Poverty, health and satellite-derived vegetation indices: their inter-spatial relationship in West Africa

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Received 29 October 2014; revised 28 December 2014; accepted 12 January 2015

Background: Previous analyses have shown the individual correlations between poverty, health and satellite-derived vegetation indices such as the normalized difference vegetation index (NDVI). However, generally these analyses did not explore the statistical interconnections between poverty, health outcomes and NDVI.

Methods: In this research aspatial methods (principal component analysis) and spatial models (variography, factorial kriging and cokriging) were applied to investigate the correlations and spatial relationships between intensity of poverty, health (expressed as child mortality and undernutrition), and NDVI for a large area of West Africa.

Results: This research showed that the intensity of poverty (and hence child mortality and nutrition) varies inversely with NDVI. From the spatial point-of-view, similarities in the spatial variation of intensity of poverty and NDVI were found.

Conclusions: These results highlight the utility of satellite-based metrics for poverty models including health and ecological components and, in general for large scale analysis, estimation and optimisation of multidimensional poverty metrics. However, it also stresses the need for further studies on the causes of the association between NDVI, health and poverty. Once these relationships are confirmed and better understood, the presence of this ecological component in poverty metrics has the potential to facilitate the analysis of the impacts of climate change on the rural populations afflicted by poverty and child mortality.

Keywords: Child mortality, Geostatistics, Multidimensional Poverty Index, Normalized difference vegetation index, Nutrition, Poverty

Introduction

Reducing rural and urban poverty in developing countries is a key target of the Millennium Development Goals (MDG) (1990–2015).¹ In 2012, 1.2 billion people lived in poverty (21%), based on an international poverty line of US\$1.25 a day.² This figure is not representative of the wide variation in poverty across the World: from 3.7% of the population in Europe and Central Asia to more than half of the population in sub-Saharan Africa (SSA).³ The general figure of 21% is a reduction from 33% in 2000 and 43% in 1990.² At the national level, a reduction in poverty has been reported recently for China⁴, India⁵, Vietnam⁶ and Chile.⁷ However, poverty increases are still reported for some areas of SSA, despite improvements in socio-economic conditions.⁸ In SSA, 75% of the population lives in rural areas^{9,10} with agriculture

and livestock as their main source of livelihood,^{11,12} and are often under threat due to long periods of drought (e.g., the recent famine crises in the Horn of Africa and Niger). Within countries, inequality, unequal redistribution and disparities in access to resources like food and health care affect the most vulnerable groups, such as women and children, promoting poverty, poor health and disadvantages.

Complex relationships exist between poverty, health and environment. Those living in poverty experience increased vulnerability to a range of health problems due to, for example, poor living standards, lack of access to clean water, poor nutrition and inadequate access to health services. At the same time, ill health can contribute to poverty by reducing productivity (e.g., via inability to work through illness), inhibiting educational attainment and increasing financial expenditure on health care and medicines.^{13,14}

Environmental factors are also intrinsically linked with this 'vicious cycle'. Land cover, climate and water availability are related to the transmission of a range of communicable disease, such as malaria, schistosomiasis and diarrhoea. Seasonal changes in climatic factors impact particularly on those living in poverty^{15,16} via: under-nutrition, due to lack of food at different times during the agricultural calendar; varying risk of diseases dependent on climatic conditions (e.g., vector-borne diseases where vector and parasite reproduction are influenced by factors such as temperature and precipitation); and water-borne diseases (e.g., diarrhoea), due to seasonal changes in precipitation levels driving variable access to safe drinking water and the potential exposure to water contaminated by faecal matter or toxic chemicals.¹⁷ Finally, those who live in poverty often reside in vulnerable and degraded areas with fewer resources for them to respond to environmental changes.¹⁸ Hence, revealing the relationships between poverty, health and environment at a scale comparable with that considered in initiatives such as the MDGs is of substantial interest.

The correlations between poverty, health and the environment are particularly evident in SSA, where 62% of the population depend on subsistence farming, which is reliant upon environmental resources.¹⁹ In this region, HIV, tuberculosis and malaria constitute the largest individual health burdens and overall, communicable diseases together with maternal, neonatal and nutritional disorders contribute between 67 and 71% of disability adjusted life years in eastern, western and central SSA.^{20,21} The implementation of interventions aimed at health improvement and reduction of poverty depends on guidance from a variety of measures. For example, poverty or vulnerability indices can be used to prioritise the allocation of resources and allow strategic targeting of population sub-groups, or specific regions, where intervention is likely to have the greatest impact.^{1,22,23} These indices are also a vital resource for assessing temporal trends in the socio-economic status of populations, and for the evaluation and monitoring of interventions. However, the calculation of quantitative measures to represent poverty is a complex issue.

