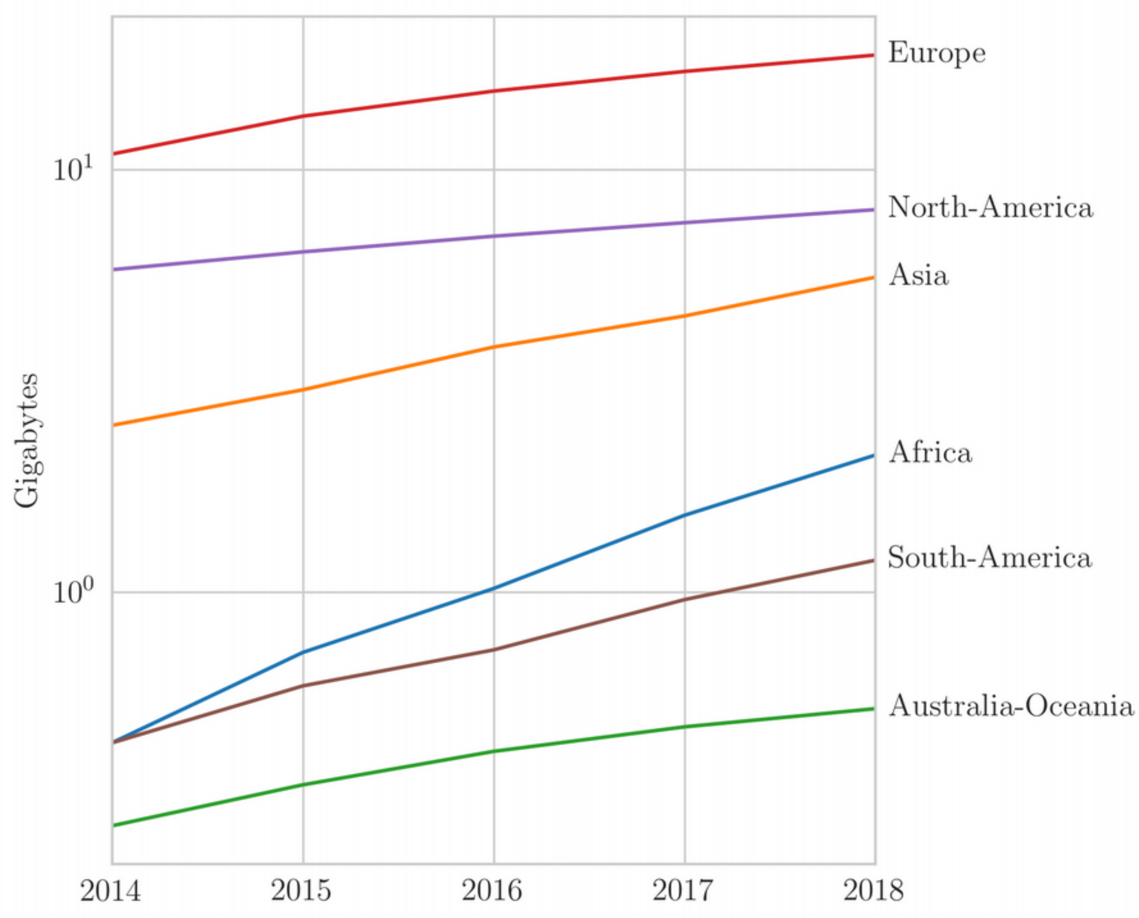


Figure 6. Bytes of informations in the OSM database for each continent between 2014 and 2018.

Built-up training samples

→ Building footprints
→ Urban blocks

Non-built-up training samples

→ Natural objects (grass, forests, sand, rocks...)
→ Leisure objects (parks, gardens, golf courses...)
→ Land use objects (farms, orchards, quarries...)
→ Distance from roads and buildings

Figure 7. Urban blocks extracted from OSM in Ouagadougou, Burkina Faso.

