Development of Pilot High-Resolution Gridded Poverty Surfaces: Methods working paper

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1.0 OVERVIEW

Improved understanding of geographic variation and inequity in health status, wealth, and access to resources within countries is increasingly recognized as central to meeting development goals. Development indicators assessed at national scales can often conceal important inequities, with the rural poor often least well represented. As international funding for development comes under pressure, the ability to target limited resources to underserved groups becomes crucial. Monitoring inequalities for targeting interventions requires a reliable and detailed evidence base. While high-resolution spatial data on population distributions in resource poor areas are now becoming available (e.g. www.worldpop.org.uk), comprehensive information on demographic, health and wealth attributes of those populations remain only usable at highly aggregated regional levels through national household surveys (e.g. www.measuredhs.com).

The Demographic and Health Survey (DHS) program has been a leader in collecting and providing cluster-randomised survey data on core development indicators. In addition to their standard open-source data files in which survey results are tabulated by first-order sub-national regions (for example at province or state level) and urban/rural strata, more recent surveys now provide geocoded data for individual clusters. The availability of the GPS coordinates for DHS clusters provides, for the first time, highly resolved locational information that can be linked with survey outputs for quantifying demographic and health status heterogeneities and inequities.

Here we present a novel spatial statistical methodology for the production of gridded surfaces of household survey-based variables, focusing on poverty mapping. A Bayesian geostatistical modeling framework, following approaches constructed for the Malaria Atlas Project, has been established to exploit spatiotemporal relationships within the data, leverage ancillary information from an extensive set of covariates, and rigorously handle uncertainties at all stages to generate robust output surfaces with accompanying confidence intervals.

