



Poverty Mapping in Uganda Using Socio-economic, Environmental and Satellite Data

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In order to reduce poverty we must first describe, explain and predict its spatial distribution over large areas with as high a level of local accuracy as possible. Poverty maps are traditionally produced by exploiting links between census (wide area) and survey (smaller area coverage) data. The detailed relationships found within the survey data are extended to the census data that must share some predictor variables in common with the survey data. Both census and survey data tend to be socio-economic in nature; the mapping thus exploits the internal correlations within potentially strongly correlated data sets – one 'measure' of poverty is often correlated with another. Rather than look at the correlates of poverty, we should like to identify its causes. We suggest that poverty is multi-dimensional and that many of its dimensions are environmentally related; people are poor because they are unhealthy, or under-fed, or without access to fuel and water etc. Each of these is environmental in some way or other, and an appropriate approach to reducing poverty might be first to identify its (environmental) causes. We have attempted to do this with survey data from Uganda and environmental data derived from multi-temporal satellite imagery that measures land-surface conditions and processes (temperature, rainfall, vegetation growth etc.). The same satellite data have already been used to understand the distribution of farming systems throughout Africa and to predict the distribution and intensity of insect and tick carriers of a variety of diseases, and the incidence and prevalence of the diseases they transmit.

In this analysis we examined to what extent satellite data (as a proxy for environmental conditions) are correlated with household survey data. Whilst correlation obviously does not automatically imply causation, we suggest an environmental approach is more likely to reveal causes than will the traditional approach of small area mapping using census and survey data. However, it is first necessary to establish the relative predictive accuracies of the traditional and environmental approaches.

Methodology

The predicted (household expenditure) and predictor (ground-based and satellite) variables are linked via discriminant analytical methods. This approach is shown diagrammatically for the simple case of two-group discrimination in Figure 1.

A discriminant axis (linear in this illustration) is defined, distinguishing the two groups. Further observations can be assigned to one or other category depending on which side of the discriminant axis they lie. In the case of the Ugandan data, expenditure was divided into ten categories and the predictor variables that best discriminated these categories were selected in a step-wise inclusive manner that maximised the fit of the model to the data (using kappa, the index of agreement between predicted and observed categories). In this case, the discriminating axes between groups were no longer linear.

Models were constructed at a variety of spatial resolutions, from 0.01 to 1.0 degree (approximately 1.1 km and 110 km at the equator). Both predictor and predicted variables were averaged at each spatial resolution before the models were constructed.

Input Data

The poverty data were derived from breakdowns of food expenditure from the 2002-2003 Ugandan National Household Survey (UNHS), which covered 9,711 households in 973 communities (Figure 2). This survey was also designed to be integrated with the 2002 National Population and Housing Census for detailed poverty mapping using small area techniques.