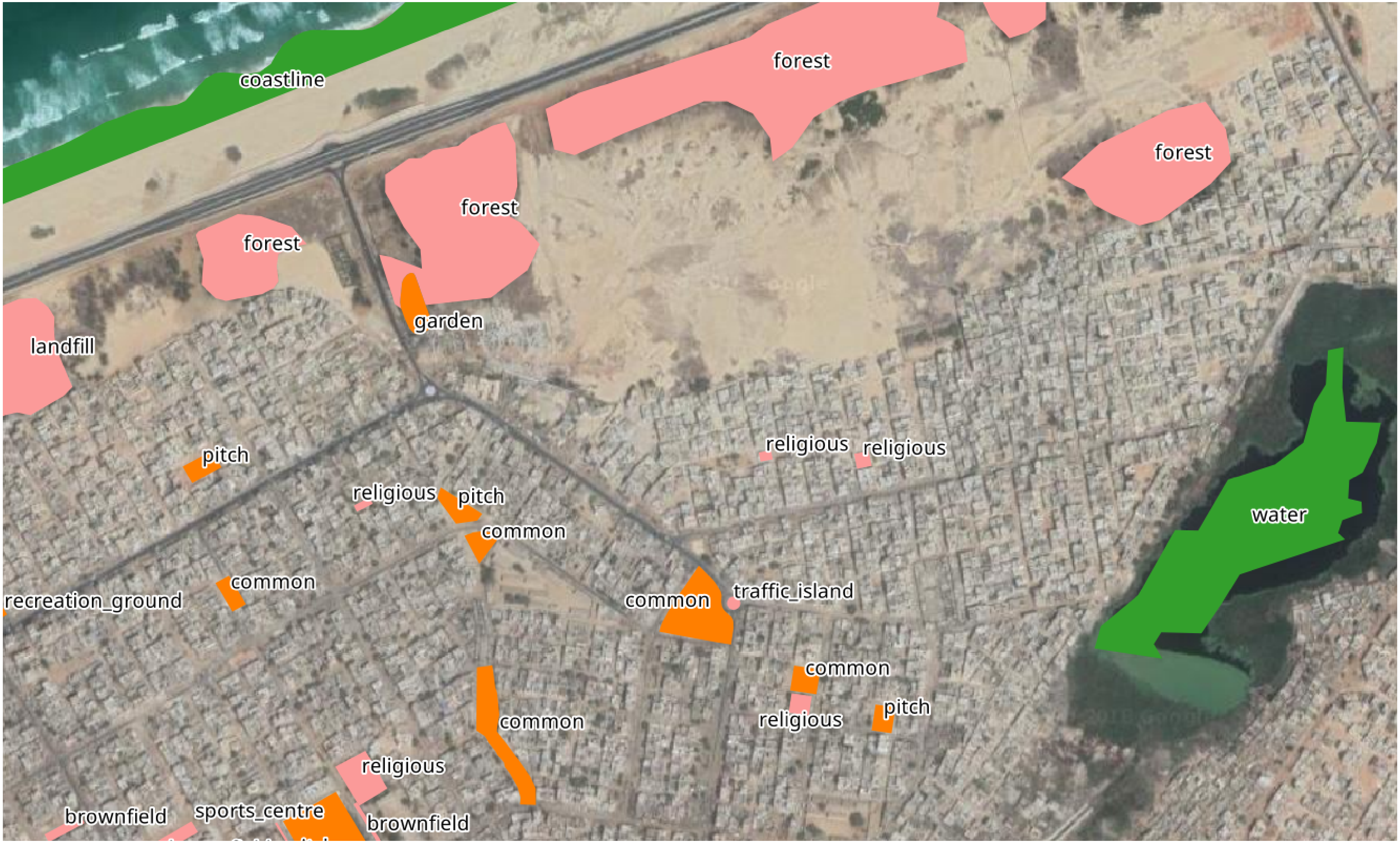


Figure 8. Leisure, land use, and natural objects extracted from OSM in Dakar, Senegal.

