

MODELLING INTRAURBAN POPULATION DISTRIBUTION USING FREELY AVAILABLE DATASETS

JE. Steele, JJ. Nieves, Y. Forget, M. Shimoni, AJ. Tatem and C. Linard

Advanced mapping of urban population patterns in sub-Saharan Africa: MAUPP Conference, Nairobi KEN 30.01.19

Why map populations? Targeting vulnerable

Mapping the denominator

Governments are reliant on accurate and up-to-date dat On population numbers and



distributions for planning health services

-What is the catchment population of my health facility? -How many people are at risk of malaria?

populations

To improve the health of the poorest and most vulnerable an target interventions to lift them out of poverty, we need to know where they are

-How much vaccine is needed for this ward?

-Do the poorest have access to bednets

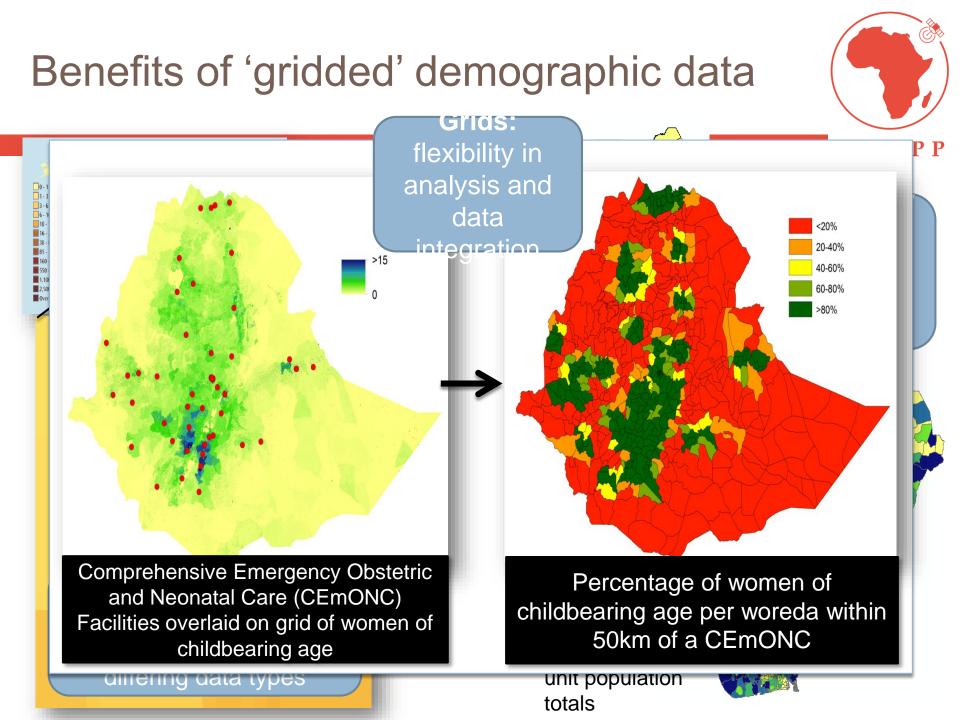
Emergency response

Effective response requires rapid and ongoing assessments of numbers of vulnerable people affected and future risks

