

INTEGRATED DEPRIVATION AREA MAPPING SYSTEM FOR DISPLACEMENT DURABLE SOLUTIONS AND SOCIOECONOMIC RECONSTRUCTION IN KHARTOUM, SUDAN

FINAL SYMPOSIUM

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Artificial Intelligence (AI) and Earth Observation (EO data to fill data gaps in rapidly transforming cities

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Using results from : Y. Forget, N. Mboga

Introduction: why EO and AI for sustainable urbanisation?



- □ Sustainable Development Goals → 232 indicators to support setting up relevant policies to « leave no-one behind »
- Indicators should be disaggregated by income, sex, age, ... and geographic location
- □ To achieve a sustainable urbanization, urban planning and land management, **need updated and geographically detailed data** → remains a challenge to find because of :
 - □ Cost of generating such data through traditional data
 - □ Shortage of skilled professionals in geospatial sciences → low national capacity of geospatial data production
 - □ Inertia regarding the **change of routine workflows** and adopting new practices that are not imposed through legal requirements

Introduction: why EO and AI for sustainable urbanisation?



- EO capabilities can provide useful information for decision making for sustainable urbanisation
- □ EO can address the 2 first points:
 - EO data are **cheaper than field measures/observation** to produce similar data
 - Training such as with IdeaMapSudan can contribute to skilled professionals
- Al allows the processing of big data sets, such as EO data on urban areas with very high spatial resolution to map small houses
- > Presentation of results from some ANAGEO research projects (since 2014) using EO and Al using mainly Open Data and Software

EO and AI for mapping urbanisation



- □ Forget Yann (2021) uses **historical EO satellite data** to map the probability of urbanisation (1995-2015) for 45 African cities in the MAUPP project (https://maupp.ulb.ac.be/):
 - □ Much optical satellite data (i.e. in visible and infrared wavelength) existing since '70's
 - □ Much radar data (passes through clouds) since '87
 - Use of OpenStreetMap data to train the Al algorithms
 - Map built-up probabilities through time



Forget, Y., Shimoni, M., Gilbert, M., & Linard, C. (2021). Mapping 20 years of urban expansion in 45 urban areas of sub-Saharan Africa. Remote Sensing, 13(3), 525. doi:10.3390/rs13030525

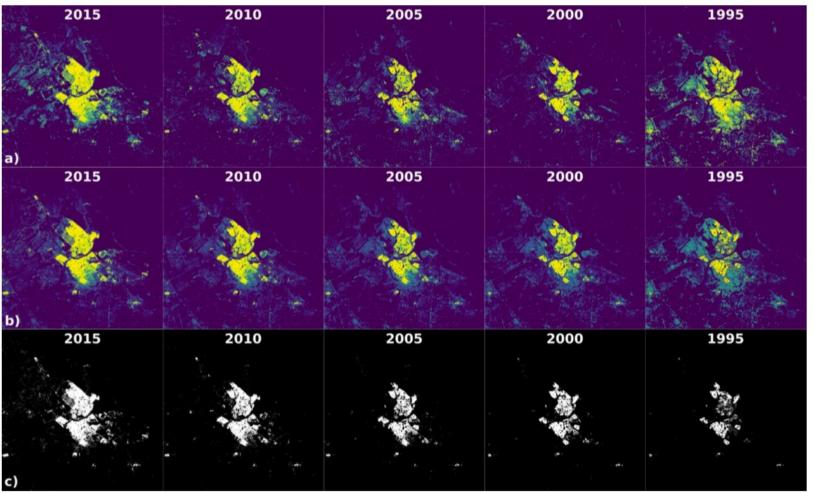


Figure 4.6: Post-processing of Ndola, Zambia. **a)** Raw RF built-up probabilities; **b)** Built-up probabilities after post-processing; **c)** Binary map (thresholded probabilities).