Figure 1: Schematic illustration of discriminate analysis

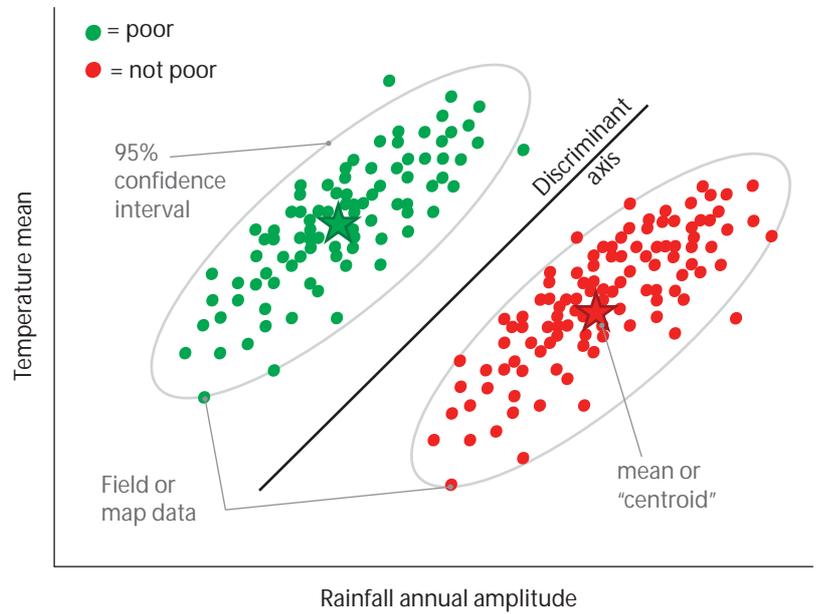


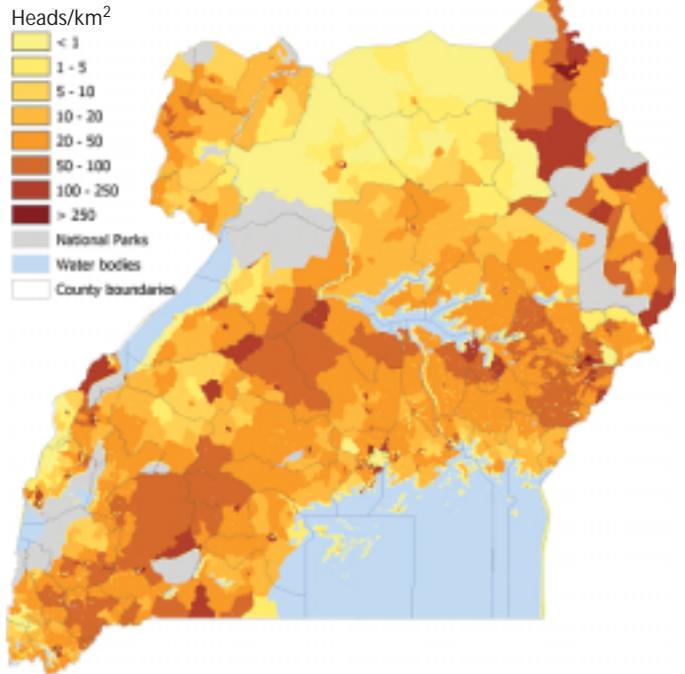
Figure 2: Distribution of surveyed households showing expenditure levels.



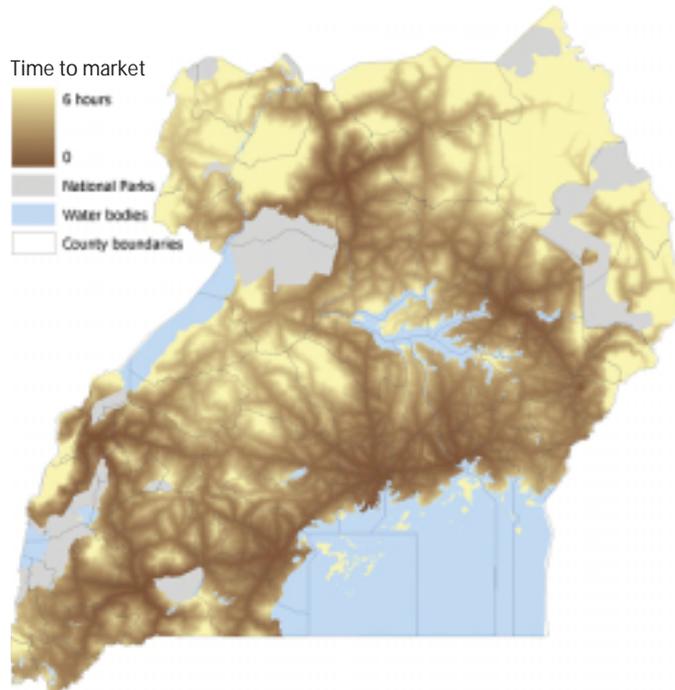
Ground-based predictors used in the analysis included human population density, livestock density (Figure 3a), 'distance' to markets (calculated as time to travel to towns of a certain size – Figure 3b), and the probability of occurrence of three important tsetse species. Satellite-derived predictor variables included an elevation surface and data layers arising from temporal Fourier analysis (TFA) of imagery from the Advanced Very High Resolution Radiometer (AVHRR) on-board the NOAA series of oceanographic satellites. TFA outputs include separate images recording the mean, maximum and minimum of each satellite channel, the amplitude and phase (= timing) of annual, bi-annual and tri-annual cycles that collectively define habitat seasonality of land-surface and air temperatures, Cold Cloud Duration (a proxy for rainfall), Vapour Pressure Deficit and vegetation activity as estimated by the Normalised Difference Vegetation Index (NDVI). For example Figure 3c shows the monthly average NDVI.