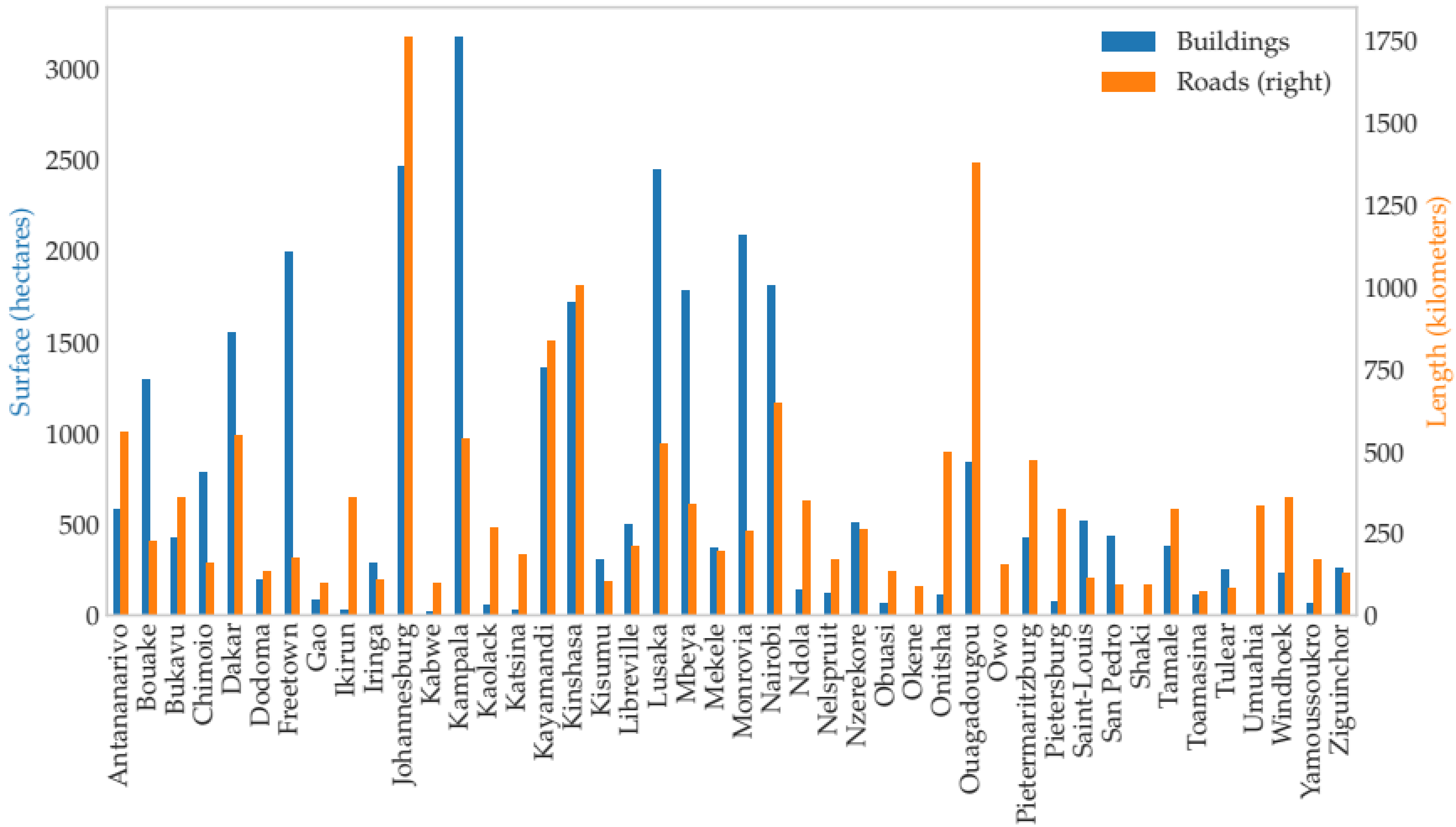
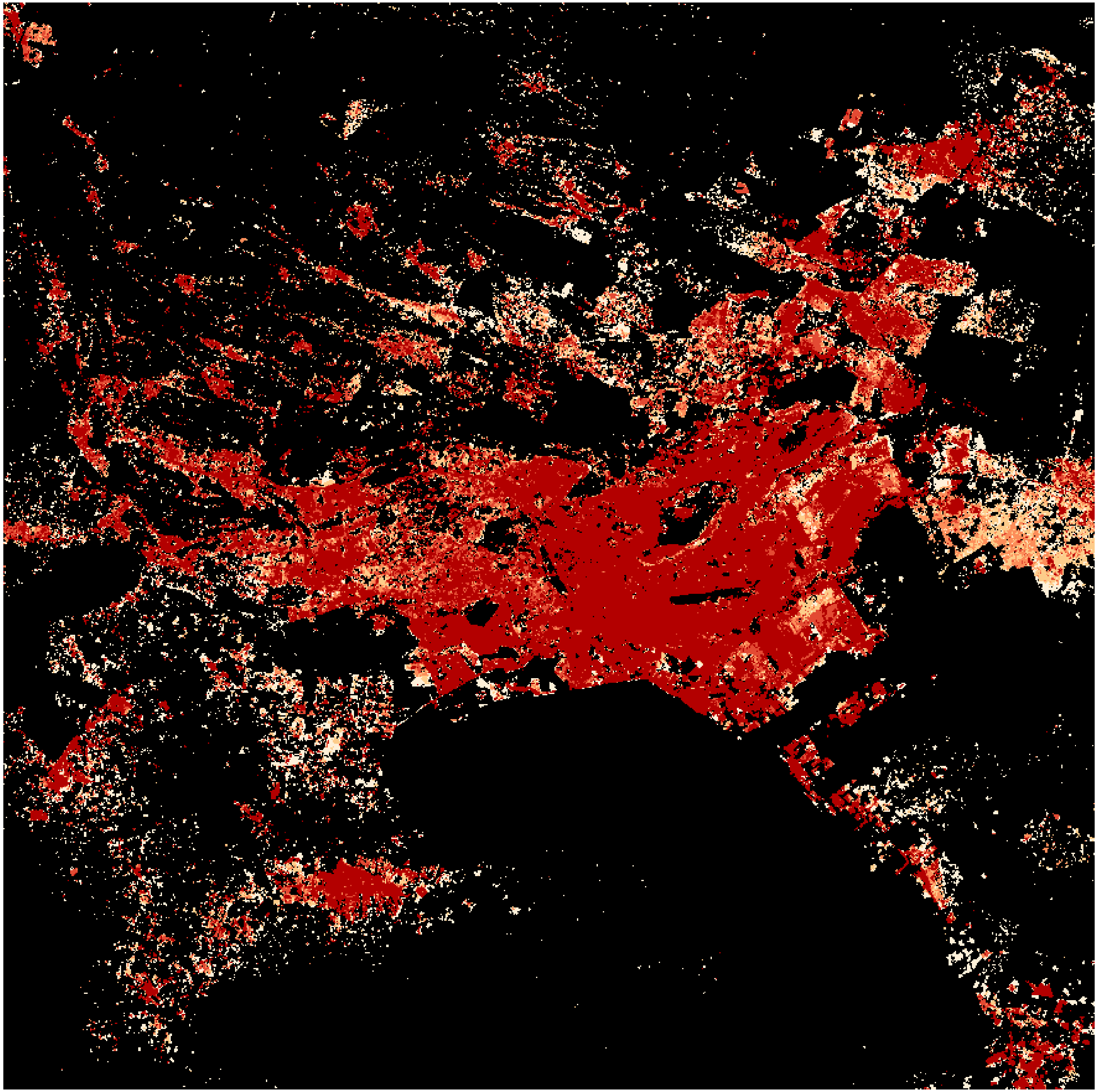
