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(IDeAMapSudan)

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

FINAL SYMPOSIUM

FEBRUARY 2023

African Population and Health Research Center

ULB

ITC UNIVERSITY OF TWENTE.

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IDEAMAP SUDAN FINAL SYMPOSIUM

Examples of Mapping multi-level deprivation on different cities

Presenter: Dr. Monika Kuffer and Dr. Caroline Kabaria

FEBRUARY 2023

DEPRIVATION: A MULTI-DIMENSIONAL CONCEPT

- **Households** might be deprived in terms of durable housing material or access to basic services (e.g., water, education,..).

- **Communities** might be deprived in terms of infrastructure or availability of open spaces.

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DEPRIVATION: A MULTI-DIMENSIONAL CONCEPT

Benefits for Mapping Deprivation

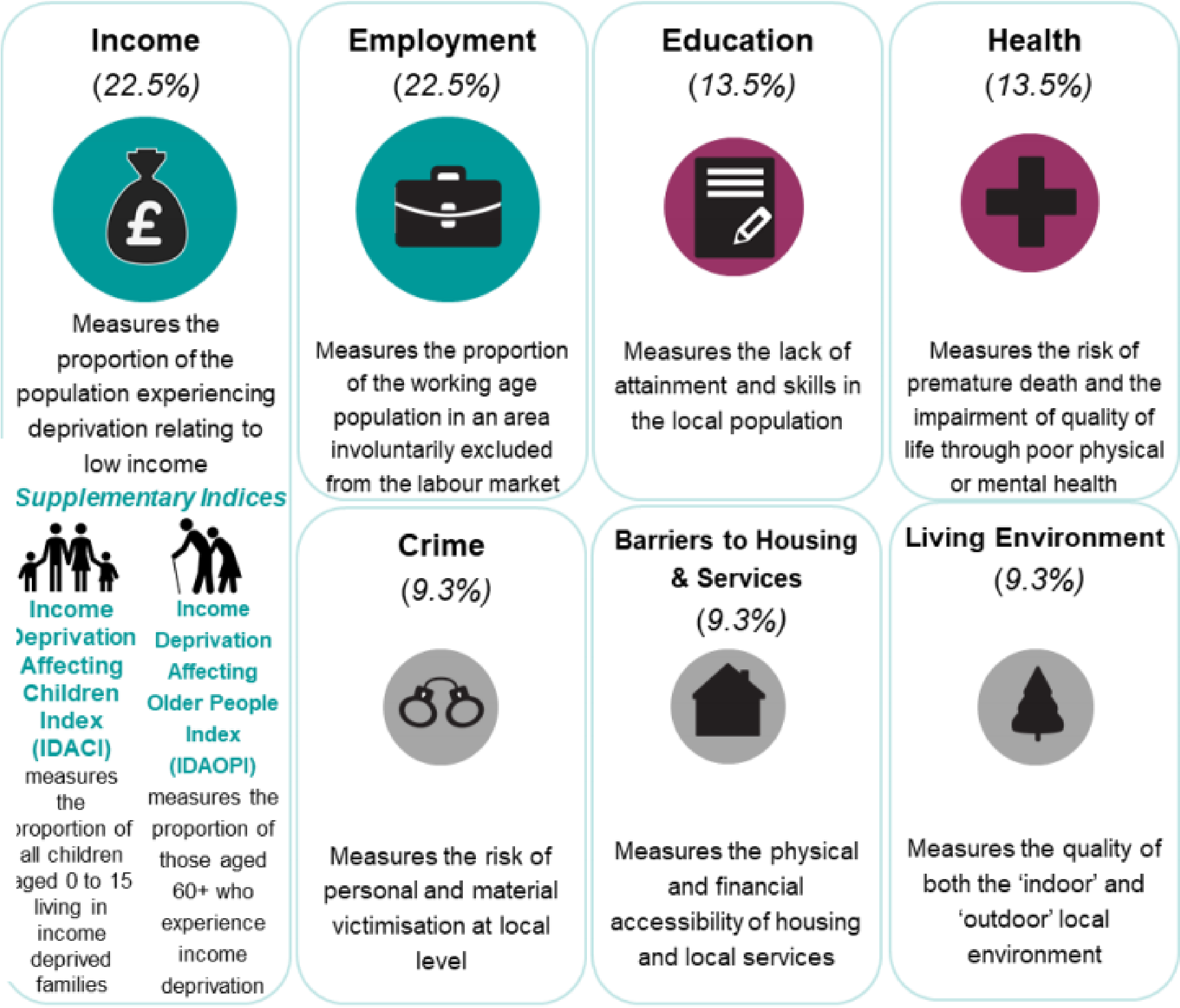
- Explore the geographical patterns of deprivation
- Identifying the most deprived areas
- Explore the domains/factors of deprivations in different areas
- Compare administrative areas (e.g., states, localities)
- Dynamics of deprivation over time

Example - Multiple Deprivation Index

There are 7 domains of deprivation, which combine to create the Index of Multiple Deprivation (IMD2019):