Figure 3: Examples of predictor variables used to map poverty

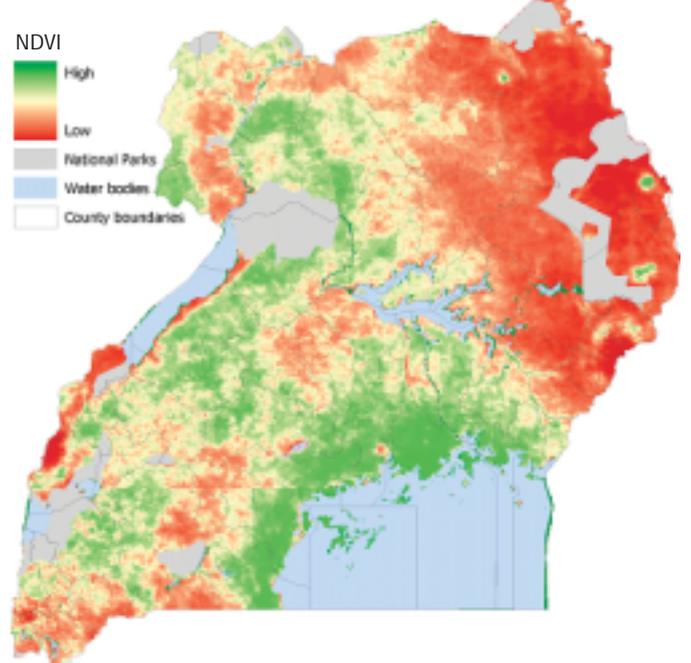
3a) Cattle density



3b) Market accessibility cost (in hours)



3c) Monthly average normalised difference vegetation index



Results

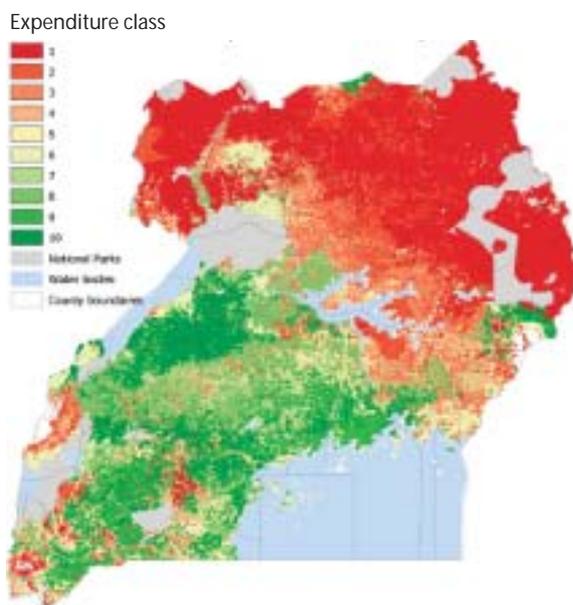
The maps below show the results of the predictions for a range of different spatial resolutions, along with a graph of the percentage explained variance (r^2) at each (Figure 4). For comparison, Figure 5 shows the results of applying the 'traditional'

small area mapping approach to data from an earlier survey carried out in 1992, which estimated welfare at the county level. As is the case with the small area mapping approach, the accuracy of the environmental approach to poverty mapping