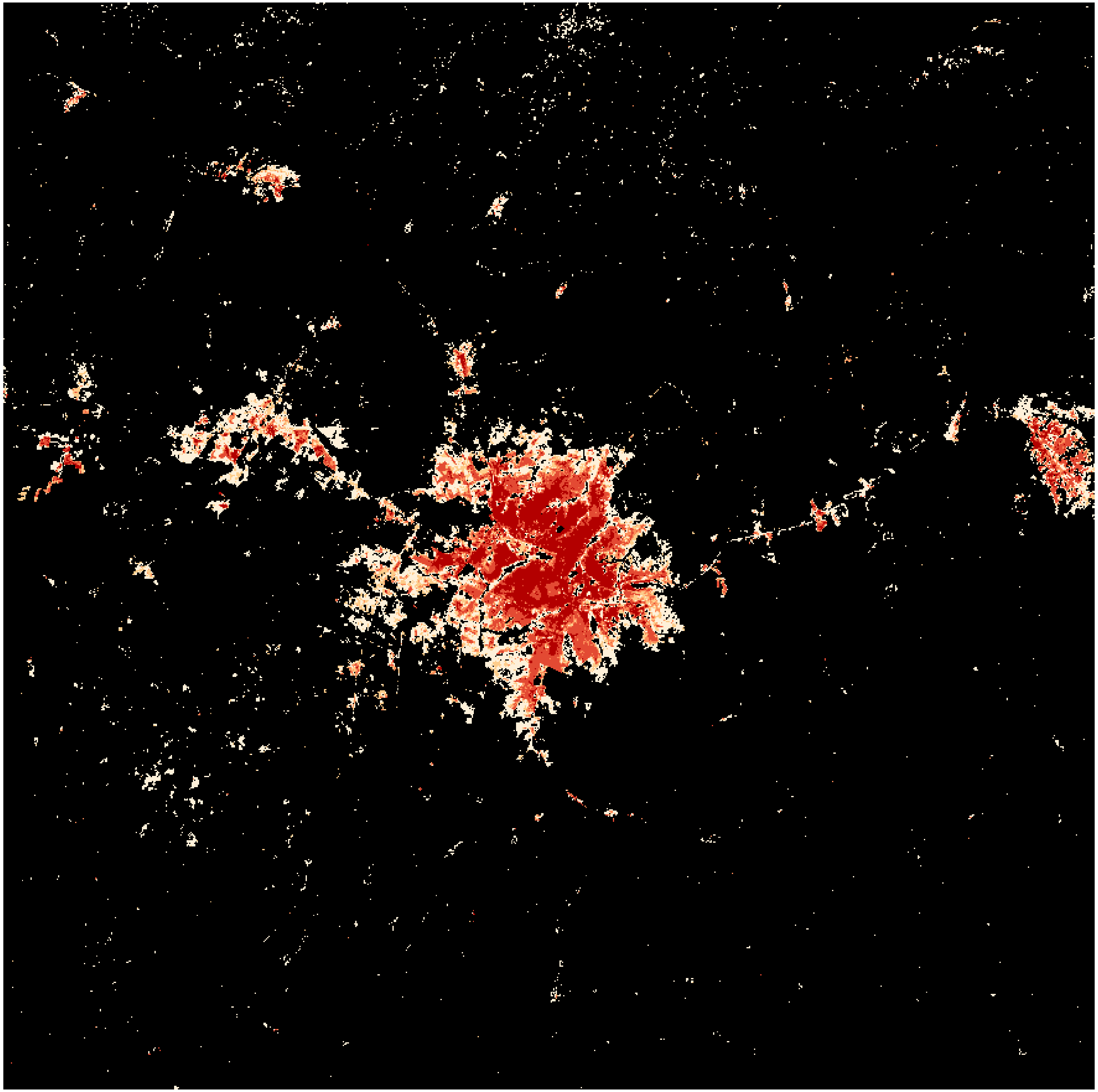


