Conclusions

The validity of an environmental approach to poverty mapping was clearly demonstrated by Rogers *et al.* (2006) and Robinson *et al.* (2007), who used discriminant analysis of Fourier-processed multitemporal satellite data, combined with other relevant environmental variables, to model and predict household expenditure in Uganda. They presented an approach to mapping poverty that took us beyond description, where the more traditional small area estimates reach their limits, and towards explaining the distribution of poverty, and possibly predicting changes in poverty that may result from changing, through careful intervention, the conditions observed to be associated with it.

Here, that analysis has been taken a step further, using regression techniques that are readily accessible from routines within the R environment for statistical evaluation. This makes the analysis performed here readily reproducible. Three levels of spatial disaggregation have been investigated: global and regional analyses using ordinary least squares regression and a geographically weighted regression. As would be expected, dividing the area into zones, livestock production systems in this case, prior to regression improves the predictive power considerably. Because a zonation highly relevant to the role of livestock in agriculture and poverty alleviation was used, the relationships between poverty and the environment have been separately elucidated in these different livestock production systems; indicating which factors are most closely related to poverty in the different systems.

Only 7 of the predictor variables that were used in the original analysis (Rogers *et al.* 2006) were used, chosen largely on the grounds of avoiding variables that were highly correlated with others. This was done with the intention of getting a better understanding of the nature and relative importance of key variables at different levels of detail and using different zonations. For example, VPD and population density were consistently the two most influential factors in the OLS model at different resolutions and yet when the livestock production system zones were taken into account NDVI became more important in livestock only and in arid and semi-arid production systems. Importance is more difficult to assess in the GWR model but the maps of the GWR coefficients and their significance levels suggest that there is considerable spatial variation in the influence of factors like slope, population density and VPD.

The present analysis was restricted to rural households, and used per-adult equivalent expenditure (rather than total household expenditure) as the dependent measure of poverty. This has enabled a direct comparison of the environmentally-based results against those from the more traditional SAE approach (Emwanu *et al.* 2007), which have become available since the original (Rogers *et al.* 2006) analysis was conducted. This comparison has shown that an environmental approach to poverty mapping in Uganda consistently out-performs SAE approaches at equivalent spatial resolutions.

The 'best' performing model was the GWR at 0.05 degrees resolution (c. 5.5 km at the equator). There is a case for using the 0.03 degree resolution data to give a 20 fold increase in spatial resolution over the finest SAE map. However, caution has been exercised in the presentation of results here, and the door left open for better and finer resolution maps, which could take advantage of other environmental variables and more appropriate regional models, as indicated by the spatial patterns in the GWR parameter maps.

With respect to the SAE methodology, the disadvantage of the environmental approach is that the predictions are not made at the level of the household, so it is not possible to compute aggregate measures such as head counts and Gini indices. Nevertheless, the approaches demonstrated here, and in Rogers *et al.* (2006), have a role to play in understanding the nature of the relationships between poverty and socio-economic and environmental factors. It is not suggested that these models can identify causal links between poverty and the environment but they do form part of an accumulation of evidence that strongly suggests that spatial patterns of poverty, and possibly spatial poverty-traps, can be partially explained by environmental factors. This knowledge should lead to spatially-targeted policy support for poverty alleviation.

The GWR results show significant spatial variation and suggest that other zoning systems should be considered when designing statistical approaches to modelling and mapping poverty. One option for visualising these zones has been briefly demonstrated, to reveal regions that have similar coefficients in the model; where the relationship between poverty and the environment are consistent.