Poverty is a multidimensional measure for which no single definition and method of measurement is available. Measures for deriving poverty estimates can be divided into four major classes, namely: econometric (e.g., expenditure-based poverty index and poverty lines^{24–26}); social and wellbeing (e.g., the Human Development Index, Human Poverty Index, Gini coefficient, Sen index, the general entropy, Wealth Index, Theil index, and the recent unified approach from the world bank–AdePT²⁶); demographic (indicators such as child outcome); and vulnerability-based measures. More recently, and due to increasing concerns over environmental sustainability, indices based on food availability are often integrated with poverty information.²⁷ Multidimensional measures of poverty, which take into account elements such as health, life expectancy, literacy, freedom, security and social inclusion, contribute to the disentangling of several dimensions of poverty and more clearly disclose the interrelationships between them.²⁸ Spatial representation of these poverty indices is increasingly required to achieve greater understanding of the causes of poverty and the complex interactions between poverty, health outcomes, environment and climate. Crucially, information regarding the spatial heterogeneity of poverty is used for the spatial targeting and optimisation of interventions, ensuring the cost effective utilisation of scarce resources.^{25,29–33}

The main objective of this analysis was to test whether incorporating environmental information into spatial models for the prediction of the spatial distribution of multidimensional poverty index (MPI) increases predictive accuracy. The method employed here to allow a multivariate extension of the spatial prediction model is cokriging, a geostatistical technique that allows a potential increase in the precision of predictions when the information from a sparsely measured variable (i.e., poverty) is augmented with that from a spatially correlated and more densely sampled secondary variable, such as temperature, rainfall or normalized difference vegetation index (NDVI; a measure of vegetation 'greenness').³⁴ In fact, NDVI has been found to be positively associated with child survival and nutrition, and with wasting rather than stunting in West Africa³⁵ through increases in crop yields and additional income from tree products.^{35,36} The latter are utilized for fodder, food, house construction and wood carving.³⁷ However, this overall picture is affected by large local variability. For example, in some areas in Ghana, larger amounts of vegetation are associated with greater risks of child mortality because these populated areas are at the edge of urban settlements, and hence suffer from segregation and exclusion.^{35,38} In contrast, land degradation has never been found to be positively associated with wealth in rural West Africa.³⁹

Therefore, a series of descriptive spatial and aspatial statistics were employed to describe the deterministic and spatial correlations between the environmental attributes, poverty and health.

Materials and methods

Poverty indicators and measures

A series of poverty indicators and measures related to the MPI were obtained from the Oxford Poverty & Human Development Initiative website.⁴⁰ Although the MPI data are available for most districts in Africa, we restricted the analysis to West Africa (Benin, Burkina Faso, Cameroon, Cote d'Ivoire, Ghana, Mali, Niger, Nigeria and Togo, see [Supplementary Table 1](#)), which has one of the highest levels of rural poverty in Africa,⁴¹ even given increases in development indices⁴² relative to the period 2004 to 2010.

The three measures taken into account are the MPI,²⁸ the intensity of deprivation among the poor (A), here termed intensity of poverty, and the proportion of the population in multidimensional poverty (H).⁴³ In practice, A measures 'the average (weighted) share of dimensions in which poor people are deprived' (dimensions described below); while H, called headcount ratio, is the percentage of people who are poor. H is a measure of incidence and A is a measure of intensity which is associated to vulnerability⁴⁴ and deprivation. These three measures are related to each other through the following equation:

$$\text{MPI} = \text{HA}$$

MPI is an adjusted headcount ratio measure. For example, a value of 0.33 means that the population is experiencing one third of the total possible deprivation. That is, MPI is calculated by considering that a proportion of poor people (H) are deprived in a proportion of dimensions of poverty (identified by A). Further information on the calculation can be found in Alkire and Santos,²⁸ while, for its use and broader meaning, the reader is directed to the work of Alkire and Foster.⁴³

The MPI, H and A measures considered here are obtained from three dimensions of poverty: health, education and living standard. These three dimensions are composed from several different indicators ([Supplementary Table 1](#)): two for the health dimension: nutrition (Nut) and child mortality (Ch.m); two for the education dimension: years of schooling (Sch) and child school attendance (Ch.a); and six for the living standard dimension: cooking fuel (Fuel), improved sanitation (Im.s), safe drinking water (Wat), electricity (Ele), flooring (Flo) and assets ownership (Ass).