Figure 9. Availability of OSM roads and building footprints in each case study.

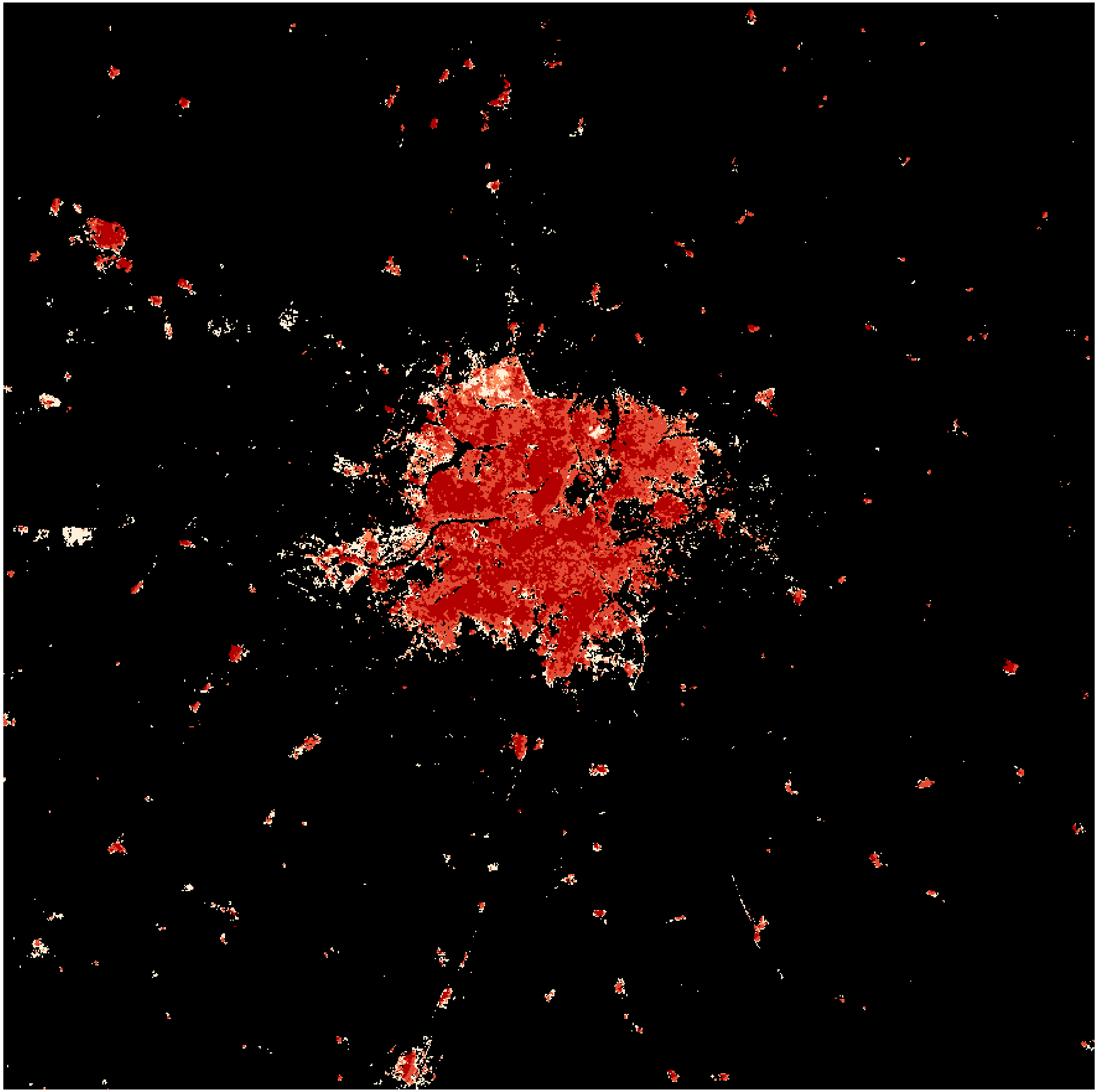
Nairobi, Kenya



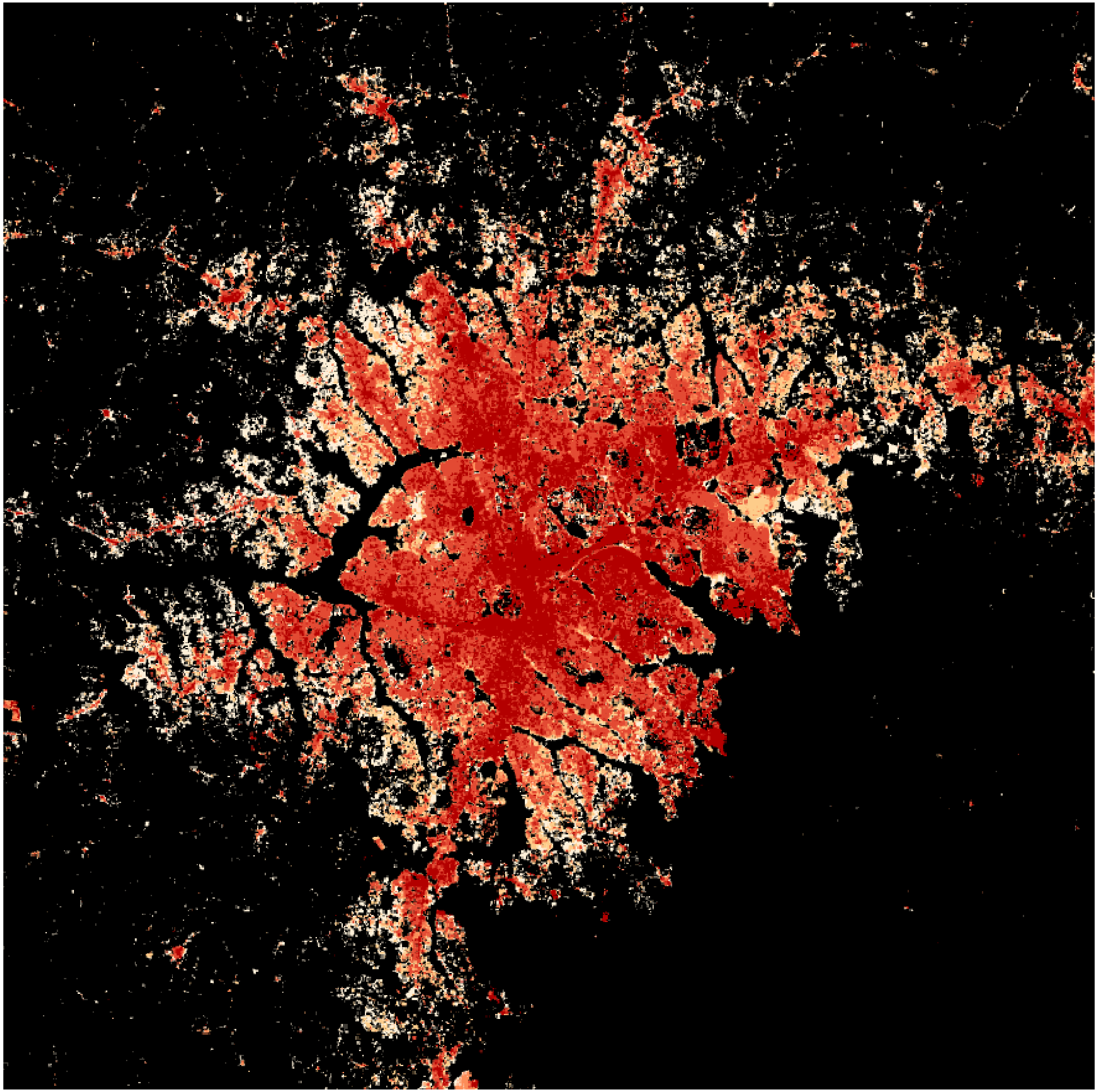
Chimoio, Mozambique



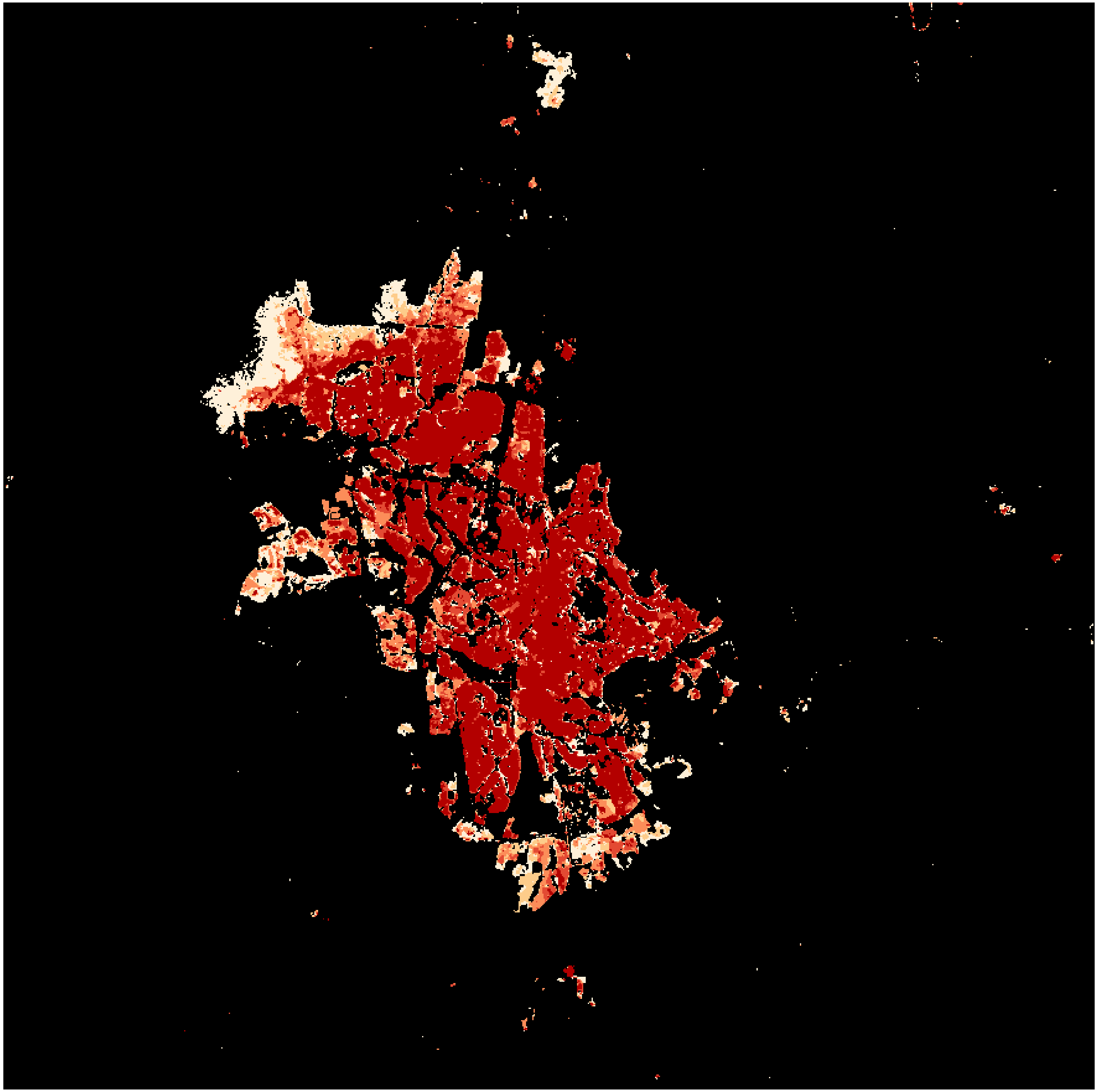
Bouake, Côte d'Ivoire