EO and AI for mapping urbanisation



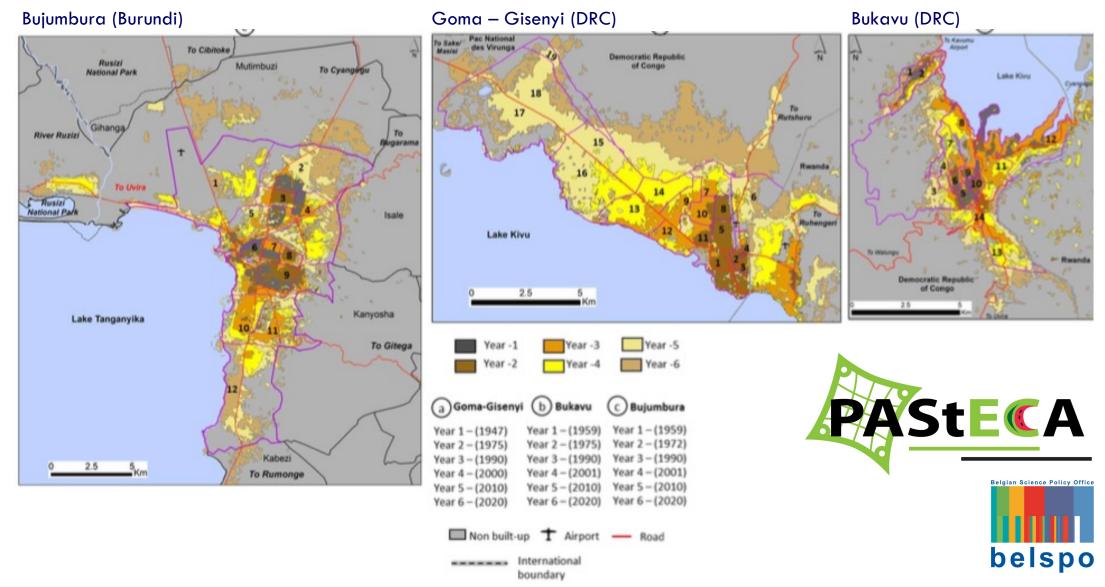
- □ Mboga Nicholus (PhD thesis, ULB, 2021):
 - uses historical EO aerial and recent satellite data
 - □ to map with Al (Deep-Learning) the long-term urbanisation (1940-2020)
 - □ For 3 cities in the Kivu region (Goma-Gisenyi, Bukavu, Bujumbura), Central Africa
 - in the PASTECA project (https://pasteca.africamuseum.be/

Mboga, N. O. (2021). Long-term mapping of urban areas using remote sensing: Application of deep learning using case-studies of data from Central Africa (<u>Unpublished doctoral dissertation</u>). Université libre de Bruxelles, Faculté des Sciences – Géosciences, Environnement et Société, Bruxelles.



PASTECA

Urbanisation mapped from old aerial photos and satellite data with AI (Deep Learning)



EO and AI for mapping detailed urban land use (LU) and land cover (LC)



- Used of very high resolution satellite imagery (± 50 cm resolution, such as <u>Pleaides</u>) in combination with 3D views for
 - Mapping detailed LC classes on several African cities according to their spectral signatures and their height thanks to Al classification techniques
- Mapping urban LU classes on several African cities at the street blocks level thanks to Al
 classification techniques based on
 - Street block geometry (shape index, area)
 - □ EO-derived information (nDSM, NDVI)
 - □ LC-derived information (Landscape/Spatial metrics)
- Codes:
 - developped by T. Grippa during his PhD thesis
 - □ available on https://github.com/tgrippa
 - Documented in the

MAUPP project's publications (https://maupp.ulb.ac.be/page/publications/) and REACT project's publications (https://react.ulb.be/publications)





