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# ONEKANA: MODELLING THERMAL INEQUALITIES IN AFRICAN CITIES

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## ABSTRACT

Africa, as a major climate change hotspot, faces severe impacts, including extreme temperatures. Notably, urban areas are unequally affected by these impacts. The urban poor are particularly vulnerable to extreme temperatures, because of the environmental and physical characteristics of their neighbourhoods, and their limited resources to develop coping strategies. Limited knowledge exists of the spatial patterns of thermal inequalities within neighbourhoods. Our overall scientific objective is to explore the potential of Earth Observation (EO) to study how and why urban dwellers in the Global South (focusing on Africa) with different levels of deprivation are divergently exposed to varying temperatures and extreme heat, and to quantify the urban population exposed to such conditions. We make use of several state-of-the-art EO/AI models, and employ innovative *in situ* data collection methods together with local stakeholders through Citizen Science. We rely as far as possible on open or low-cost satellite imagery (e.g., Sentinel-1/2, Landsat, ECOSTRESS) for scalability and transferability, and we implement Machine Learning (ML) methods, including Deep Learning (DL). Results highlight significant local differences in thermal exposure, emphasizing the need to understand and communicate these spatial patterns to support the development of cost-effective adaptation strategies.

***Index Terms***— Thermal inequalities, temperature modelling, citizen science, remote sensing, slums

## 1. INTRODUCTION

In the last decades, Africa has been experiencing very rapid urbanisation [1] that is expected to continue in the coming decades [2] due to natural population growth and migration driven by the massive impacts of climate change, local and regional conflicts (often related to water and other natural resources), and urban opportunities (e.g., education, employment and services). The growing urban population, in particular in Deprived Urban Areas (DUAs), is exposed to more frequent, prolonged and intense heat and temperature variations [3] due to climate change [4]. Yet, the quantitative assessment and explanation of how different environmental factors and living conditions influence near-surface air temperature across space and time, and ultimately the divergence of heat exposure and the number of vulnerable people exposed, are absent from existing data, models and local dwellers' knowledge [5]. In ONEKANA, we combine Earth Observation (EO), Machine-Learning/Deep-Learning (ML/DL), and Citizen Science (CS) to explore how and why urban citizens with different deprivation levels are divergently exposed to varying temperatures. Citizens are actively involved in our research design.

## 2. METHODOLOGY

The methodology has a step-wise design. The models are first developed and tested in one African city (Nairobi, Kenya) and then transferred to a very different African city (Lagos, Nigeria). The megacity Lagos is very different in terms of location, environment, size, and morphology. To test global transferability, our models will also be transferred to a city in Latin America. Outputs are gridded maps with a spatial resolution of 100 m x 100 m. Our methodology consists of three major steps (Fig. 1).

First, we model near-surface air temperature. Most studies on urban temperature variations only draw upon EO-based thermal images that actually measure surface temperature, and model the surface urban heat islands, but not the air temperature [6] that influences human thermal comfort [7]. Also, most models are developed in data-rich environments (e.g., Europe, the US or China) and not in situations of data scarcity [8]. Worse still, heat exposure analysis rarely addresses the extremes that affect the most vulnerable groups, such as those living in DUAs. We build advanced AI-based statistical models using a large set of heat-sensitive EO-based covariates (e.g., thermal infra-red (TIR), land cover, urban morphology) and in situ measurements to model air temperature and diurnal temperature variation: (a) fixed sparse near-surface air temperature measurements, and (b) mobile

[*]Thanks to Belspo agency for funding.