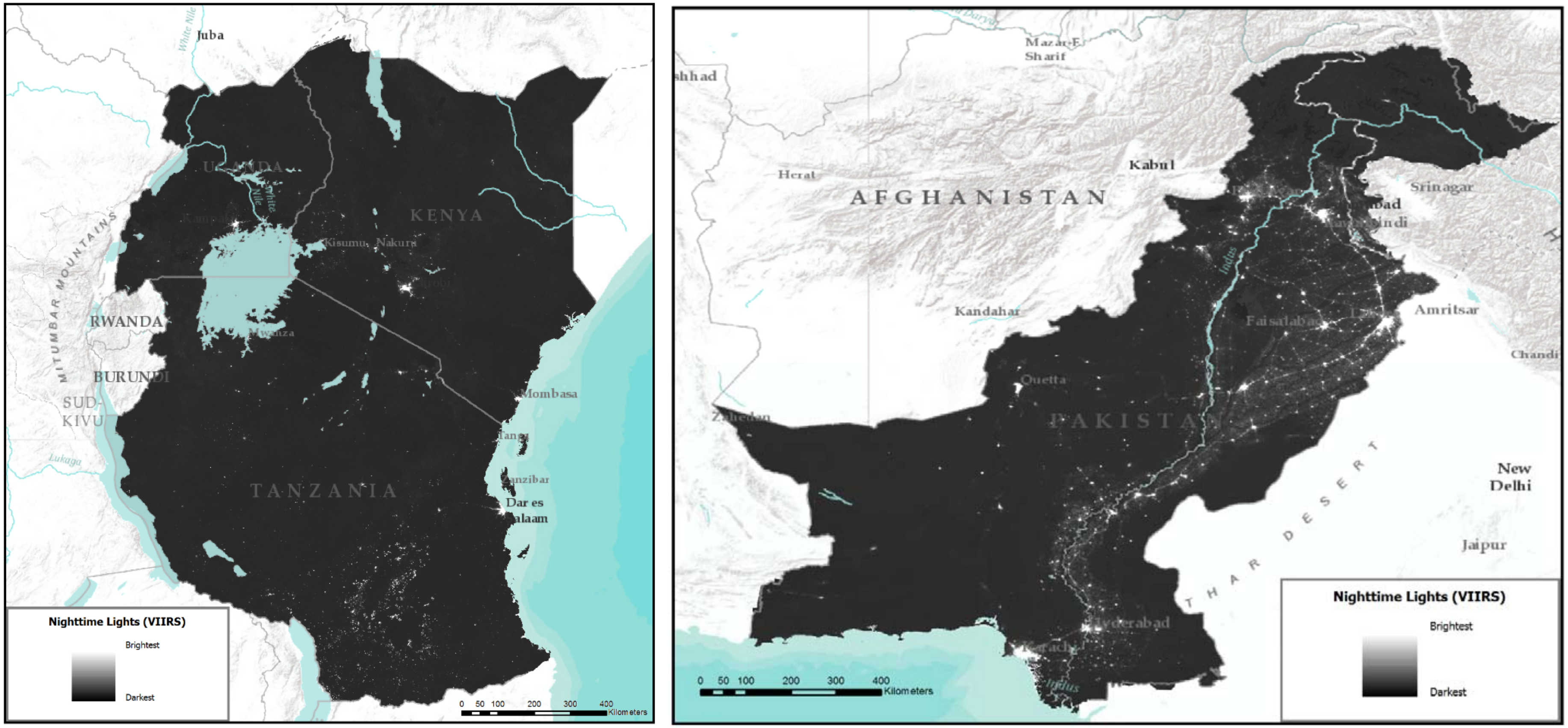
2.0 ASSEMBLING CANDIDATE GEOSPATIAL COVARIATES OF POVERTY

A suite of geospatial covariates were assembled for use in the mapping, focussing on factors likely to have an impact on determining levels of poverty. Table 1 provides details on each of the geospatial covariate datasets. The datasets are all provided at differing formats, spatial resolutions, projections and extents. Thus, algorithms were constructed and applied to convert polygon files to gridded datasets and then regrid each gridded dataset to a common 1km spatial resolution grid-frame for use in map production. Figures 1 and 2 show examples of two of the datasets described in table 1 (lights2 and evi). While a large suite of data was compiled, not all of the datasets in table 1 were included in the mapping due to differing levels of reliability, relevance and variations in data formats. Many datasets were ultimately left out due to poor spatial resolution and/or categorical inputs that were tested and didn't add sufficient extra information to improve model accuracies.

Table 1. Details of geospatial covariates assembled for use in mapping.