Environmental variables

The environmental variables used for this analysis have commonly been found to be significantly correlated with poverty and health.^{9,45} They are the day- and night-time land surface temperature (DLST and NLST, respectively), normalized difference vegetation index (NDVI) and elevation measured via a digital elevation model (DEM) obtained from the MODIS sensor of NASA's Terra and Aqua satellites: each of these variables are available at a spatial resolution of 1 km. DLST, NLST and NDVI were taken as the mean for the period 2001–2010 from 8-day composite values⁴⁶ and are congruent with the MPI data (2004–2010). In addition, yearly mean rainfall (average of monthly rainfall) data interpolated from ground stations were obtained at a spatial resolution of approximately 1 km from the WorldClim project.⁴⁷

Spatial domain

The poverty indicators (hereafter simply indicators) and measures related to the MPI (H and A) were referenced to the first sub-national administrative level for West Africa and the main cities. Given an absence of information about the administrative boundaries of these cities, the poverty values of the five cities incorporate (by averaging) into their relative districts: Yaounde and Douala in Cameroon were merged with the districts of Centre Cameroon

and Littoral Cameroon, respectively; Lomé in Togo with the district of Maritime Togo; Niamey in Niger with the district of Tillabery; Bamako in Mali with the district of Koulikoro. Hence, the entire analysis focuses on districts composed for the majority by rural areas, and for this reason the results must be referred to as rural poverty.

To apply spatial statistics, the district values of DEM, DLST, NLST, NDVI and rainfall were averaged. These environmental values and the single values of poverty measures and poverty indices were referenced to the geometric centroid of each district polygon (e.g., transformed into spatial points data).⁴⁸ The predictive grid (grid of nodes where estimations are made) was built with a spatial resolution of 0.07° (8 km).

Methods

The methods employed here belong to the field of geostatistics⁴⁹ which is based on the fitting of explicit spatial and spatio-temporal correlation functions to parameterise a Random Function (RF) model for subsequent use in spatial prediction. In particular, the spatial relationships between environment, poverty indices and indicators were explored using geostatistical methods. These spatially explicit methods were deemed appropriate for the present spatial prediction task as poverty has been found previously to be spatially autocorrelated⁵⁰ (see [Supplementary data](#) for full description of the methods and results).

In the univariate case, geostatistical prediction involves calculation of the experimental variogram (or spatial covariance) which characterises the spatial pattern in the property of interest,⁴⁹ the fitting of an appropriate model to the estimated variogram (usually chosen from a set of so-called 'permissible' models) and the subsequent use of the fitted variogram model parameters in geostatistical spatial prediction or 'kriging' to unobserved locations. In this univariate case, the variogram models parameterise the underlying RF model. In the multivariate case,

Table 1. Pearson product moment correlation coefficients between: intensity of poverty (A), indicators^a and the normalized difference vegetation index (NDVI). Here are reported only the significant ($p < 0.001$) and large (values larger than 0.6 or lower than -0.6) correlations, and for this reason 'low' means correlations between 0.59 to -0.59 and/or not significant

Variable	A	Sch	Ch.a	Ch.m	Nut	Ele	Im.s	Wat	Flo	Fuel	Ass	NDVI
A	1	0.92	0.96	0.91	0.66	0.87	0.88	low	low	low	low	-0.62
Sch	0.92	1	0.93	0.76	0.69	0.90	0.84	low	low	low	low	-0.72
Ch.a	0.96	0.93	1	0.85	0.68	0.89	0.87	low	low	low	low	-0.66
Ch.m	0.91	0.76	0.85	1	0.64	0.81	0.85	low	low	low	low	low
Nut	0.66	0.69	0.68	0.64	1	low	0.63	low	low	low	low	-0.66
Ele	0.87	0.90	0.89	0.81	low	1	0.90	low	low	low	low	-0.67
Im.s	0.88	0.84	0.87	0.85	0.63	0.90	1	low	low	low	low	low
Wat	low	low	low	low	low	low	low	1	0.87	0.78	low	low
Flo	low	low	low	low	low	low	low	0.87	1	0.85	low	low
Fuel	low	low	low	low	low	low	low	0.78	0.85	1	low	low
Ass	low	low	low	low	low	low	low	low	low	low	1	low
NDVI	-0.62	-0.72	-0.66	low	-0.66	-0.67	low	low	low	low	low	1