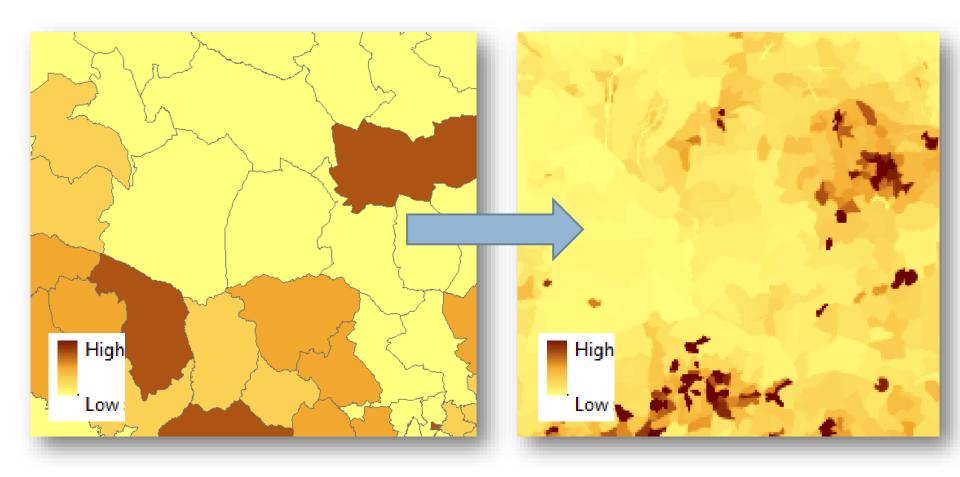
-How many people are in the outbreak area? -How many vulnerable people were affected and displaced by the <u>earthquake?</u>



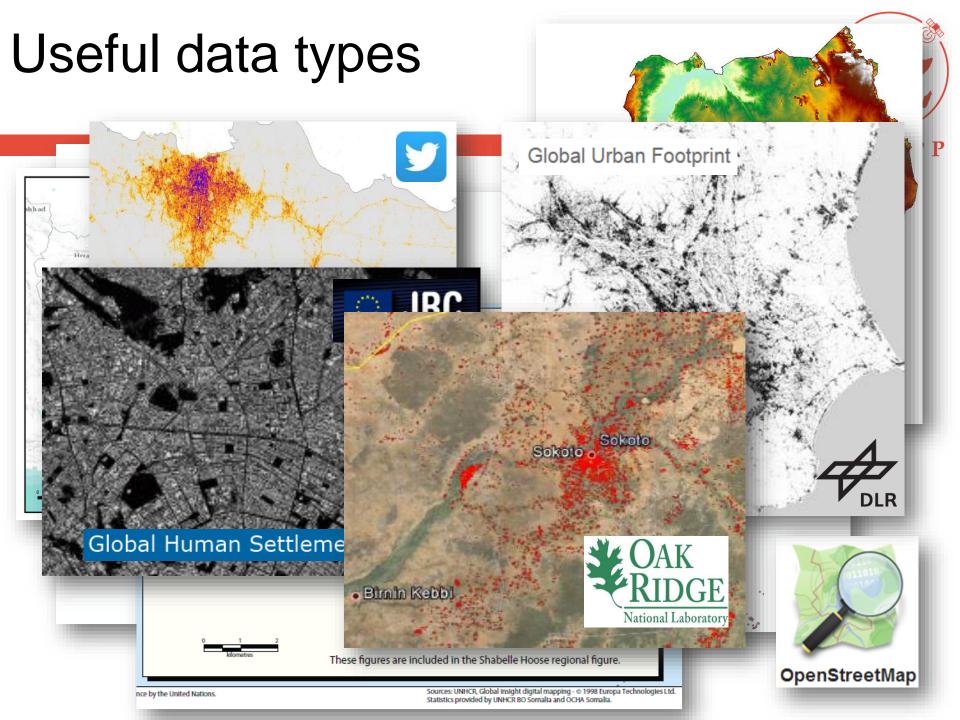




How can we go from aggregated counts of population to fine-scale gridded estimates?



MAUPP



Population Density Vietnam Administrative Unit Level 002



> 30 People Per Ha

0

Vietnam MDA GeoCover Land Cover (30 m Pixels)

Cultivated Woody Shrubby Herbaceous Aquatic **Urban Built** Bare Water **Rural Bufilt**

NOAA Suomi VIIRS-derived Lights at Night 2012 for Vietnam

Global Human Settlement Layer 2014 for Vietnam

Population Density Vietnam Administrative Unit Level 002



> 30 People Per Ha

0

Vietnam RF Distributed Population Counts Using Non-Default Ancillary Data (OSM)