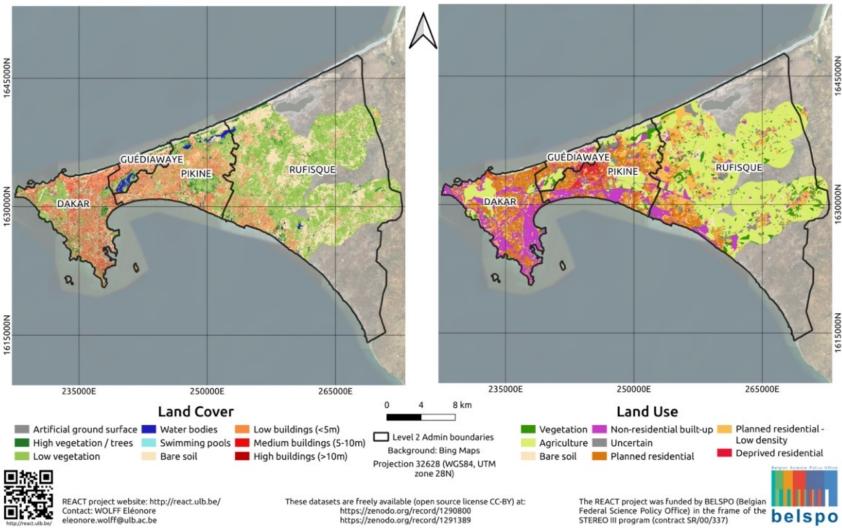






Dakar land cover and land use

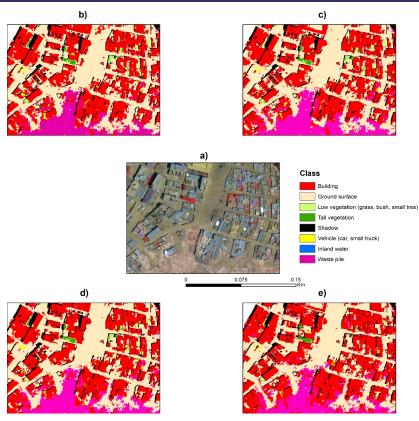




EO and AI for mapping detailed urban land use (LU) and land cover (LC)



- In deprived urban areas(Slumap project https://slumap.ulb.be/):
 - Mapping land cover
 - Mapping waste piles
 - Used as indicators of urban deprivation









EO and AI for mapping detailed urban land use (LU) and land cover (LC)

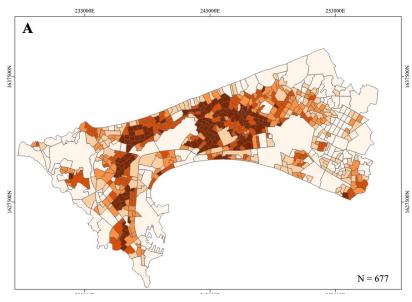


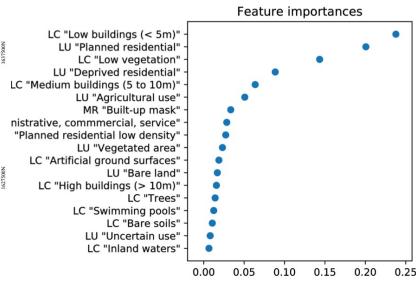
- Mapping such detailed LC and LU :
 - □ Required the acquisition of VHR data (full price >10\$/sqkm)
 - Once the codes are developed, the processing isheavyOuagadougou example
 - 615 km² (>95% LC publication deal with <3km²)
 - +200 Gb data in total
 - +15 10⁶ segments
 - +50 Gb tabular file (csv)
 - Segmentation: ± 10 days using 17 cores
 - Segment stats and classification: ±2 days
 - Post-classification: ±1,5 days
 - Land use: ±2 days

EO and AI for mapping detailed population estimation



- Use of the LC and LU maps with census population statistics at the finest administrative level
- □ to estimate and map population densities thanks to Al techniques
 (REACT project https://react.ulb.be/ publications, data available)





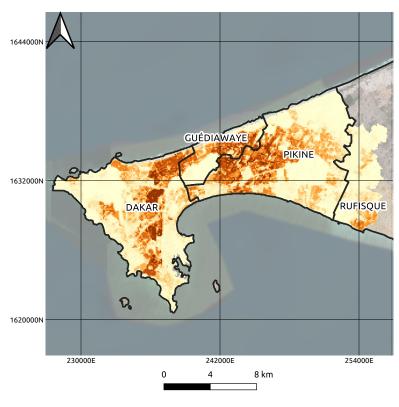




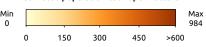


Dakar population estimates









Level 2 Admin boundaries

Background: Bing Maps

Projection 32628 (WGS84, UTM zone 28N)



This dataset is freely available (open source license CC-BY) at: https://penodo.org/record/2525672
REACT project website: http://react.ulb.be/
Contact: WOLFF Eléonore
eleonore.wolff@ulb.ac.be