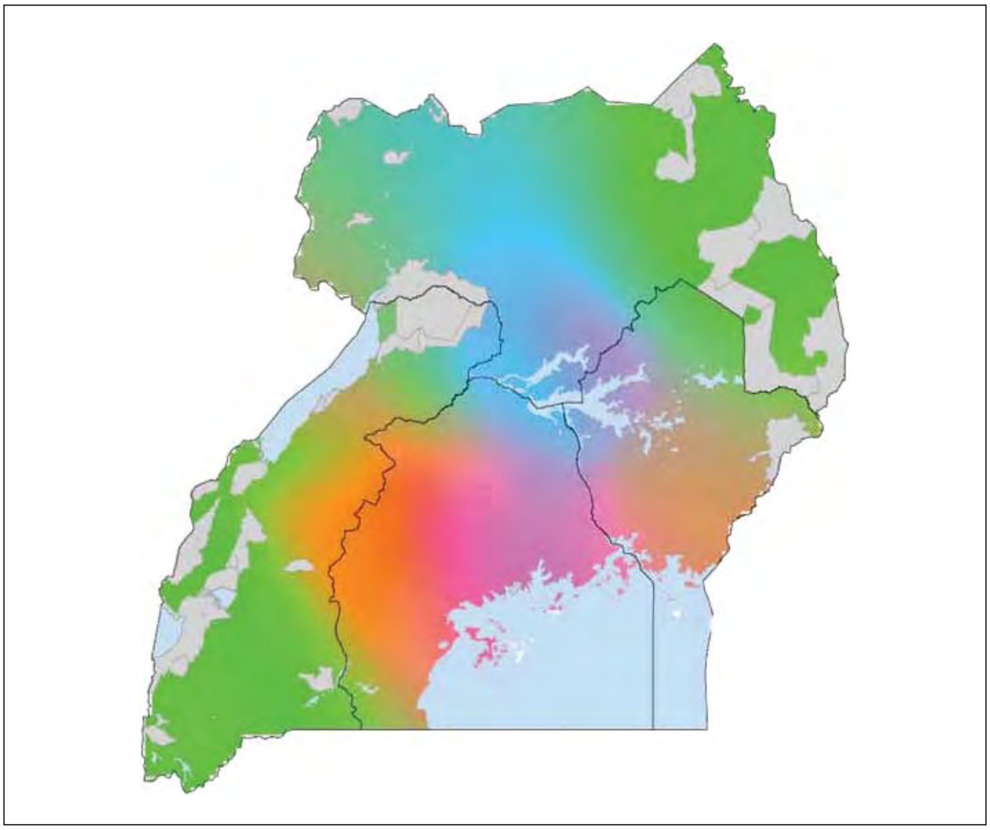
Figure 18 was derived from the GWR coefficient maps by first reducing the dimensionality of the data from eight (seven coefficients plus the intercept) to two, using a non-linear dimension-reduction technique called Sammon mapping (Sammon 1969), although Principal Components Analysis would also have served as a linear dimensional reduction technique. The purpose of dimension reduction is to reduce the N (8) variables to n (2) independent and orthogonal components that represent the maximum amount of information in the original N variables demonstrable in only two dimensions.

Each pixel was assigned a colour based on these two components using the CIELAB colour space which was three axes, L - lightness, a – hue and, b – chroma (CIE 1976). CIELAB is a unique colour space in that the distance between colours is perceptually uniform so there is a direct correspondence between distance or dissimilarly between data points and their assigned colours. Other colour spaces such as RGB do not have this property, which makes interpretation of RGB composite images challenging. In Figure 21 the two components have been assigned to the a and b CIELAB elements, and L held constant.

Figure 18 represents the multivariate spatial structure of the coefficients. The strong spatial patterns in the colour coding suggest that it is possible to use GWR to identify suitable zones of analysis based on the spatial relationship between poverty and its possible determinants. This is a very different approach to the more usual clustering and typologies that can be derived from the input variables, because the typologies here have been derived based on the *influences* that these variables may have on poverty, not based on the values of the variables themselves.

The colour coding serves merely to distinguish among different clusters of relationships between expenditure and environmental variables – the map cannot be interpreted beyond that; green is not 'better', or less poor, than red, for example. This simple linear combination must, however, be treated with caution since, ideally, each parameter should be weighted depending on its local significance. The cluster map presented in Figure 18 does, however, reveal intriguing spatial patterns that should be explored further.

Figure 18. Colour coded composite map of the GWR parameters at 0.05 degrees resolution



All of the models presented here are linear. The original discriminant analysis approach to this same dataset (Rogers *et al.* 2006; Robinson *et al.* 2007) employed an essentially non-linear technique, although it suffered from the constraint of discriminant analysis that the continuous expenditure data had to be binned into a number of expenditure categories before analysis. Descriptions and predictions were made based on the co-variance matrices of the key predictors best able to separate the different categories. This sort of discriminant analysis quite flexibly describes many different sorts of non linearities, as would alternative flexible approaches such as generalised additive models (GAMs). Alternatively the present linear models could incorporate certain sorts of non-linearities through the use of transforms (e.g. squares, square roots) of the descriptor variables, although these are fairly restrictive and must be specified in advance of modelling, rather than during it.

Many new questions are posed by this analysis. Is there scope for combining these kinds of environmental-geographical models with the census-survey data approach as used in the development of Small Area Estimate poverty maps? Can GWR be used to suggest zonations for different SAE models? Should environmental variables be used more commonly directly within the SAE methodology? These are all issues that should be explored further (i) to extract as much useful information as possible out of detailed spatial datasets, (ii) to develop more refined poverty estimates and, most importantly, (iii) to better understand the spatial patterns of rural poverty, and how these patterns relate to the environment.

Rogers *et al.* (2006) concluded '*what we have been able to show here is the step beyond exploiting correlations within internally correlated socio-economic data sets (the traditional small area mapping approach) to a situation where we have been able to show that external, independent data appear to have at least as much descriptive power for poverty mapping. The precise interpretation of the correlations obtained here will require more research effort but at least we have shown that this effort is both justified and appropriate.*' The work presented in this paper reinforces the justification of the environmental approach and takes some steps further towards explaining the pattern of poverty in Uganda.