The English Index of Multiple Deprivation (IMD)

based on 39 indicators, organized across seven domains,:



the index of multiple deprivation (IMD2019) - seven domains of deprivation

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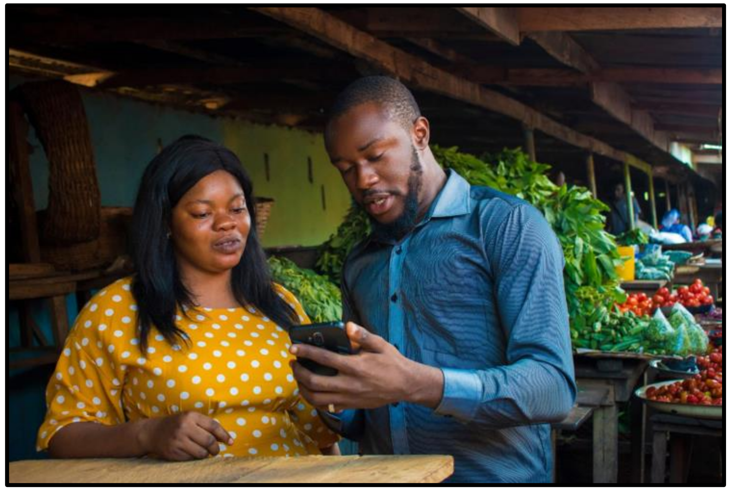
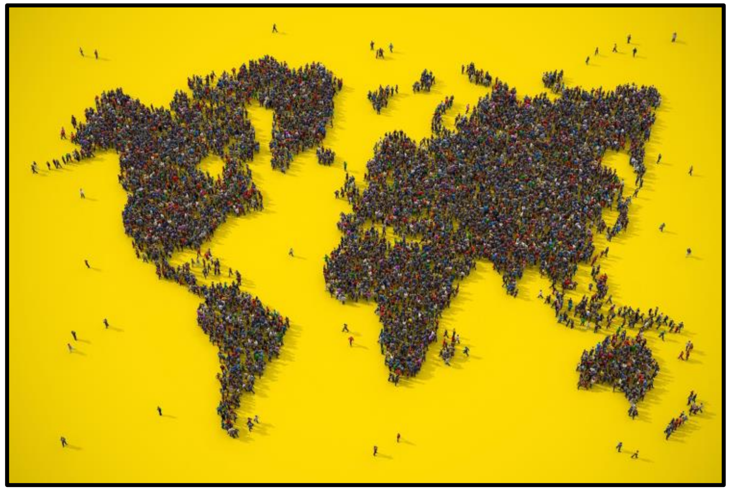
Combining “slum” mapping approaches

Field Mapping using GPS or drawing on printed imagery. Often performed by residents to generate data for planning and advocacy.





Census & Survey approaches use household-level data to classify “slum” households, then aggregate. An area with >50% “slum” households is a “slum” area.

Computer models using AI or machine-learning methods and satellite imagery. Requires training data of slum/ non-slum areas.

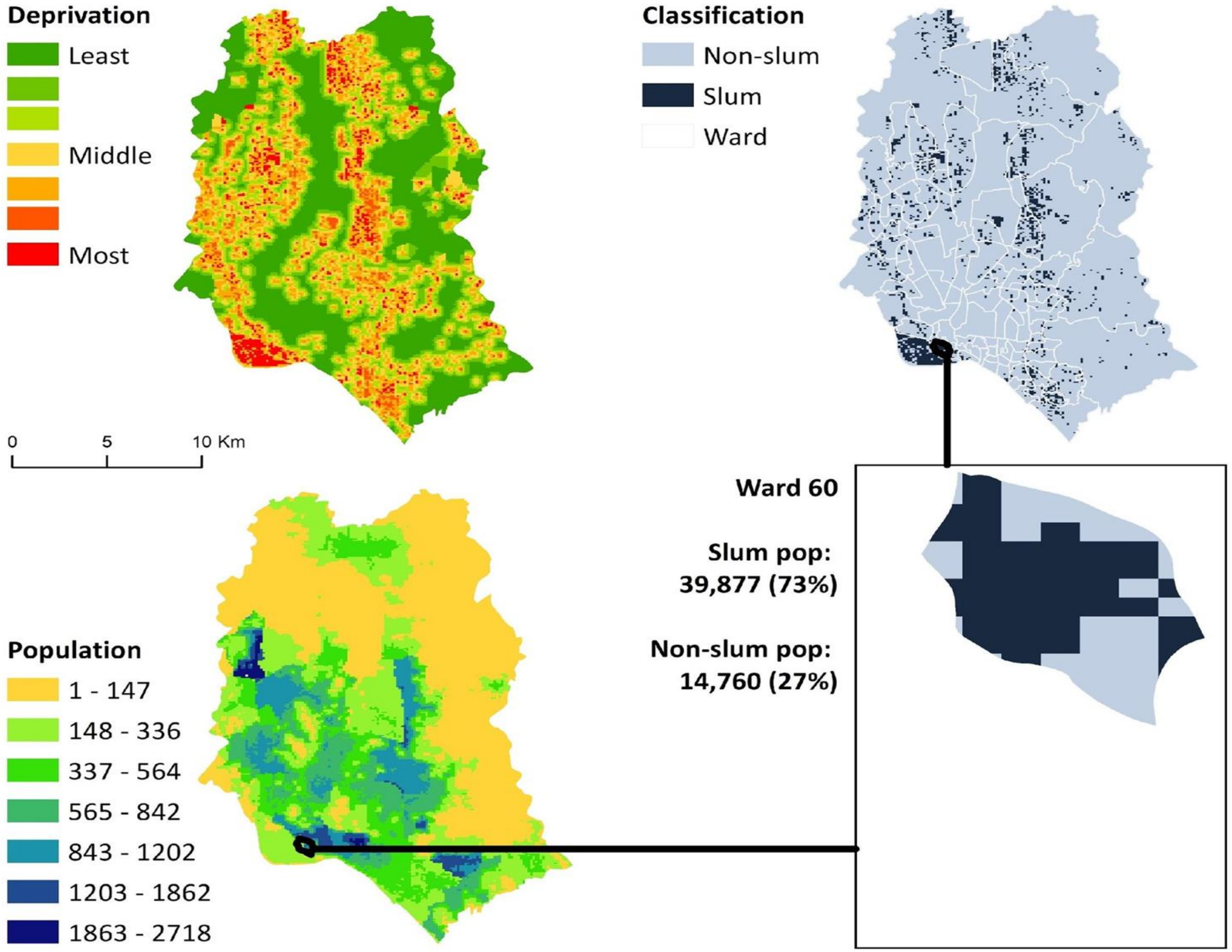
Digitising imagery is done manually in GIS software, some times by a person unfamiliar with the local context. Digitized imagery is often used to train computer models.