The REACT project was funded by BELSPO (Belgian Federal Science Policy Office) in the frame of the STEREO III program (contract SR/00/337)



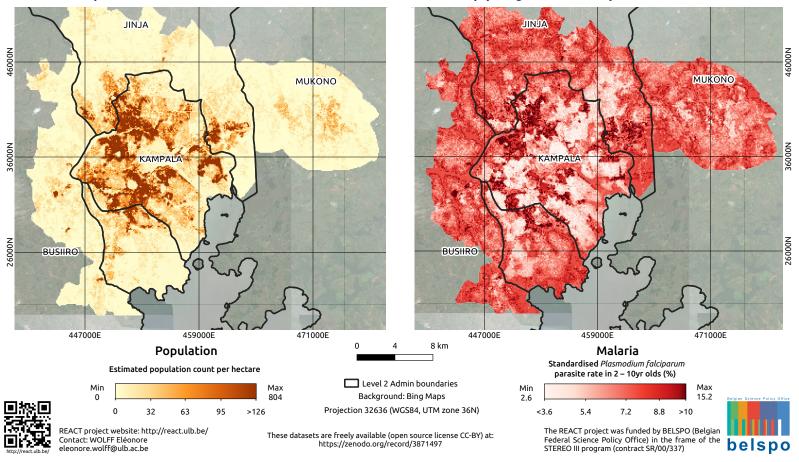




Kampala population and malaria estimates



Population's estimates = denominator for mapping malaria parasite rate



EO and AI for mapping wealth



Attempts to estimating and mapping wealth in urban areas from:

- □ DHS Wealth Index (WI) computed from
 - □ the detailed data of the **Demographic and Health Surveys** (DHS)
 - ullet Data available for points which are dislocated of \pm 1 km
- □ Satellite-derived VHR land-use/land-cover (LULC) datasets

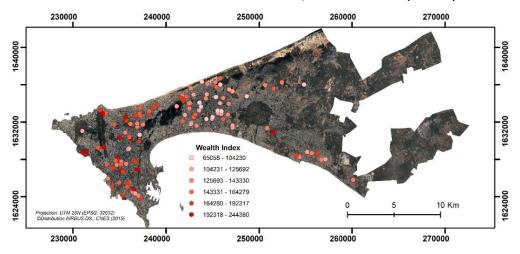


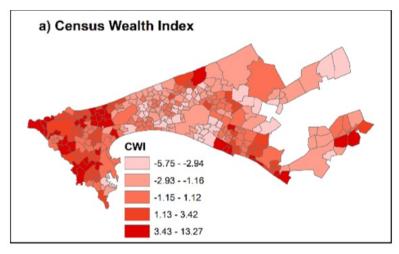
Figure 2. Demographic and Health Surveys (DHS) Wealth Index across Dakar between 2008–2016.

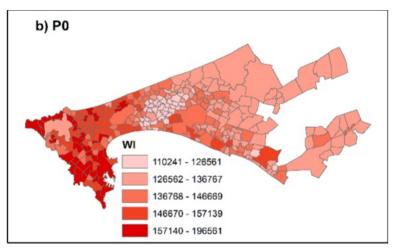
Reference article: Georganos, S.; Gadiaga, A.N.; Linard, C.; Grippa, T.; Vanhuysse, S.; Mboga, N.; Wolff, E.; Dujardin, S.; Lennert, M. Modelling the Wealth Index of Demographic and Health Surveys within Cities Using Very High-Resolution Remotely Sensed Information. *Remote Sens.* **2019**, *11*, 2543. https://doi.org/10.3390/rs11212543

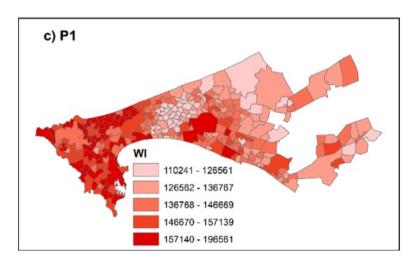


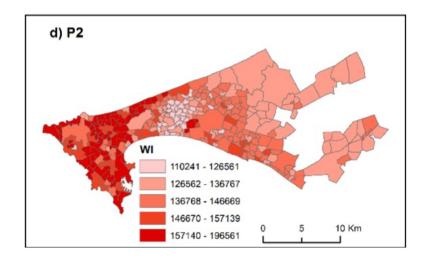


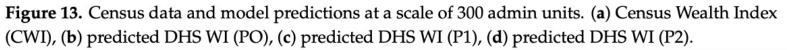
Encouraging results but needs to be refined