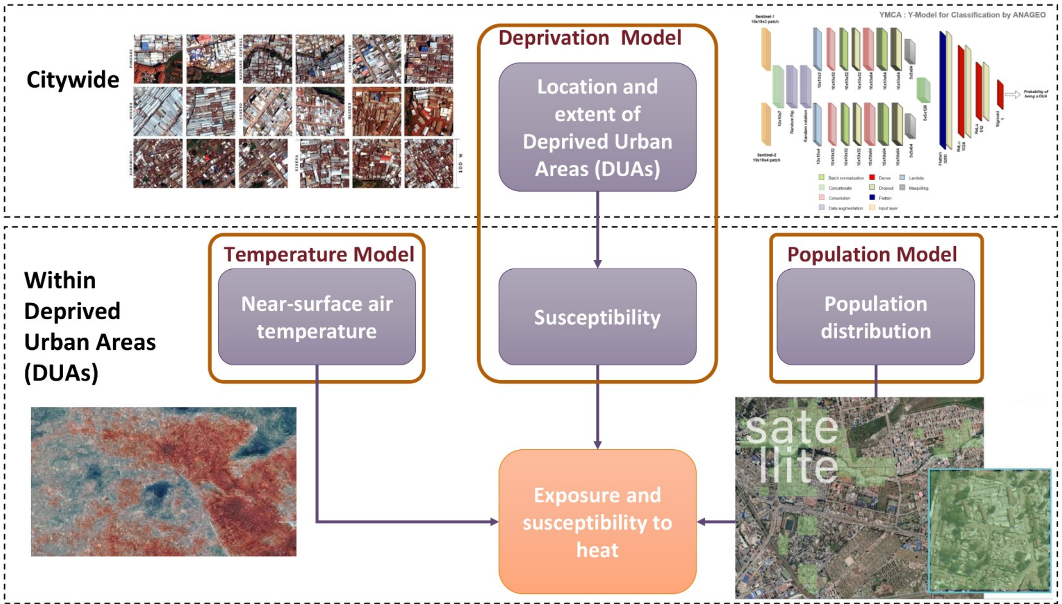


**Fig. 1**. Overview of the ONEKANA Methodology.

(low-cost) measurements by citizens. The main innovations are the statistical quantification of the spatio-temporal variations of near-surface air temperature and the development of an i*n situ* data collection strategy based on low-cost citizen measurements with a limited number of fixed (high-cost) monitoring stations. A low-cost design is essential to support the transferability and scalability of the methods.

Second, we develop ML models aiming at scalability and transferability to (i) map the location and extent of DUAs citywide and (ii) predict a susceptibility index in great spatial detail within DUAs, using EO data, ancillary open Geodata, and micro-surveys conducted by residents. ML has been leveraged in many studies to map DUAs, and recent studies have also explored the use of DL for this purpose. Nevertheless, there are still key challenges to overcome, such as the sparsity of data for training models [9], the development of models that provide fine-grained predictions while being scalable and transferable [10], and the limitations associated with the use of open or low-cost EO data, particularly in terms of spatial resolution.

Third, we model population distribution in great spatial detail within DUAs using EO data, open Geospatial data and micro-surveys in a multi-modal DL model. Population distribution modelling in DUAs faces similar challenges as those mentioned for deprivation modelling, and it has been demonstrated that current official figures and global open layers underestimate the number of DUA dwellers [11][12]. We model and map population distribution in DUAs, harnessing the power of multi-modal deep learning, EO and ancillary data such as publicly available building footprint datasets, following on the tracks of recent state-of-the-art

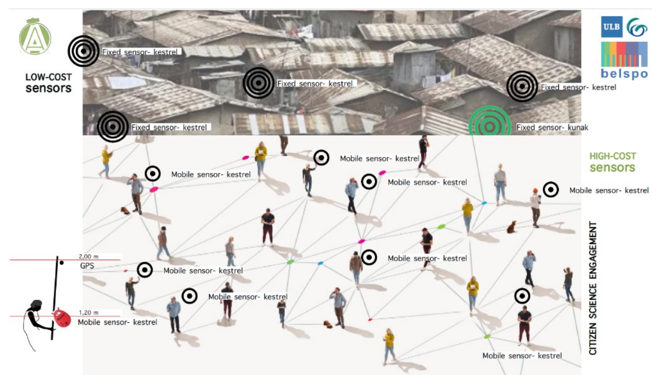


**Fig. 2**. Low-cost set-up of measuring air temperature with local community groups.

research [13]. By combining the outputs of our models, we aim to capture urban heat exposure in African cities through a process that actively involves citizens, to provide knowledge on key urban factors for heat adaptation, stimulate debate on the use of local building materials and urban designs to better adapt to climate change impacts, and provide evidence to support planning processes to protect residents with limited resources from increasing climate change impacts (e.g., through a policy brief).

## 3. RESULTS

This section describes our preliminary results based on the case study of Nairobi, Kenya. The transferability within

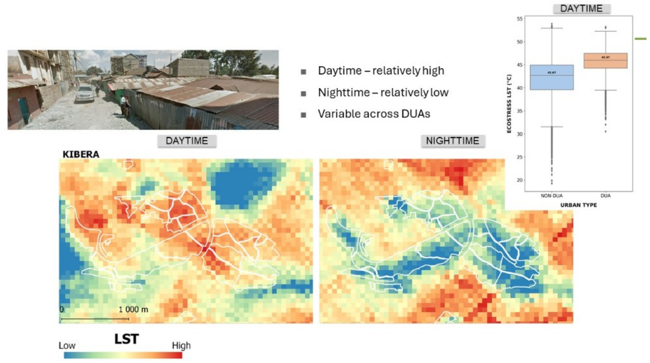


**Fig. 3**. Surface temperature differences measured by ECOSTRESS (Nairobi).

Africa and to Latin America will be analysed in a second phase. Citizen Science is essential throughout the project, as the research is being co-designed with citizen groups (community-based organizations), local academics, and pro-poor government representatives from our case study cities. Moreover, local citizens are actively involved in the field data collection campaigns and the transfer of field knowledge to enhance the models (Fig. 2).

### 3.1. Temperature Patterns

Nairobi has a temperate climate due to its location at an altitude of more than 1700 m above sea level. However, Fig. 3 shows that in terms of land surface temperature, there are variations across neighbourhoods. DUAs tend to heat up more than other urban types during daytime, presumably because of their built-up density and building surface materials (e.g., iron sheet roofs). The opposite is observed during nighttime, i.e., DUAs tend to cool down more than their surroundings. Both phenomena cause high levels of thermal discomfort for inhabitants, as the latter have little protection from high temperatures during the day and low temperatures during the night. *In situ* air temperature data were collected during a field campaign and are currently being processed.