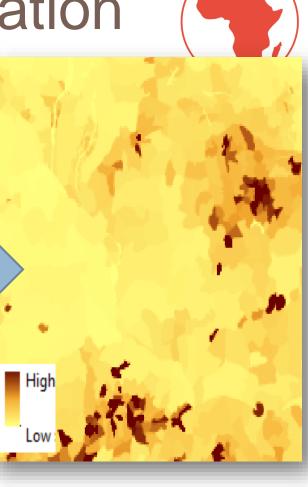
> 30 People Per Pixel

Low : 0

Census data disaggregation

High Low

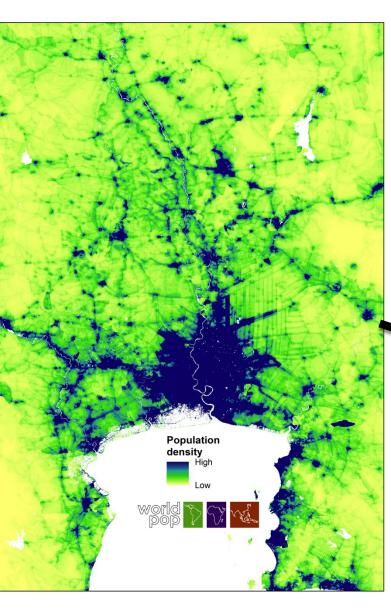
Census counts generally aggregated at coarse, irregular administrative unit level, making integration and comparisons with other data challenging



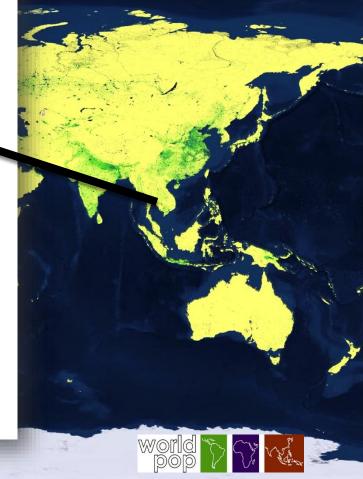
Integration with satellite/GIS data related to human population distribution patterns to disaggregate counts to regular grids using machine learning

Wor

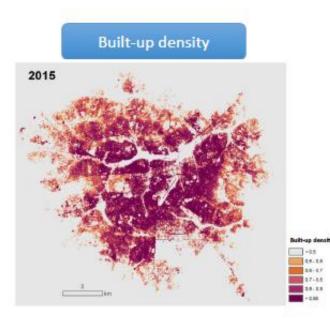




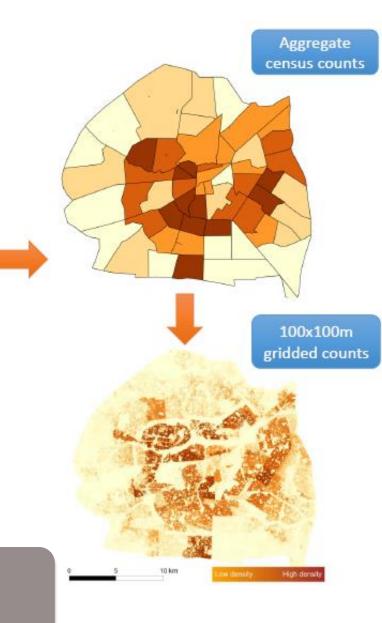




Population density models



Disaggregation of admin-unit based census/official estimate counts



Urban population mapping in Africa

Challenges

- Heterogeneity of the build-up structures, and corresponding human population density
- Lack of good quality training datasets

Objective

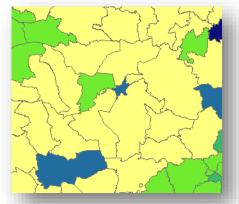
Test the added value of the built-up probability/density layer produced by MAUPP to improve models of human population density within urban extents