What do we envision achieving together?

Improved data on slums and deprived areas

Project partners, communities, governments, researchers in Lagos, Kano and Nairobi

Identification of slum areas



What do we envision achieving together?

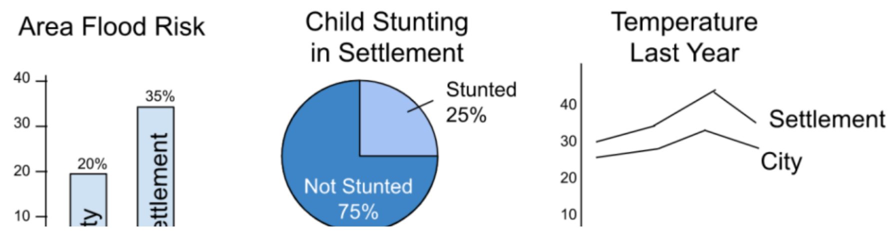
IDEA MAPS Network

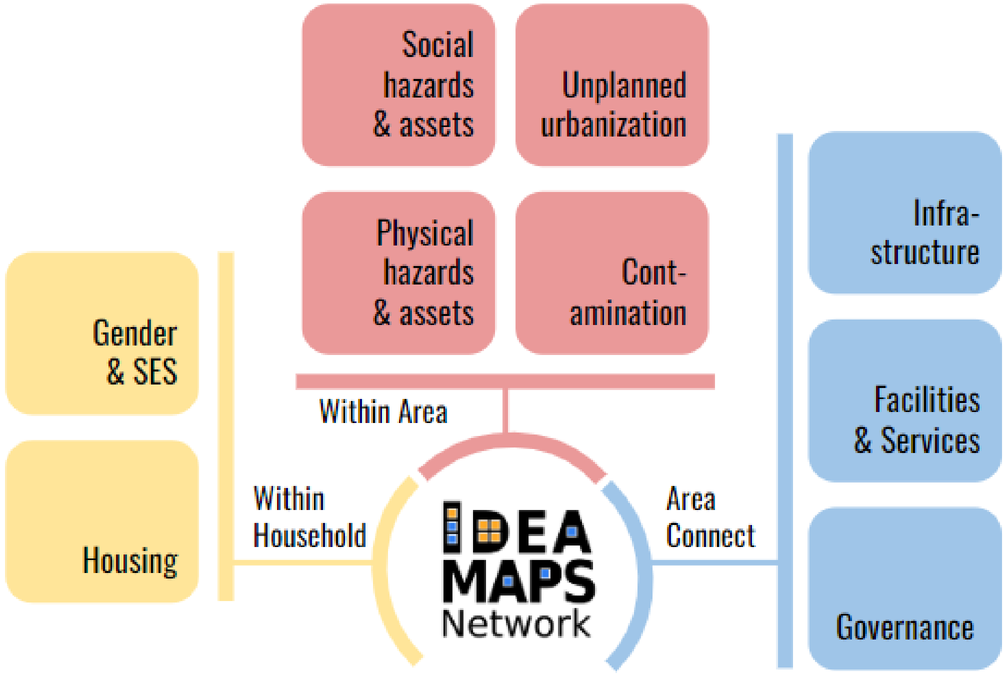
Project partners, communities, governments, researchers in Lagos, Kano and Nairobi

Improved data on slums and deprived areas

Improved access to data and characterisation of places and priorities

Characterisation of slum areas





Domains or Deprivation paper:
https://doi.org/10.1016/j.compenvurbsys.2022.101770

What do we envision achieving together?