^a Ass: assets ownership; Ch.a: child school attendance; Ch.m: child mortality; Ele: Electricity; Flo: flooring; Fuel: cooking fuel; Im.s: improved sanitation; Nut: nutrition; Sch: years of schooling; Wat: safe drinking water.

it is necessary to calculate the auto-variograms for each variable (one primary variable to be predicted and one or more secondary variables or covariates), as well as the cross-variograms between

each variable pair. Further, the fitted models must be such that the multivariate RF, known commonly as the linear model of coregionalization (LMC), is positive definite (broadly, predictions arising from it cannot have negative uncertainty).⁵¹ In this analysis, the optimal parameters of the LMC model were chosen through employing a weighted least square approximation, and the LMC optimal model according to cross-validation⁵² (see [Supplementary data](#)). The LMC can then be used in multivariate spatial prediction (ordinary cokriging).⁵³ Factorial kriging is an extension of kriging that allows decomposition of a given variable into different spatial structures, and spatial prediction of those structures separately (akin to low pass and high pass filtering). Here, factorial kriging was employed to estimate the contribution of each variable to variation in the intensity of poverty⁵⁴ and ordinary cokriging was used to predict spatially the intensity of poverty in West-Central Africa based on covariates.

In addition to the above methods, the geostatistical approach includes the calculation of distributional parameters (e.g. skewness since the variogram is sensitive to departures from normality) and the correlation matrix, in order to evaluate the degree of association between all the variables and departures from normality, which may require data transformation. The presence of a trend (a geographic gradient in the variables) was also investigated using the geostatistical approach proposed by Delfiner,⁵⁵ since its presence requires specific spatial model corrections.

Figure 1. Experimental variograms for A (variance multiplied by 10), indicators and normalized difference vegetation index (NDVI) (variance divided by 50). A: intensity of poverty; Ass: assets ownership; Ch.a: child school attendance; Ch.m: child mortality; Ele: Electricity; Flo: flooring; Fuel: cooking fuel; Im.s: improved sanitation; Nut: nutrition; Sch: years of schooling; Wat: safe drinking water.

Results

After a pre-analysis, based on correlations and cross-validations through cokriging, it was found that the intensity of poverty (A)

Figure 2. Auto- and cross-variograms for intensity of poverty (A) and normalized difference vegetation index (NDVI). From the upper-left corner and clockwise: experimental (black line) and model (grey line) auto-variogram for A; table with model variogram parameters for each variable; experimental (black line) and model (grey line) auto-variogram for NDVI; experimental (black line) and model (grey line) cross-variogram between NDVI and A.

Table 2. Error and standardized error (SE) for the cross-validation of intensity of poverty (A) and each indicator^a, considering their auto-variograms in kriging and their auto-variograms and cross-variogram (with NDVI) in ordinary cokriging. The increase in precision is expressed in terms of error reduction

	Kriging		Cokriging with NDVI		Increase in precision
	Error	SE	Error	SE	
A	0.18	0.79	<0.01	0.79	reduced more than 4 times
Sch	0.06	0.87	0.05	0.91	reduced less than 2 times
Ch.a	0.44	0.77	0.26	0.83	reduced less than 2 times
Ch.m	0.5	0.86	0.13	0.86	reduced between 3 and 4 times
Nut	0.09	0.86	0.25	0.92	increased between 1 to 2 times
Ele	0.25	0.87	0.56	0.84	increased more than 2 times
Im.s	0.54	0.95	0.37	0.97	reduced less than 2 times
Wat	0.48	0.77	-0.17	0.85	reduced between 2 and 3 times
Flo	-0.17	0.94	-0.36	0.89	increased more than 2 times
Fuel	0.11	0.66	-0.21	0.62	increased between 1 to 2 times
Ass	-0.05	1.01	-0.15	1.04	increased more than 2 times
PC1	-0.01	0.80	-0.09	0.02	increased more than 2 times