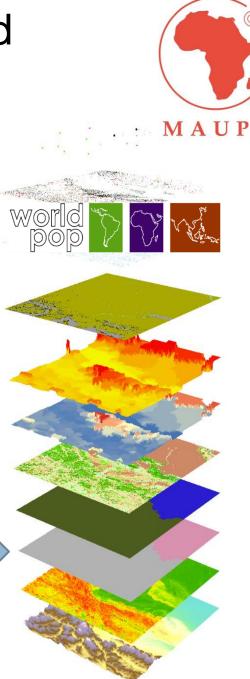


Random Forest Classification and Regression

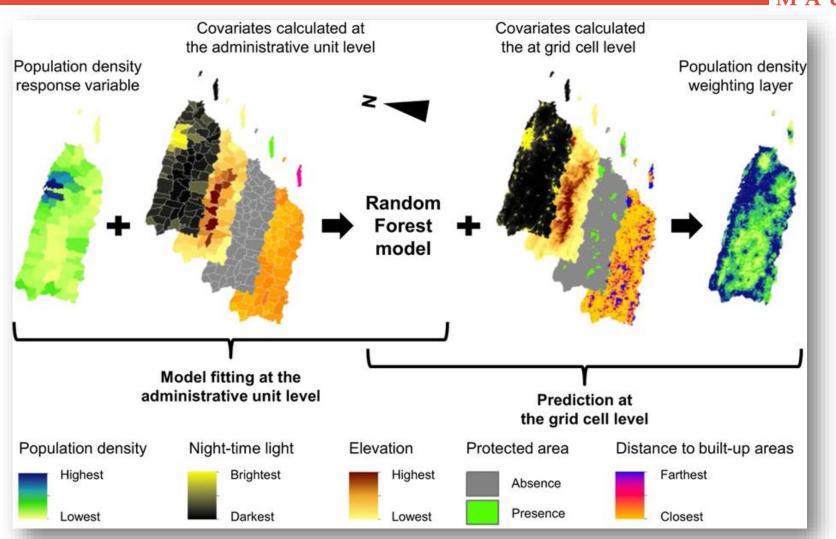
- 'Machine Learning' approach
- Create predictions of population density estimates at a pixel level using Random Forest models
- Robust to outliers and noise
- Provides useful internal estimates of error, strength, correlation and variable importance, built-in cross-validation



Breiman (2001) Machine Learning; Stevens et al (2015) PLoS One



City-specific models

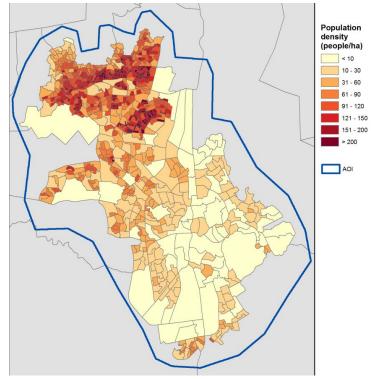


Stevens et al (2016) PLoS ONE; Sorichetta et al (2016) Nature Sci Data

Census population data: select African cities

CITY	COUNTRY	N. census units		
Windhoek	NAM	743		
Antananarivo	MDG	228		
Iringa	TZA	147		
Toamasina	MDG	138		
Kampala	UGA	116		
Mbeya	TZA	113		
Nairobi	KEN	106		
Dodoma	TZA	54		
Ouagadougou	BFA	44		
Dakar	SEN	43		
Tulear	MDG	42		
Tamale	GHA	24		
Lusaka	ZMB	24		
Kisumu	KEN	19		
Kinshasa	COD	17		

All others: < 10 (31 cities within only 1 unit)