IDEA MAPS Network

Project partners, communities, governments, researchers in Lagos, Kano and Nairobi

Improved data on slums and deprived areas

↓

Improved access to data and characterisation of places and priorities

↓

Improved capacity to use and update data to enable change

Capacity for action planning, update and monitoring

What do we envision achieving together?

IDEAMAPS Network

Project partners, communities, governments, researchers in Lagos, Kano and Nairobi

Improved data on slums and deprived areas

Improved access to data and characterisation of places and priorities

Improved capacity to use and update data to enable change

Actions and interventions to effect change

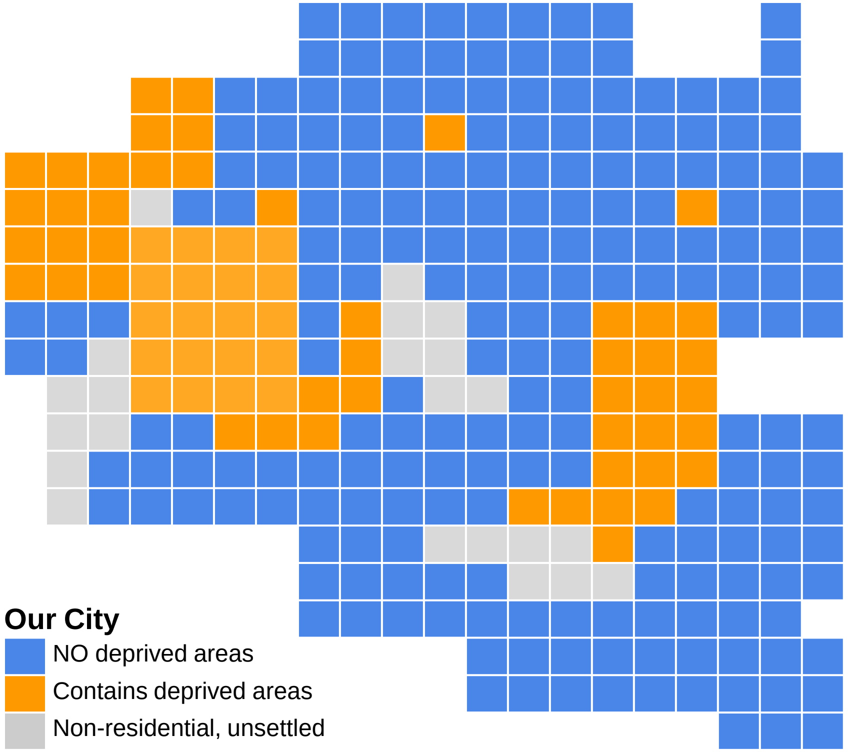
Just, equitable and sustainable cities that provide essential services for all

11 SUSTAINABLE CITIES AND COMMUNITIES

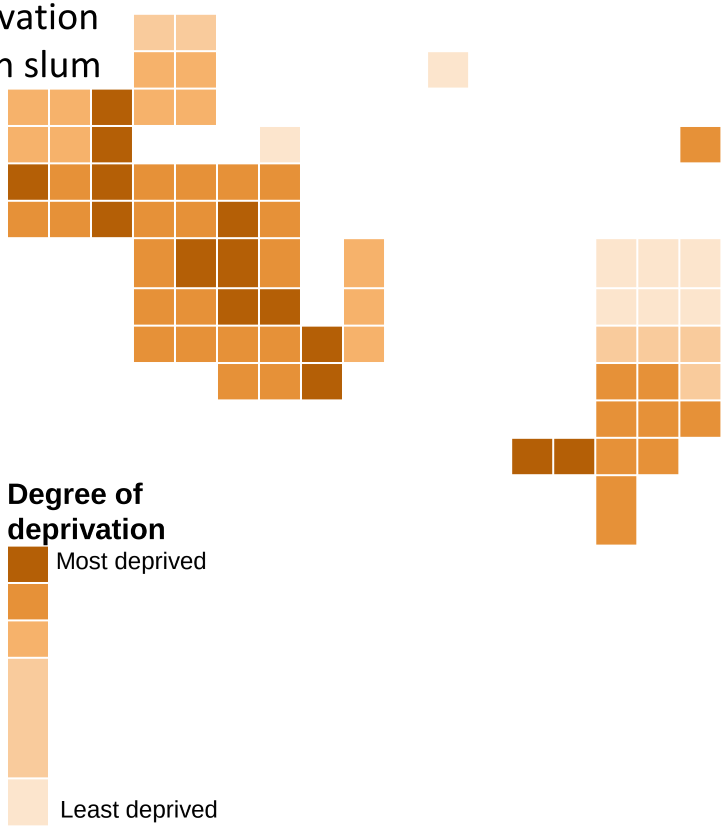
Key output:
One (or more) sets of models