### 3.2. Deprivation Model

At the citywide level, we previously demonstrated that fully supervised multi-modal Random Forest models processing open optical and SAR (Sentinel-1/2) imagery, with or without the addition of open global Geodatasets, are able to capture DUA patterns with a high degree of accuracy despite the wide variability in Nairobi DUA characteristics [14]. However, the bottleneck of this approach is the time-consuming production of manually annotated labels, which is a barrier to scalability. Therefore, in this research we are investigating unsupervised and semi-supervised learning. Besides, the prospect of regular updates and wide coverage of open building footprints

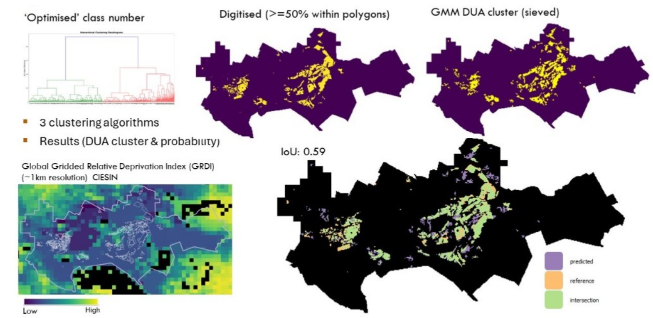


**Fig. 4**. Unsupervised clustering based on features derived from imagery, urban morphometrics, and open geospatial data.

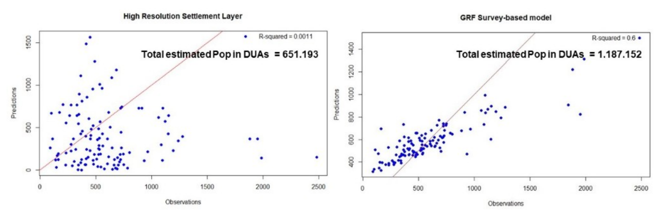


**Fig. 5**. HRS (Facebook) compared to the ONEKANA EO-based population model (observation: survey data for Nairobi).

[15] led us to include morphometrics derived from that dataset in the process. A comparison of the performance of different unsupervised clustering algorithms showed that Gaussian Mixture Models (GMM) obtained the best results in isolating DUAs from other types of urban neighbourhoods (Fig. 4). The semi-supervised approach aims at increasing the accuracy of the prediction obtained from unsupervised methods. Pseudo-labels derived from the urban clusters are automatically binarised and used to train a random forest model. A preliminary validation against reference data generated from extensive field knowledge and visual interpretation of VHR imagery indicates an F1 score of 0.85 for the class DUA, based on 1000 stratified random samples. In the next phase, we will assess the susceptibility of the population residing in DUAs, using mainly spatial covariates, and also *in situ* survey data collected using a co-designed questionnaire for fine-tuning and validation.

### 3.3. Population Model

None of the existing open population datasets can capture the high population densities and their complex spatial patterns in DUAs [11]. One of the highest-resolution population layers (Facebook) is compared with our Sentinel-based population model against local survey data (Fig. 5). The result shows that the Sentinel-based model is able to predict the complex population distribution with an R2 of 0.6. Furthermore, the number of DUA inhabitants is almost double as compared to the HRL population model. An essential element for building our methodology is our strong collaboration and partnership with local stakeholders, who have been involved from the outset. Without collaborating with local citizens, the research design and data collection would not have been feasible. We have been developing this partnership already within a previous research project (SLUMAP [16]). The strong engagement and motivation of communities living in DUAs is also an asset.

## 4. CONCLUSIONS

We addressed a new research topic of great importance with innovative approaches, and propose an EO application with a high potential societal impact. Our approach is built as much as possible on low-cost solutions and free and open data. An essential element of success is the collaboration with reliable and committed local networks, with whom we have established partnerships in previous research projects (both in Nairobi and Lagos). The use of open and/or low-cost datasets is an asset for scalability and transferability. Our developments will be made available as open code, and the results as open data that will be added to our existing SLUMAP webGIS application.

## 5. ACKNOWLEDGMENTS

The research pertaining to these results received financial aid from the Belgian Federal Science Policy (BELSPO) according to the agreement of subsidy no. SR/11/405 (ONEKANA). We would like to acknowledge CommunityMappers for the discussion and co-development of the upcoming fieldwork.

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Full citation: S. Vanhuysse, A. Abascal, S. Georganos, J. Wang and M. Kuffer, "ONEKANA: Modelling Thermal Inequalities in African Cities," IGARSS 2024 - 2024 IEEE International Geoscience and Remote Sensing Symposium, Athens, Greece, 2024, pp. 1571-1575, doi: 10.1109/IGARSS53475.2024.10641265.
Link : https://ieeexplore.ieee.org/document/10641265