MAUPP

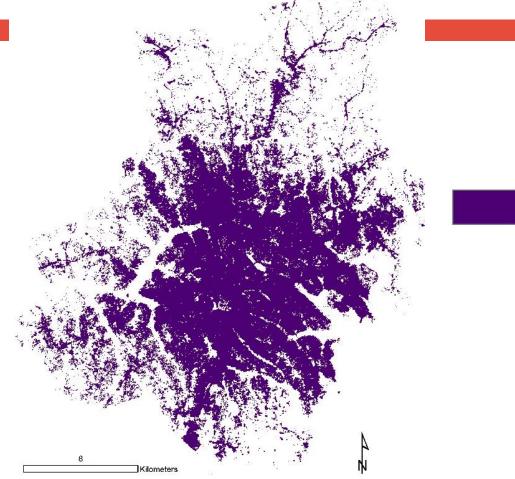
Windhoek, Namibia

MAUPP Variables description



- Built-up density: derived from the binary output of the classification (built-up / non-built-up)
 - Spatial resolution: 12.5m binary raster aggregated to 100m (x8)
 - Values between 0 and 1
- Built-up age: Normalized age of built-up density
 - Spatial resolution: 12.5m binary raster aggregated to 100m (x8)
 - Values between 0 (recent) to 1 (old)
- Population density: derived from census data
 - Spatial resolution: census units
 - Units: people/ha

Urban built-up density Kampala

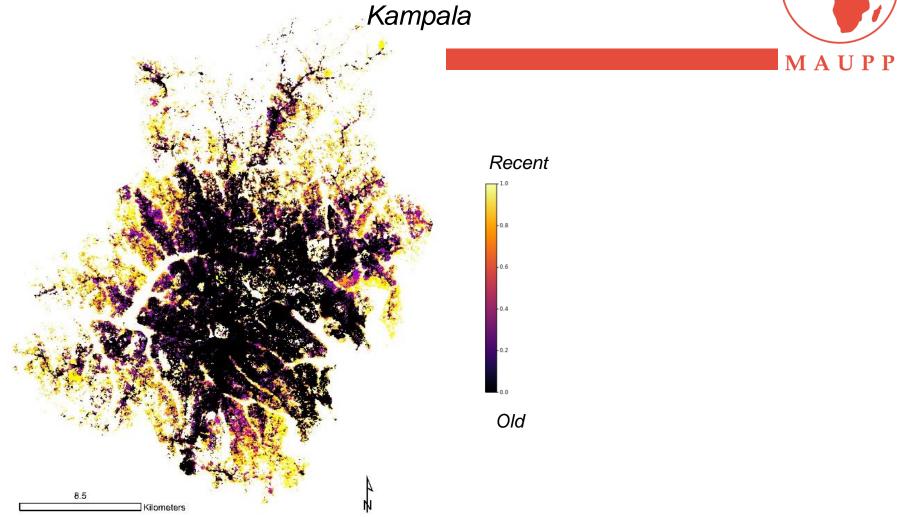




Built-up

Forget et al. Preprints 2018, (doi: 10.20944preprints201810.0695.v1)

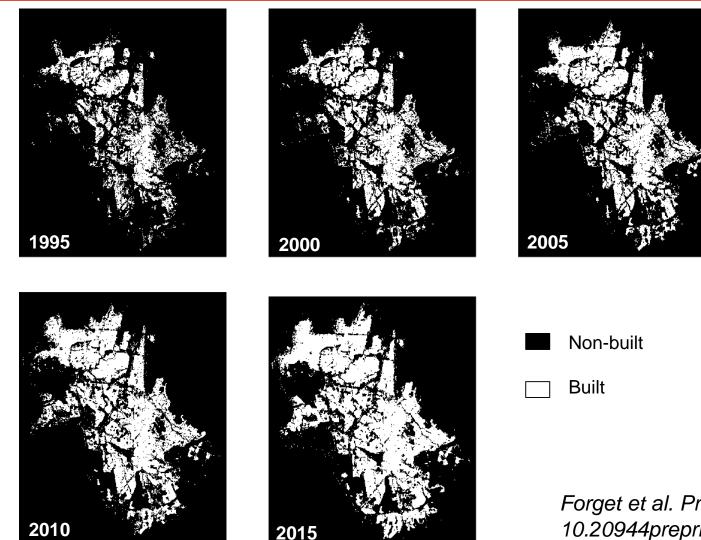
Normalized age of built-up From 0 (past) to 1 (present) Kampala



Forget et al. Preprints 2018, (doi: 10.20944preprints201810.0695.v1)