^a Ass: assets ownership; Ch.a: child school attendance; Ch.m: child mortality; Ele: Electricity; Flo: flooring; Fuel: cooking fuel; Im.s: improved sanitation; NDVI: normalized difference vegetation index; Nut: nutrition; PC1: first principal component; Sch: years of schooling; Wat: safe drinking water.

and the NDVI presented the greatest correlation (-0.62 A/NDVI, -0.54 H/NDVI, -0.59 MPI/NDVI, smaller than 0.1 for the correlations with elevation, smaller than -0.5 for the correlations with rainfall) and the lowest cokriging error. For this reason, the following results describe only the relationship between A, its indicators (health dimension included) and NDVI. However, employing H or MPI instead of A will give similar results since their inter-correlations are very high (0.93 A/H and 0.97 A/MPI).

The data were not transformed as they were found to be normally distributed (no violations of the required assumptions for variogram calculation). A and NDVI have an inverse relationship (Pearson correlation) confirmed by a linear regression estimating A from NDVI, in which the estimated beta coefficient for NDVI is -0.03 ($p < 0.001$). Hence, NDVI acts as the spatial trend for A as confirmed by the trend tests, but also for the indicators of health (nutrition [$r = -0.66$], child mortality [$r = -0.66$]) and education (schooling [$r = -0.72$], child attendance [$r = -0.61$]) (Table 1) (see [Supplementary data](#) for full description of the results).

A and NDVI show a similar form and parameters values in their spatial variation (Figure 1), and both show the largest sill variation in the north to south direction (0°), and smallest in the west to east direction (135°) (a characteristic called anisotropy which requires coefficient adjustments in the variogram function). In addition, increasing the distance between points produces a decreasing correlation between the two variables with inversion in their correlation coefficient at distances larger

Table 3. Correlation coefficients between the original variables^a and the first two regionalized factors (named Factor 1 and Factor 2) for each linear model of coregionalization component (nugget and power) and the percentage of the variance accounted for by each factor (var perc)

	Nugget		Power	
	Factor 1	Factor 2	Factor 1	Factor 2
Ass	0.25	-0.08	0.31	0.42
Ch.a	-0.25	-0.28	0.29	-0.28
Ch.m	-0.24	-0.26	0.18	-0.11
Ele	-0.28	-0.41	0.33	-0.35
Flo	0.32	-0.22	0.45	0.29
Fuel	0.61	-0.44	0.39	0.34
Im.s	-0.21	-0.48	0.26	-0.37
Nut	-0.22	-0.19	0.13	-0.24
Sch	-0.23	-0.21	0.32	-0.32
Wat	0.28	-0.29	0.24	0.31
NDVI	<0.01	<-0.01	-0.36	-0.44
A	-0.10	-0.11	0.48	-0.38
Var perc	52.84	38.91	76.54	18.57

^a A: intensity of poverty; Ass: assets ownership; Ch.a: child school attendance; Ch.m: child mortality; Ele: Electricity; Flo: flooring; Fuel: cooking fuel; Im.s: improved sanitation; NDVI: normalized difference vegetation index; Nut: nutrition; Sch: years of schooling; Wat: safe drinking water.

than 6° . However this positive correlation stays weak at large distances. The correlation is close to 0 at distances around 5° . The spatial range within 3° used for the variogram models (Figure 2) allows the use of the maximum correlation between the two variables. This large correlation and spatial interdependence between A and NDVI allow a consistent reduction in the prediction error of A and child mortality by an amount not obtained for the other indicators (Table 2).

In terms of further analysis of the spatial variation of the variables, the use of factorial kriging confirmed that the largest correlation between A and NDVI is in the spatially dependent component of the variogram (Table 3), and the differences with the noise component demonstrated that spatial variation in NDVI is both structural (functional) and scale-dependent. In contrast, child mortality acts at spatial scales shorter than NDVI and A, due probably to the influence of societal, population and individual-based characteristics with a weak spatial effect component.

Finally, the sub-national administrative values for A and its predicted values and prediction errors are shown in Figure 3. Cokriging shows a small error in the south (bottom map in Figure 3) and over-predicts in the north of the area. The patchy distribution of the errors is due more to the sparser distribution of data on A (values referred to centroids) than for the correlation between A and NDVI and, in fact, the errors increase when departing from the centroids (Figure 3). Therefore, in this analysis, cokriging was found to be an effective tool for mapping A using NDVI.