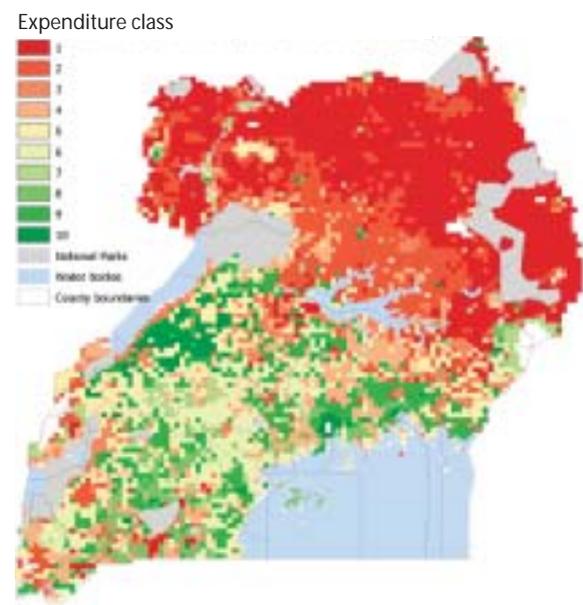
increases as spatial resolution decreases. The environmental method explains more than 50% of the variance in the poverty data at a spatial resolution of about 0.20 to 0.30 degrees – a result comparable with that of the traditional methods.

Figure 4: Predicted household expenditure at a range of spatial resolutions. Expenditures in classes 1-10 is as shown in Figure 2.