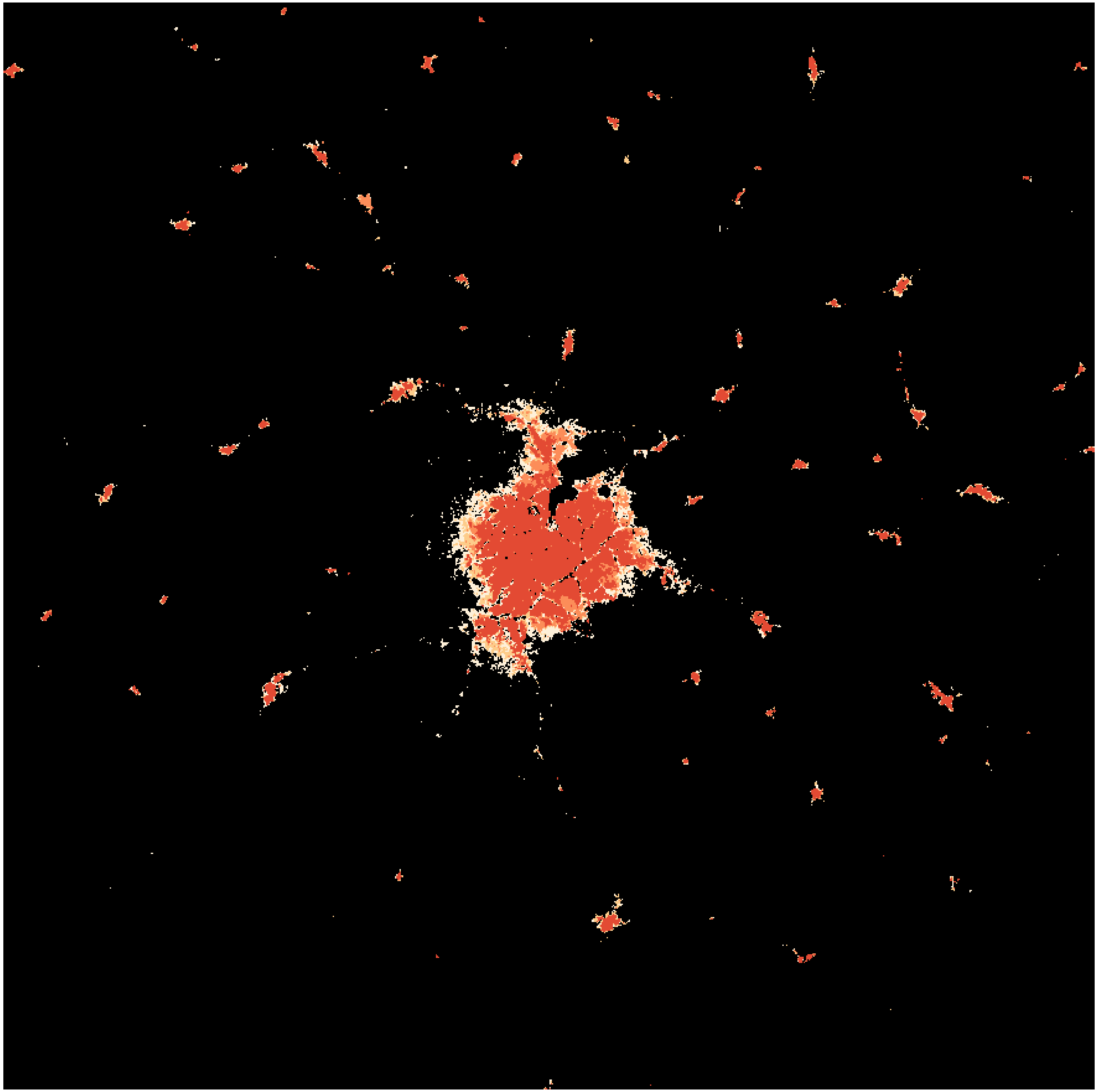
Kampala, Uganda



Windhoek, Namibia



Nzerekore, Guinea



Validation

	2000	2005	2010	2015
Antananarivo		0.88		0.93
Bukavu		0.88	0.87	0.87
Chimoio		0.91		0.95
Dakar		0.91		0.96
Dodoma				0.95
Gao	0.9			0.93
Johannesburg		0.95		0.95
Kampala		0.92		0.94
Katsina	0.92			0.97
Kinshasa		0.9		0.81
Nairobi			0.97	0.95
Okene				0.97
Onitsha				0.96
Ouagadougou	0.94		0.94	0.95
Saint-Louis		0.97		0.98
Umuahia				0.94
Windhoek		0.94		0.91

Figure 16. Validation against an independent dataset (F1-scores).