Figure 3. Intensity of poverty at administrative level 1 (top map) and interpolated intensity of poverty for the study area using cokriging (central map). The bottom map shows the interpolation errors.

Discussion

Here, we have demonstrated the spatial interconnections between poverty and vegetation and between vegetation and the indicators associated to health used to calculate poverty in West Africa. This research shows that the incidence of poverty and child mortality varies inversely with NDVI (high NDVI associated with low poverty and child mortality, where high NDVI values indicate greater vigour and amounts of vegetative growth). These relationships exist not only on a point-basis, but they are spatially structured in space. That is, the relative location of people in poverty and child mortality is dependent on the values of NDVI. While the correlation between A and the indicators are determined by the weights applied to the indicators to produce A, the NDVI is independent from the process of calculating A, therefore, the NDVI correlation results are not process-driven.

As described above, this is not the first analysis showing a large correlation between NDVI and various measures of poverty in Africa,^{44,56} where NDVI is a proxy for the availability of natural resources, favourable agroclimatic conditions and the potential for household production and stocks;^{34,57} instead it is the first analysis dissecting the spatial characteristics of this association, with potential utility for improving the MPI measure and its mapping. In fact, the correlation between A and the first principal component (PC1) on the indicators (Supplementary Table 2) increases when NDVI is taken into account, from -0.942 to -0.951 ($p=0.04$, one-tail test for the difference between two dependent correlations with one

variable in common) but also for the world MPI values the correlation between A and PC1 increases to -0.87 leading to two potential improvements in the MPI calculation: use of the first two components of the principal component analysis of the indicators, rather than a simple analytical combination of them (statistically not assessable); an increase in the significant association between the indicators and A. Also, accounting for NDVI can reduce the number of indicators required to measure the intensity of poverty; and when used in mapping it can allow continuous estimation of poverty and some of its indicators.

Quantifying the relationship between poverty, child mortality and NDVI allows environmental delineations: changes (e.g., due to natural hazards impacts) can be detected quickly from remote sensing analysis rather than population survey and census. It has been shown that child mortality is associated to environmental characteristics and hazards⁵⁸ and climate change.³⁵ The latter, through changes in temperature, precipitation, evapotranspiration, run-off and soil moisture, is linked to variation in outcomes related to health, water availability, food security, migration and socio-political equilibria. For these reasons, the developing world is facing strong climate-related pressure against efforts to reduce poverty.⁵⁹

These conclusions can be extended to drylands in general (40% of the world's land surface), which host 2 billion people in nearly 100 countries, half of whom are recognised as living in poverty.⁶⁰ Although field work and further analyses are required to fully understand the causes of the strong associations between NDVI, poverty and health in West Africa; at this stage it is recommended for these areas (which comprise SSA) to include or test the NDVI variable in any environmental poverty analysis and mapping, since it is associated with the distribution of poverty in West Africa, and can be used to improve the geographic targeting of pro-poor interventions, in light of the upcoming United Nations Sustainable Development Goals (SDGs) framework. In addition, it is recommended that similar statistical procedures are applied to other potential environmental components (such as land use, population density and accessibility) in order to define those variables with large spatial and aspatial statistical correlations which can, along with NDVI, improve poverty mapping.

Supplementary data

Supplementary data are available at International Health Online (<http://inthehealth.oxfordjournals.org/>).

Authors' contributions: LS, AJT and DJR conceived the study; LS undertook the data collection and carried out the statistical analysis; LS, DJR, DWM, PMA, NAW, CP, AS and JK carried out the literature review; LS, DJR and PMA contributed to the interpretation of the statistical analysis; LS drafted the manuscript. All authors reviewed the draft and read and approved the final manuscript. LS and AJT are guarantors of the paper.

Funding: This work was supported by NIH/NIAID [U19AI089674], the Bill & Melinda Gates Foundation [OPP1106427, 1032350], and the RAPIDD program of the Science and Technology Directorate, Department of Homeland Security, and the Fogarty International Center, National Institutes of Health to AJT; by the NERC ESPA DDDAC project [NE-J001570-1] to PMA; and by Medical Research Council [project MR/J012343/1] to

NAW and PMA. This work forms part of the WorldPop Project (www.worldpop.org.uk) and the Flowminder Foundation (www.flowminder.org). The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

Competing interests: None declared.

Ethical approval: Not required.

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