Outputs

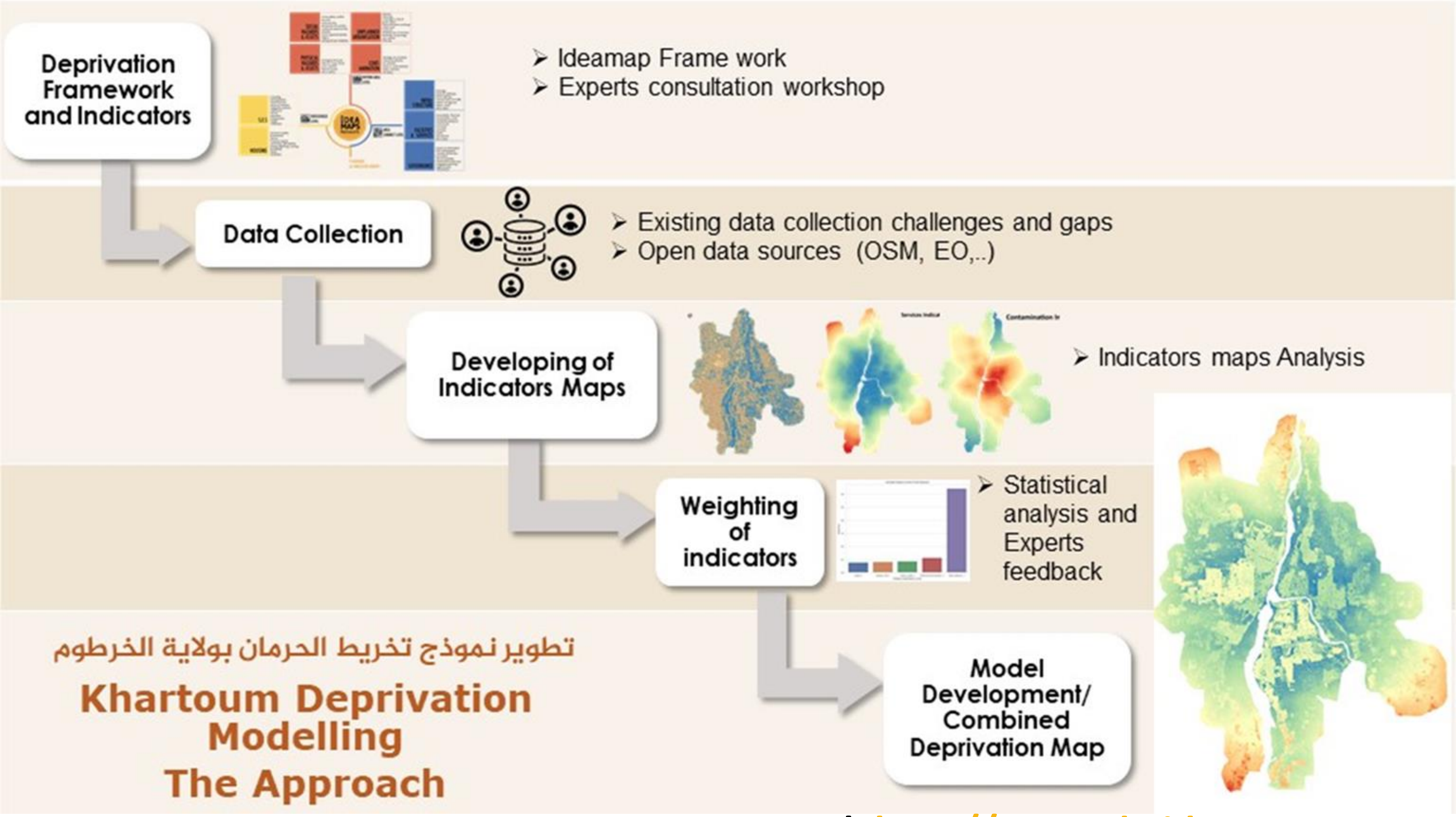
Classify binary slums first



Then define degree and/or type of deprivation within slum areas



Model 1: Domains combining secondary data (IdeaMapSudan)