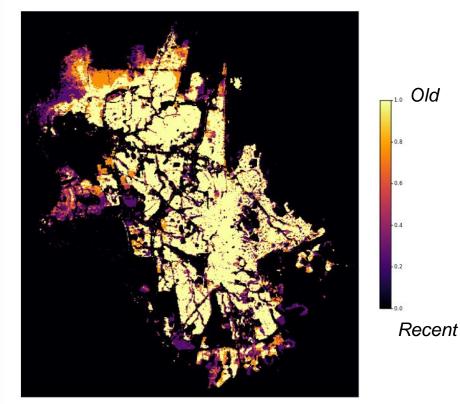
Urban change (Windhoek)





Forget et al. Preprints 2018,(doi: 10.20944preprints201810.0695.v1





Age of built-up From 0 (recent) to 1 (old)

Forget et al. Preprints 2018, (doi: 10.20944preprints201810.0695

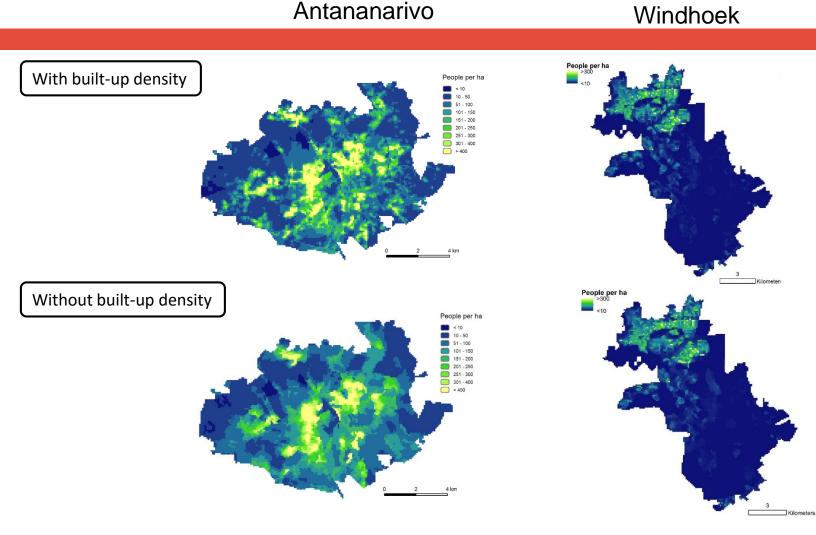
MAUPP

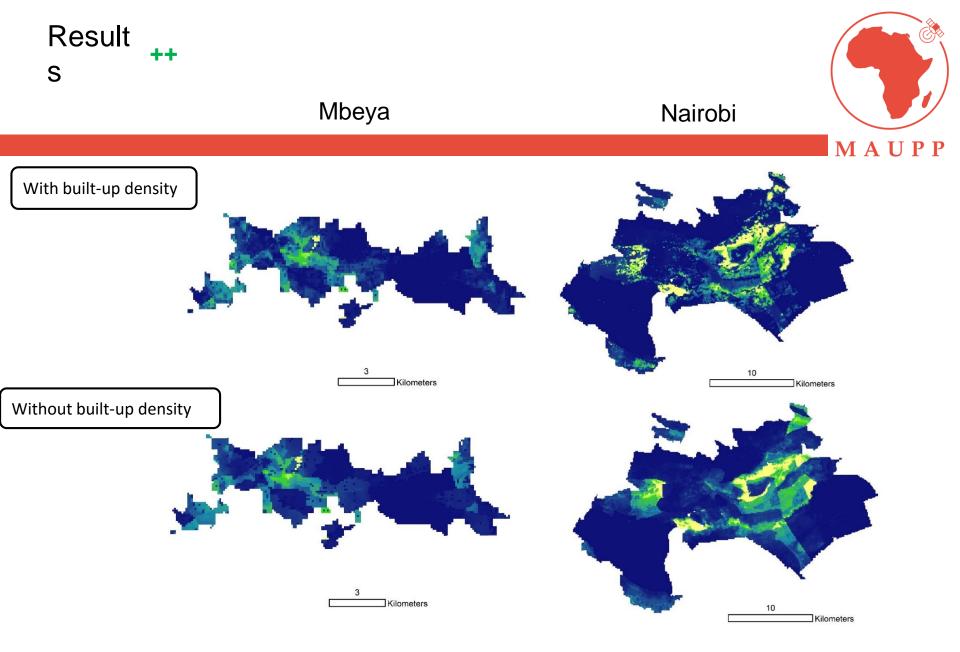
Final Model Data List		Source			
Built-up density	t	MAUPP			
	t-1				
	t-2				
Built-up age	Normalized age of built-up density	MAUPP			
Landcover	Cultivated terrestrial lands	ESA-CCI			
	Woody / Trees				
	Shrubs				
	Herbaceous				
	Other terrestrial vegetation				
	Aquatic vegetation				
	Water bodies				
	No data, cloud/shadow				
	Industrial area				
Nightlights		Suomi NPP-VIIRS, NOAA			
Topography	Elevation	HydroSheds (3 s GRID: Void-filled DEM), WWF			
	Slope				
Roads (distance-to)	Primary	OpenStreetMap			
	Secondary				
	Others				
Railways (distance-to)		OpenStreetMap			
Rivers (distance-to)		OpenStreetMap			
Natural areas		OpenStreetMap			
Industrial landcover class (distance-to)		OpenStreetMap			
Points of interest		OpenStreetMap			