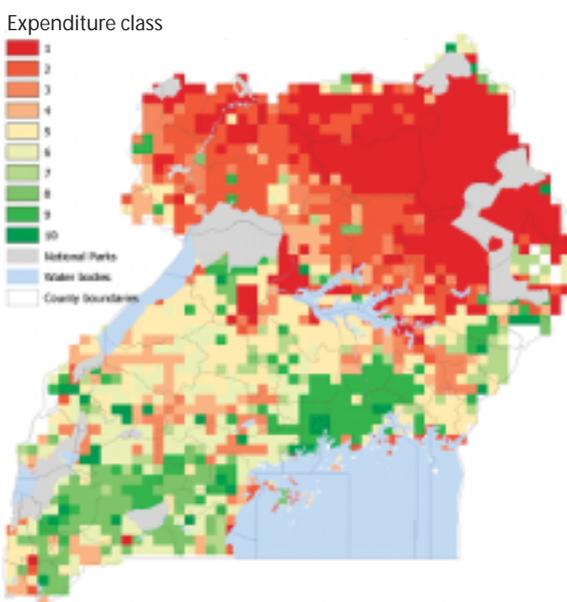
4a) Spatial resolution = 0.01 degree



4b) Spatial resolution = 0.05 degree



4c) Spatial resolution = 0.1 degree



4d) Spatial resolution = 0.3 degree

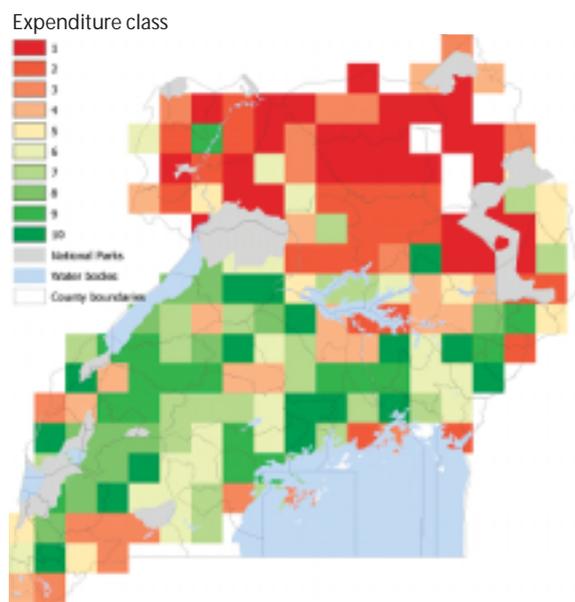
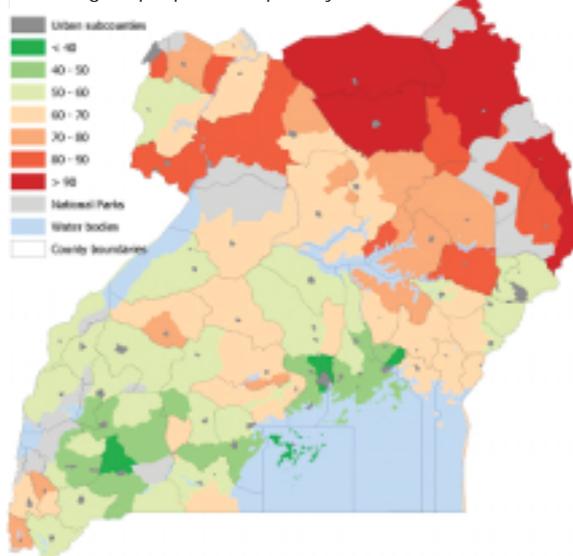


Figure 5: Poverty Incidence in 1992 at county level

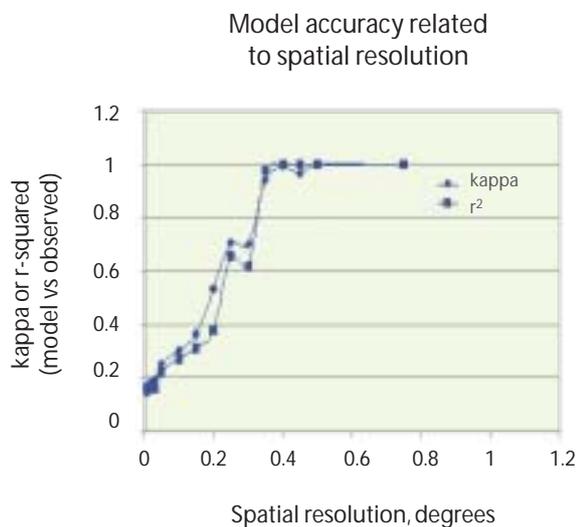
Percentage of people below poverty line



Source:

Emwanu T., Okwi, P.O., Hoogeveen, J.G. and Kristjanson, P. (2003) Where are the poor? Mapping patterns of well-being in Uganda. Kampala: Uganda Bureau of Statistics.

This graph shows the increase in the model's statistical accuracy (r^2 or kappa) as spatial resolution decreases (i.e. grid cell size increases). r^2 of 50% or greater are generally thought to be acceptable statistically, but the appropriate spatial resolution at which to map poverty will also depend upon the uses to which the maps are to be put.



Conclusions

- Environmental data derived from ground surveys and satellites appear to be at least as good as census and survey data at describing the spatial distribution of poverty in Uganda.
- The accuracies of both methods are scale-dependent. The environmental approach gives satisfactory results at spatial scales of about 20km and above (r^2 of 50% or greater).
- The environmental approach is more likely to identify the causes of poverty than is the traditional approach, and thus leads more naturally to appropriate interventions.
- It is likely that the ultimate causes of poverty vary locally; the environmental approach can establish the environmental correlates of these causes which may include soil fertility, agricultural production, health and the availability of fuel and water. Appropriate, targeted intervention can thus be designed once the causes are identified from their environmental correlates.

Document for reference:

PPLPI Working Paper 36:

Poverty Mapping in Uganda: An Analysis Using Remotely Sensed and Other Environmental Data

www.fao.org/ag/againfo/projects/en/pplpi/docarc/wp36.pdf