Data portal: http://geonode.idea-maps.net

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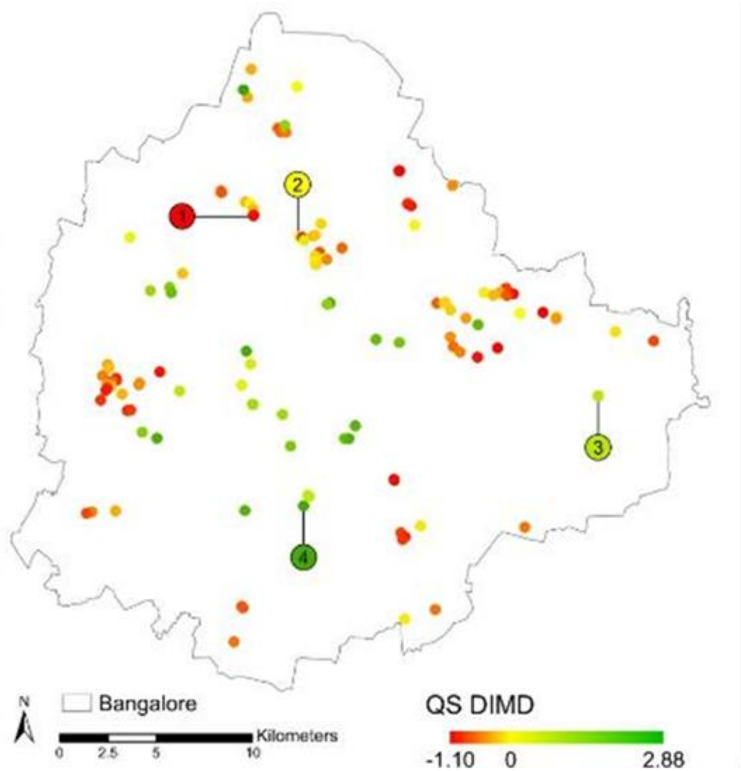
Model 2: EO Models trained from area observation survey

Bangalore, India



CNN-based model **Transfer learning**

Classification problem
Distinguishing slum from formal
2000 samples for training

Distinctive features

Regression problem
Predicting Deprivation indices
<121 samples for training

CNN model

Ajami, Kuffer, Persello and Pfeffer, 2019
https://www.mdpi.com/2072-4292/11/11/1282

Model 2: EO Models with image features (SLUMAP approach)