Result ++ S



Antananarivo



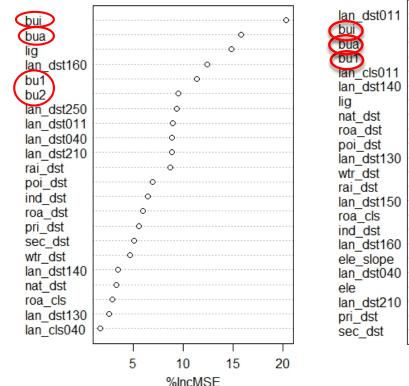


Covariate importance

Kampala



Antananarivo



%IncMSE Covariate importance plots for the models including built-up density layers for Antananarivo, Kampala and Mbeya. Built-up density layers are highlighted in red (bui = built-up density for time t - time period closest to the census data -; bu1 =built-up density for t-1; bu2 = built-up density for t-2; bua = normalized built-up

15

10

Mbeya

10

%IncMSE

bu1

bui

bu2

ele

roa dst

pri_dst

wtr dst

nat_dst

sec dst

poi_dst

ele slope

lig

lan dst011

lan dst130

lan dst040

Covariate importance (continued)



Windhoek Iringa Nairobi lan_dst011 bu1 bui bu2 bu1 lig rai dst bua bu1 bu2 bui bui ind dst wtr dst lan dst011 ele poi_dst bua roa_dst bu4 lig pri_dst lan dst040 lan_dst011 nat dst bu3 rai_dst nat dst sec_dst wtr dst ele wtr_dst lan dst130 sec_dst poi_dst sec dst lan_dst130 lan_dst130 lan dst210 pri_dst ele_slope ele_slope poi_dst lan dst040 ele ele_slope nat dst lig 2 10 12 ind dst roa dst %IncMSE lan cls130 roa dst lan cls040 5 15 10 5 10 20 25 30 15 %IncMSE %IncMSE