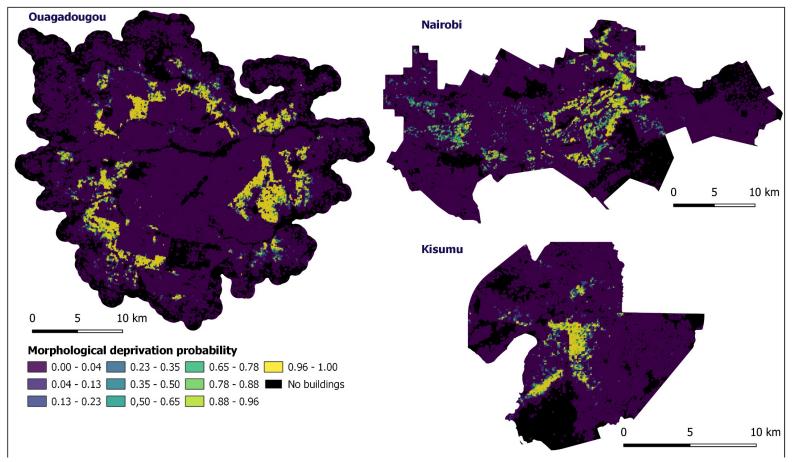




EO for mapping deprivation probability

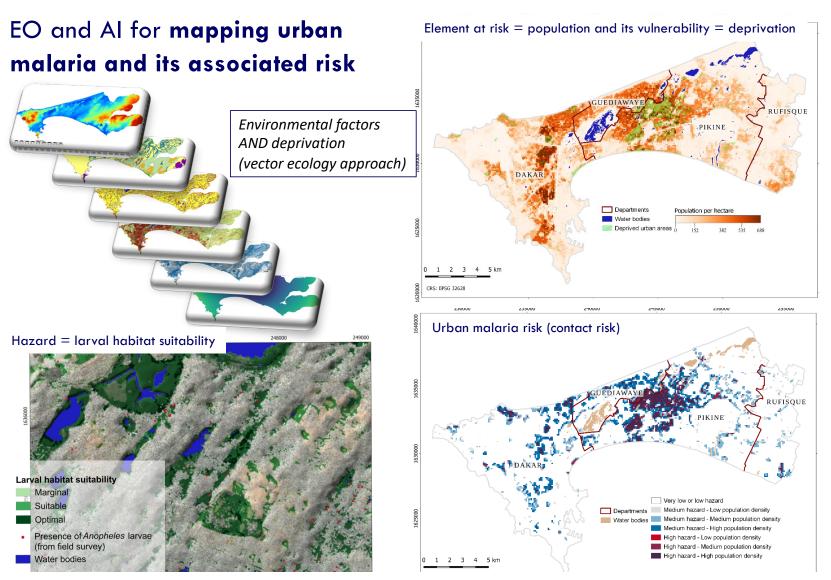


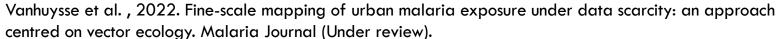
Machine Learning and a mix of open data -> gridded probability maps (100m x 100m)





belspo





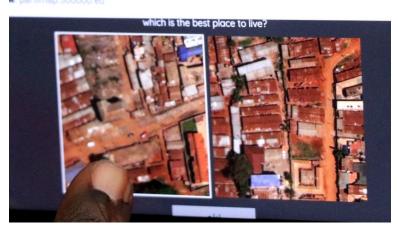


EO and citizen science to map perceived deprivation in slums



- □ Citizen science :
 - Participation of people from 7 deprivedareas in Nairobi
 - Selecting on their smart-phones the best place to live, between two satellite or street views
- □ EO and GIS data:
 - □ Land cover classes, extracted buildings, OpenStreetMap data (roads, rivers, ...)
- □ Ai processing → map of perceived deprivation in slums