Validation

Method assessment

→ High average accuracy (0.93)

→ Lower scores in areas located in a mountainous and densely vegetated environment, e.g. Bukavu, D.R. Congo.

→ Lower scores as we go back in time

→ Lower scores in urban areas with low data availability (satellite or OpenStreetMap)

Conclusion

Combining Optical and SAR data

→ Higher data availability in tropical areas

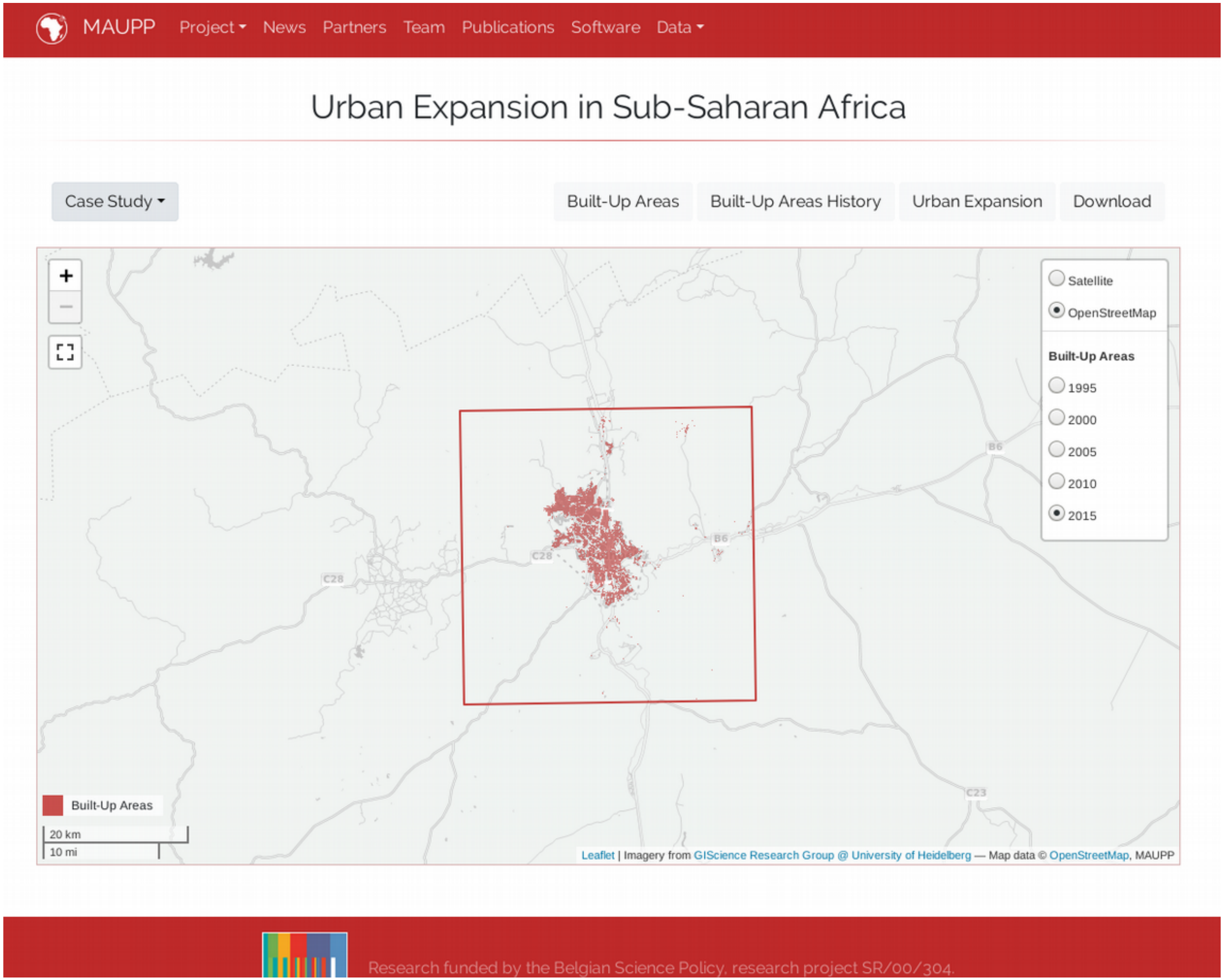
→ Better classification performance in arid regions

OpenStreetMap as training data

→ Can act as a reference dataset to support the training of the classification models

→ Open-access and growing

Data



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