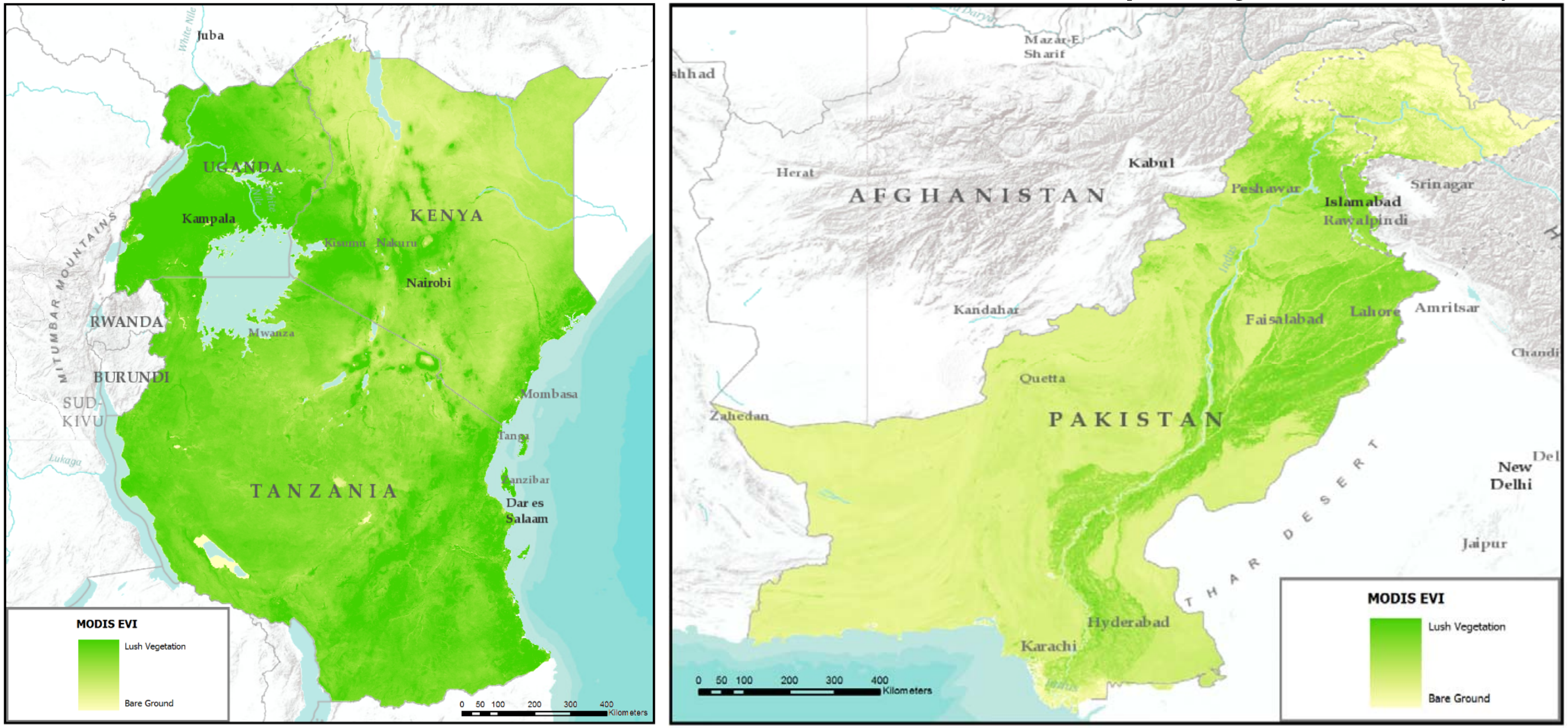
Category	Dataset Name	Dataset description	Continuous or Categorical	Data Source	Date	Used in mapping
Accessibility	access1	Accessibility to cities with > 50k via all transport methods	Continuous	http://bioval.jrc.ec.europa.eu/products/gam/download.htm	2000	Y
Accessibility	access2	Accessibility via road to towns and cities. Three classes of settlements (size based) and two road types (major and minor) were combined to make a distance weighted layer.	Continuous	Custom product derived from ESRI population datasets and MapAbility road datasets	Population - 2011 Roads - ??	Y
Population / Urban	aa_pop	Afripop and Asiapop combined dataset	continuous	http://www.afripop.org/ http://www.asiapop.org/	2010	Y
Population / Urban	grump	GRUMP Population Density	continuous	Malaria Atlas Project Master Grids Archive	2010	Y
Population / Urban	gpw	GRUMP population count	continuous	http://sedac.ciesin.columbia.edu/data/set/gpw-v3-population-count/data-download	2000	Y
Crop Suitability	crop61	Map6_61 Suitability of currently available land area for rainfed crops, using maximising crop and technology mix (FGGD)	Quasi Continuous	http://www.fao.org/geonetwork/srv/en/main.home	2007	
Crop Suitability	crop63	Map6_63 Combined suitability of global land area for pasture and rainfed crops (intermediate input level) (FGGD)	Categorical	http://www.fao.org/geonetwork/srv/en/main.home	2007	
Aridity	arid	Mean annual aridity	continuous	http://csi.cgiar.org/Aridity/	1950-2000	Y
Potential Evapotranspiration	pet	Mean annual Potential Evapotranspiration	continuous	http://csi.cgiar.org/Aridity/	1950-2000	Y
Livestock	buffalo	Global buffalo density	Continuous	http://www.fao.org/geonetwork/srv/en/main.home	2005	
Livestock	cattle	Global cattle density	Continuous	http://www.fao.org/geonetwork/srv/en/main.home	2005	
Livestock	goat	Global goat density	Continuous	http://www.fao.org/geonetwork/srv/en/main.home	2005	
Livestock	pig	Global pig density	Continuous	http://www.fao.org/geonetwork/srv/en/main.home	2005	
Livestock	poult	Global poultry density	Continuous	http://www.fao.org/geonetwork/srv/en/main.home	2005	
Livestock	sheep	Global sheep density	Continuous	http://www.fao.org/geonetwork/srv/en/main.home	2005	
Livestock	smrum	Global small ruminant density	Continuous	http://www.fao.org/geonetwork/srv/en/main.home	2005	
Night-time Lights	light1	Global DMSP-OLS Nighttime Lights Time Series	continuous	http://www.ngdc.noaa.gov/dmsp/download.html	2010	
Night-time Lights	lights2	VIIRS Nighttime Lights-2012	continuous	http://www.ngdc.noaa.gov/dmsp/download.html	2012	Y
Ethnicity	ethnic	Geo-referencing of ethnic groups	Categorical	http://www.icr.ethz.ch/data/other/greg	1994	
Elevation	elev	Shuttle Radar Topography Mission (SRTM) Near-global Digital Elevation Models (DEMs)	Continuous	http://webmap.ornl.gov/wcsdown/wcsdown.jsp?dg_id=10008_1	2000	Y
Irrigation	irriga	Global Map of Irrigation Areas version 4.0.1	continuous	http://webmap.ornl.gov/wcsdown/wcsdown.jsp?dg_id=10013_1	2000	
Landcover	lc1	ESA global landcover	Categorical	http://due.esrin.esa.int/globcover/	2009	
Landcover	lc2	IGBP Landcover	Categorical	https://lpdaac.usgs.gov/products/modis_products_table/mcd12q1 ftp://e4ftl01.cr.usgs.gov/MODIS_Composites/MOTA/MCD12Q1.051/2011.01.01/	2011	
Landcover	synmap_1k	Synergetic land cover product (SYNMAP)	categorical	http://webmap.ornl.gov/wcsdown/wcsdown.jsp?dg_id=10024_1	2000	
Protected Areas	protect	United Nations Environment	Categorical	http://geodata.grid.unep.ch/mod_download/download_geos	2009	

		Programme – International Protected areas		patial.php?selectedID=1756&newFile=download_pro/WDPA_NATpol2009_po_shp.zip		
MODIS	evi	Mean value for all dates	Continuous	Malaria Atlas Project MasterGrids Archive	2001-2005	Y
MODIS	lst	Mean value for all dates	Continuous	Malaria Atlas Project MasterGrids Archive	2001-2005	Y
MODIS	midir	Mean value for all dates	Continuous	Malaria Atlas Project MasterGrids Archive	2001-2005	Y
Water Bodies	water	WWF Global Lakes and Wetlands Database	Categorica	http://worldwildlife.org/pages/global-lakes-and-wetlands-database	2012	



(a) (b)

Figure 1. Examples of geospatial covariate datasets: Annual composite nighttime light satellite imagery from the VIIRS satellite sensor (‘lights2’) for (a) East Africa and (b) Pakistan.