Abascal, A., Rodríguez-Carreño, I., Vanhuysse, S., Georganos, S., Sliuzas, R., Wolff, E., & Kuffer, M. M. (2022). Identifying degrees of deprivation from space using deep learning and morphological spatial analysis of deprived urban areas. *Computers, environment and urban systems*, 95, 101820. doi:10.1016/j.compenvurbsys.2022.101820







EO and citizen science to map perceived deprivation in slums





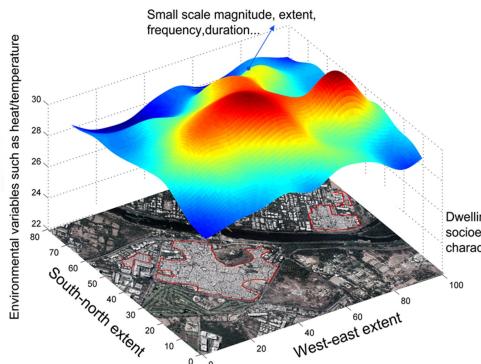




Recently started project: exposure to temperature variations and extreme heat (ONEKANA)

Research question: How and why are urban dwellers with different levels of deprivation divergently exposed to variations of temperatures and extreme heat?





Using citizen science & open or low-cost satellite images, FOSS, and AI, it is possible to:

- model location, extent and characteristics of areas combining both high levels of deprivation and high levels of temperature variation/extreme heat)
- quantify vulnerable populations exposed to such conditions

Dwelling groups with different socioeconomic and demographic characters.

Methodology

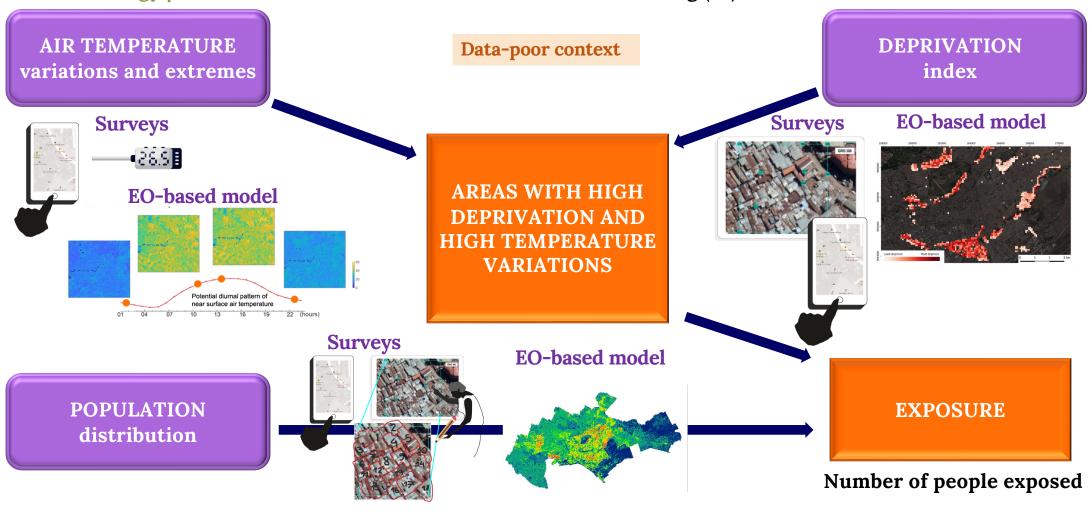
EARTH OBSERVATION



CITZEN SCIENCE

Recently starting project: exposure to temperature's variations and extreme heat (ONEKANA)

Methodology | Citizen science & Earth Observation-based modelling (AI)



Conclusion



- □ EO data regularly covers large areas → allows regular updates
- □ EO data:
 - □ Are **open and free of charge** up to a 10m resolution
 - Are costly for sub-metric resolution but much cheaper than the equivalent data collected on the field
 - Processed images available for free in the case of disasters (e.g. Floods) with the Charter activation by local authorities (https://disasterscharter.org/)
- Crucial data source to
 - □ Maps of land cover, urbanisation, urban morphology, urban deprivation, ...
 - Combine with statistical data using spatial models to estimate and map urban population, urban malaria hazards and risks,
 - Combine with socio-economical household survey data to estimate and map wealth using spatial models
 - **...**



Thank you for your attention Questions?