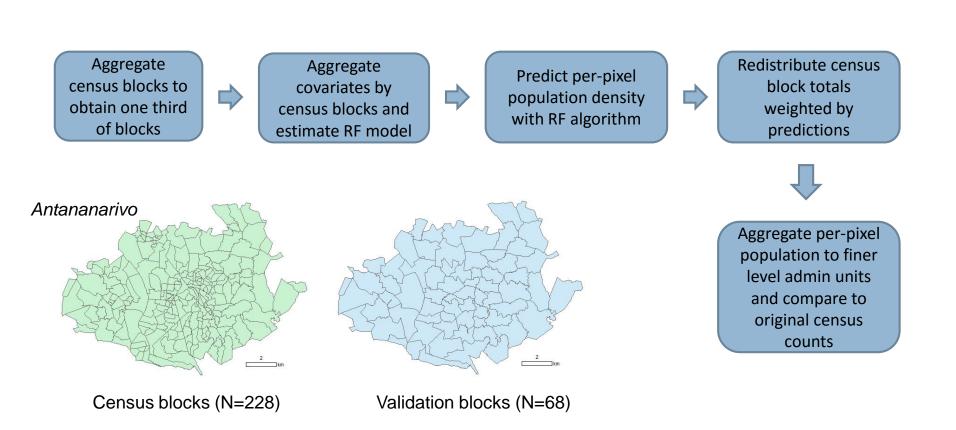
Intra-urban population maps



City	Country ID	N. admin. units	% explained variance with built-up layers	% explained variance without built-up layers	
Windhoek	NAM	743	80	69	++
Antananarivo	MDG	228	64	56	++
Iringa	TZA	147	42	43	-
Toamasina	MDG	138	70	70	
Kampala	UGA	116	67	60	+
Mbeya	TZA	113	38	25	++
Nairobi	KEN	106	62	45	++

% Explained variance for population models with and without built-up density layers for the 7 cities with more than 100 administrative units.

Accuracy Assessment



MAUPP

Accuracy Assessment statistics



City	Countr y ID	admin.	N. admin units for validation	RF With built-up layers		RF Without built- up layers		
				%RMSE	MAE	%RMSE	MAE	
Windhoek	NAM	743	230	43.3	129	51.7	150	++
Mbeya	TZA	113	34	56.4	798	69.3	937	++
Nairobi	KEN	106	32	73.9	13761	93.2	17490	++
Antananarivo	MDG	228	68	42.9	1851	49.4	2125	++
Iringa	TZA	147	44	56.5	231	52.4	219	-
Toamasina	MDG	138	41	34.3	484	33.4	471	-
Kampala	UGA	116	35	35.4	3375	39.7	3687	+

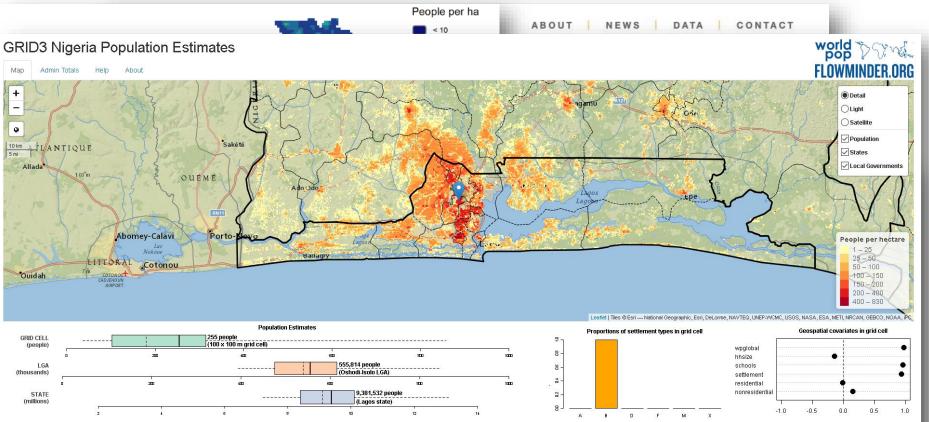
Summary



- Satellite imagery can be processed to map intraurban heterogeneities in African cities
- Including built-up density layers in urban population models produces clear improvements accuracy of model outputs
- Many useful freely available datasets exist for mapping populations and their characteristics
 - Proper statistical methodologies essential
 - Clear communication of accuracy assessment and limitations
- Next steps: Extending to all other MAUPP cities, documentation, open tools, open outputs, training

Data availability: www.worldpop.org









Further information





Modelling and forecasting African Urban Population Patterns for vulnerability and health assessments

A.J.Tatem@soton.ac.ul







www.worldpop.org @WorldPopProject

maupp.ulb.ac.be



Under the funding of BELSPO – the Belgian Science Policy S O O