(a) (b)

Figure 2. Examples of geospatial covariate datasets: Mean annual enhanced vegetation index ('evi') from the MODIS satellite sensor for (a) East Africa and (b) Pakistan.

3.0 CREATION OF PILOT POVERTY MAPS

Using either the Multidimensional Poverty Index (MPI) or consumption-based <$1.25/$2 a day headcounts as our test variable, we implemented a model-based geostatistical framework to generate pilot poverty maps at 1x1km resolution. Here we describe the exploratory analysis and model formulation.

3.1 METHODS

3.1.1 Model structure

Our initial model structure is a class of generalized linear mixed model, with an approximation of a multivariate Normal random field (i.e. a Gaussian Process) used as a spatially autocorrelated random effect term. This family of models derives from a body of theory knows as model-based geostatistics.

The poverty headcount ratio (proportion of individuals considered 'poor' according to the MPI or consumption-based index – in the example notation, MPI is used here) $MPIh(x_i)$, at each location x_i was modeled as a transformation $g(\cdot)$ of a spatially structured field superimposed with additional random variation $\epsilon(x_i)$. The count of individuals considered poor N_i^+ from the total sample of N_i in each survey cluster was modeled as a conditionally independent binomial variate given the unobserved underlying $MPIh(x_i)$ value. The spatial component was represented by a stationary Gaussian process $f(x_i, t_i)$ with mean μ and covariance C. The unstructured component $\epsilon(x_i)$ was represented as Gaussian with zero mean and variance V. Both the inference and prediction stages were coded using the INLA framework, primarily in R.

3.1.1.1 Mean and covariance definition

The mean component μ was modelled as a linear function of n=12 environmental covariates, $\mu = \boldsymbol{\beta}\mathbf{X}$,where $\mathbf{X} = 1, X_1(x), ..., X_n(x)$ was a vector consisting of a constant and the covariates indexed by spatial location x, and $\boldsymbol{\beta} = \beta_0, \beta_1, ..., \beta_n$ was a corresponding vector of regression coefficients. Each covariate was converted to z-scores before analysis. In this pilot stage, we took an inclusive approach to covariate selection, with most of the assembled variables being included in the model. As our library of covariates becomes more refined, we will implement more formal model selection procedures to identify optimal covariate suites for inclusion.

Covariance between spatial locations was modeled using a Matern covariance function C:

$$C\left(d(x_i;x_j)\right) = \sigma^2 \frac{1}{\Gamma(\upsilon)2^{\upsilon-1}} \left(\sqrt{2\upsilon}\frac{d(x_i;x_j)}{\rho}\right)^{\upsilon} K_{\upsilon}\left(\sqrt{2\upsilon}\frac{d(x_i;x_j)}{\rho}\right)$$

Where $d(x_i;x_j)$ is the geographical separation between two points; σ,υ,ρ are parameters of the covariance function defining, respectively, its amplitude, degree of differentiability, and scale; K_υ is the modified Bessel function of the second kind of order υ, and Γ is the gamma function.

3.1.2 Model implementation and output

Bayesian inference was implemented using the INLA algorithm to generate approximations of the marginal posterior distributions of the outcome variable $MPIh(x_i)$ at each location on a regular 1 × 1 km spatial grid across the country of interest and of the unobserved parameters of the mean, covariance function and Gaussian random noise component. At each location, the posterior distribution was summarized using the posterior mean as a point estimate, and the posterior inter-quartile range as a measure of model precision. Maps were generated of each of these metrics in ArcGIS 10.2.

3.1.3 Validation

The predictive performance of each model was assessed via out-of-sample validation. We implemented a ten-fold hold-out procedure whereby 10% of the data points were randomly withdrawn from the dataset, the model run in full using the remaining 90% of data, and the predicted values at the locations of the hold-out data compared to their observed values. This was repeated ten times without replacement such that every data point was held out once across the ten validation runs. Standard validation statistics were computed as measures of model precision (root mean square error, mean absolute error), bias (mean error), and correlation between observed and predicted. We also generated a scatter plot of observed versus predicted values. Outputs for each country are available upon request and will be published in an extended manuscript.

4.0 ACKNOWLEDGEMENTS

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