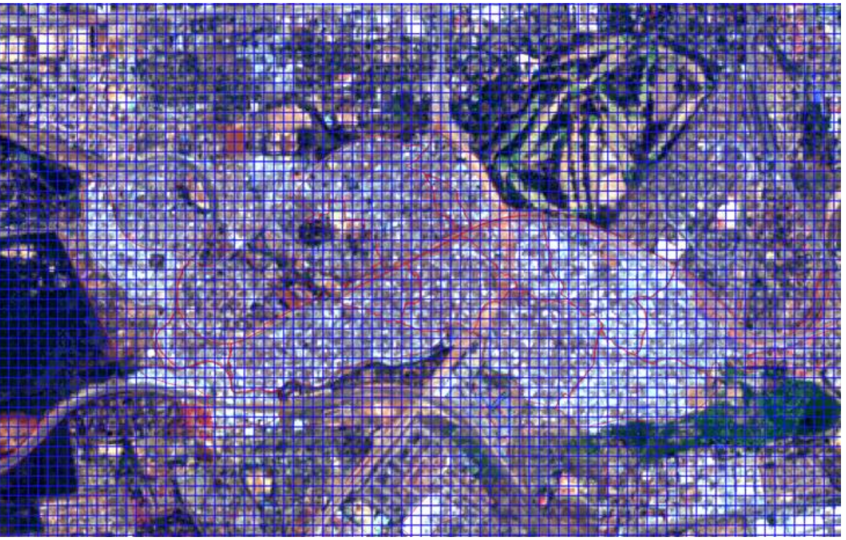
Nairobi, Kenya

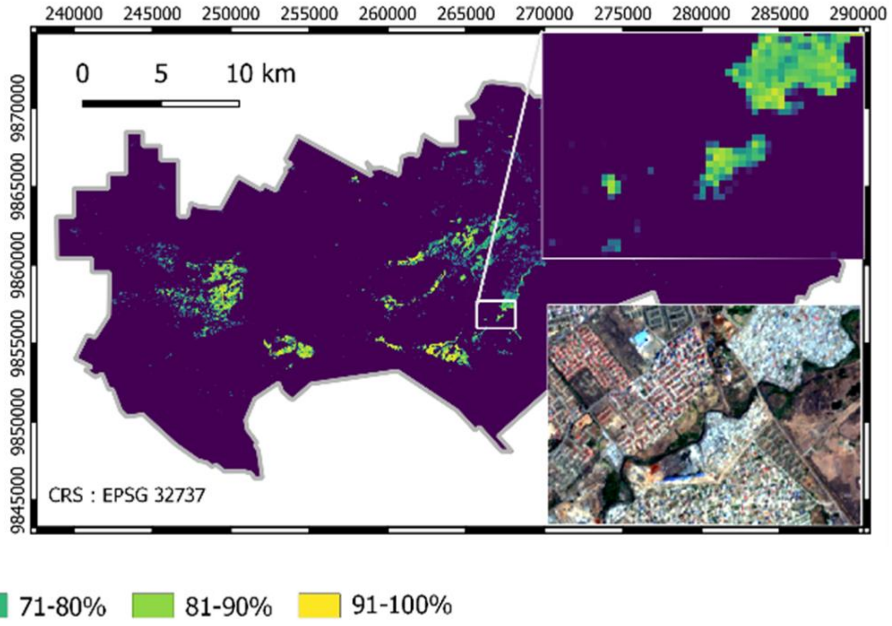
Sentinel 1/2 +Contextual features

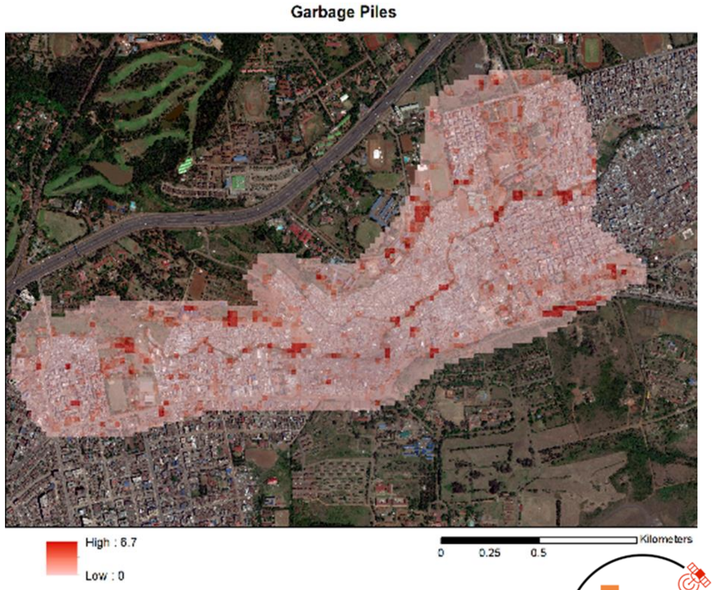
\+ Labelled training data

Deprivation probability of a grid cell

Specific environment conditions (e.g., waste)







https://doi.org/10.3390/rs13244986

SLUMAP

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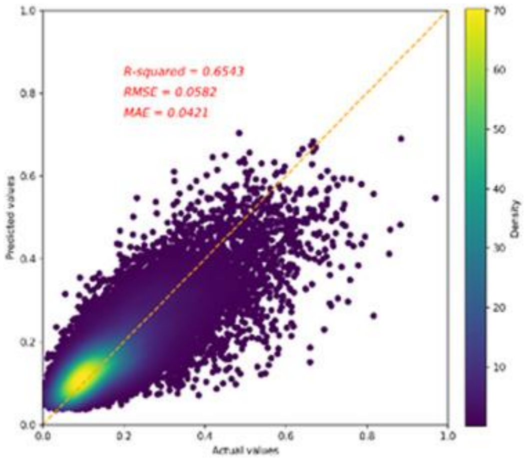
Model 3: Using Earth Observation Data using Advanced AI

Nairobi, Kenya

Input Data

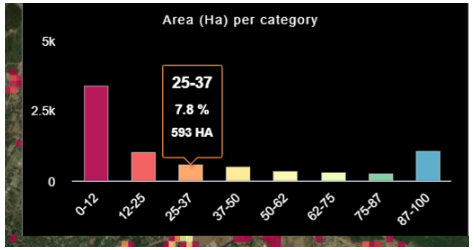
Models used

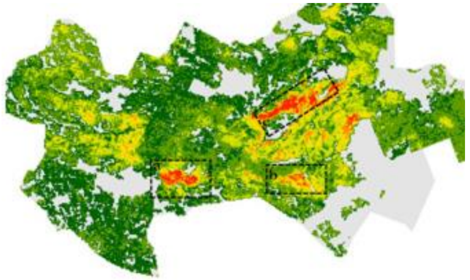
- Classifical ML models
- Deep-learning



Outputs

- Maps
- City and area stats





Validation + Improvement

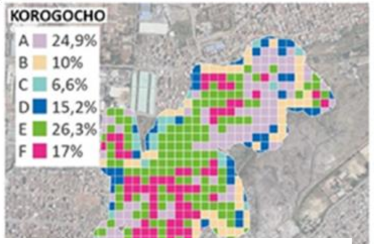
- Accuracy
- Fit of purpose

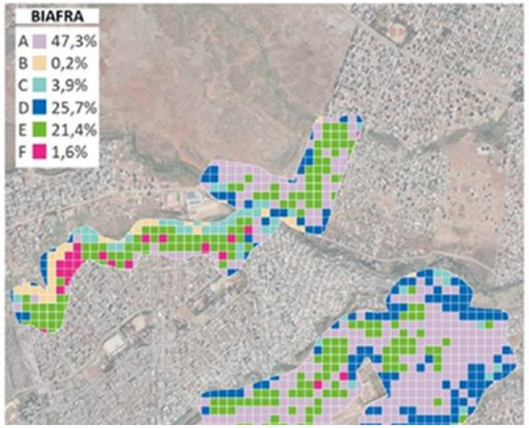
Example: https://www.mdpi.com/2220-9964/11/12/631

Source: https://doi.org/10.1016/j.scs.2022.104033

Model 4: Training EO models trained with community knowledge

Nairobi, Kenya





LC FEATURES: Waste Piles, Building, Low Vegetation, Tall Vegetation, Vehicles, Shadow, Ground Surface, Water

CLUSTERS	DESCRIPTION
A	High Ground Surface coverage; Medium Building Density; Some presence of Waste Piles and Vehicles.
B	High presence of Water bodies; High presence of Waste PIles; Some Tall and Low Vegetation; Medium-Low Building Density.
C	High presence of Tall Vegetation; High presence of Shadows; Some presence of Low vegetation and Low Vuilding density.
D	High Low Vegetation coverage; Some Tall Vegetation; Some presence of Waste Piles.
E	High-Medium Building Density; High presence of Shadows; Little Low and Tall Vegetation; Some Waste Piles and Vehicles.
F	High Building Density; Medium presence of Shadows; Some presence of Vehicles; Lack of Vegetation.

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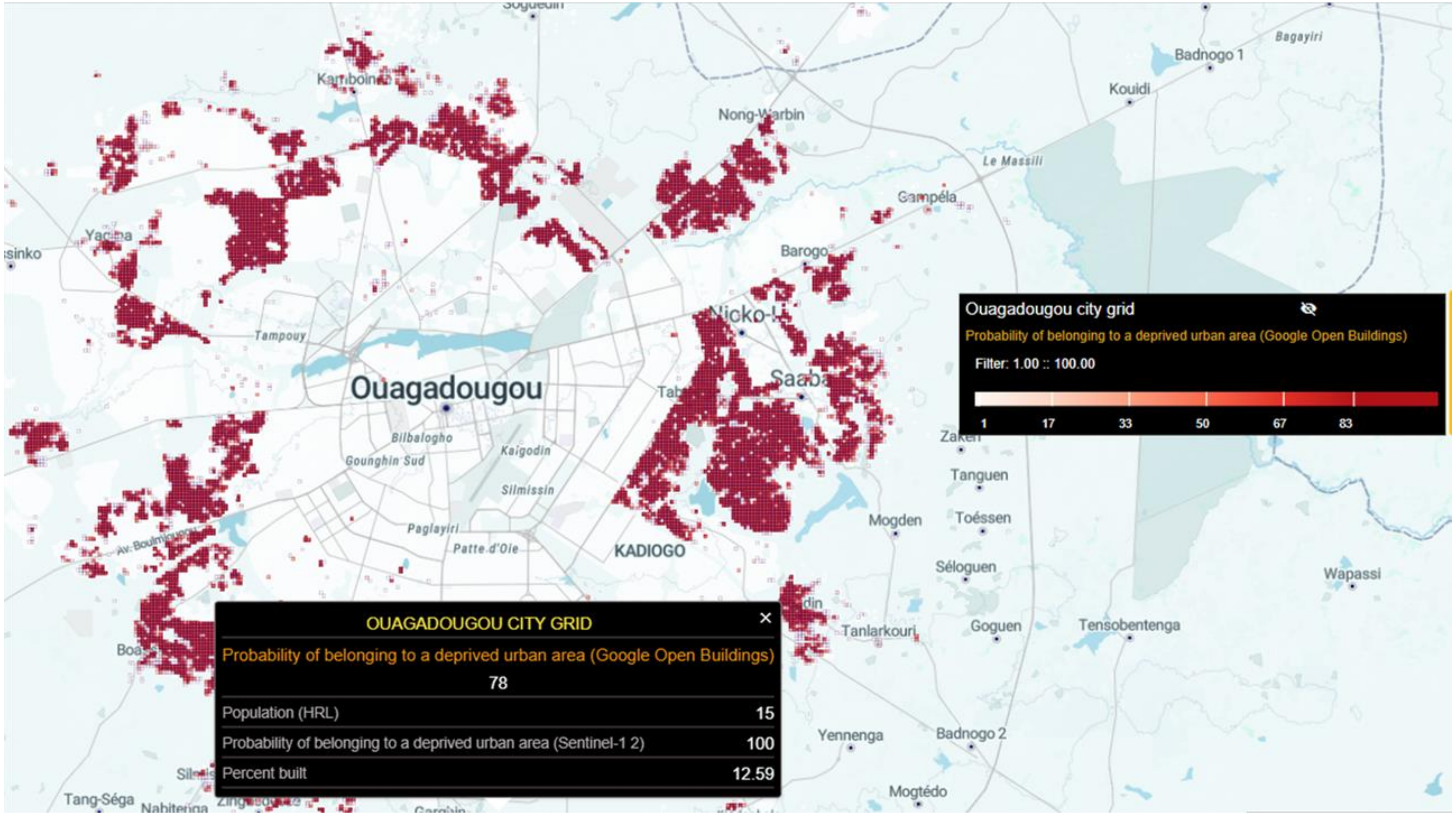
Model 5: Transferring model

https://pere.gis-ninja.eu/slumaps/

Transferring EO Models to a large set of cities



Overview

“Type” of training data in models

- ❑ Ground photos
- ❑ Field data
- ❑ Modelled from secondary data
- ❑ Community knowledge

Type of input features (e.g., EO vs maps)

- ❑ Open geospatial data
- ❑ Municipal data
- ❑ Commercial images
- ❑ Open and free EO images

AI Model complexity

- ❑ Deep-learning
- ❑ Transfer learning
- ❑ Classical ML

Output type

- ❑ Gridded map (continuous)
- ❑ Gridded map (binary)
- ❑ Summary stats