Livelihood mapping and poverty correlates at a meso-level in Kenya

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Abstract

We identify and map critical spatial factors grouped into natural, human, social, financial and physical capital assets, which largely determine livelihood options, strategies and welfare of agro-pastoral communities in a semi-arid district of southern Kenya. Our approach builds upon new, relatively high-resolution spatial poverty data and refines participatory land-use mapping methods, making valuable information on natural and social resource availability and access useful

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for policy makers. While most poverty analyses focus on the household, we employ quantitative spatial data analysis methods to examine the spatial correlates of meso-, or community-level poverty incidence. The results suggest that variables influencing poverty levels in this district include pasture potential, livestock density, distance to a major town, road density, access to education, access to security, soil fertility and agricultural potential. Because of the participatory research process taken, these results are already feeding into both local- and national-level policy processes aimed at reducing poverty in Kenya.

Keywords: Livelihood assets; Poverty; Spatial analysis; Targeted poverty reduction strategies

Introduction

Our study makes use of new, subdistrict poverty maps for Kenya (CBS, 2003) to examine in detail the spatial variation in poverty incidence and the factors influencing differential poverty levels for Kajiado District. We are interested particularly in the role that livelihood assets play in determining and explaining poverty incidence. The concept of sustainable livelihood strategies and assets provides a way of more deeply exploring the role of environmental resources in the livelihoods of the poor (Chambers and Conway, 1992, Reardon and Vosti, 1995, Ashley and Carney, 1999, Koziell, 2001). A core feature of the sustainable livelihood framework is an analysis of the five different types of assets upon which individuals draw to build their livelihoods. These are natural, social, human, physical and financial capital (Carney, 1998, Ashley and Carney, 1999, Bebbington, 1999).

To our knowledge, this is the first time the challenge of spatially mapping livelihood assets and analysing their relationship with poverty incidence has been addressed at a meso-community level. The livelihood assets framework does not provide guidance as to which indicators of each asset type policy makers may most effectively map and use, nor which assets are critical correlates of poverty in different settings, systems or areas. The lack of theory to guide our selection of the appropriate independent variables to include in the analysis presented us with a model selection challenge. Thus the livelihood assets framework both guided the research questions addressed by our study, and led to the model selection analytical approach taken to answer those questions.

Table 1 shows the spatial variables we hypothesized will affect poverty incidence, and the expected relationships, with examples from the literature where these relationships were explored.

Research site

Kajiado District is located in Kenya's southern Rift Valley Province, bordered by Tanzania to the south-west and Nairobi Province to the north. It is an expansive and thinly populated area with an uneven distribution of social and economic infrastructure. It is subdivided into 7 divisions and 120 sublocations. Plains and a few volcanic hills and valleys characterize the general topography. The land rises in altitude from about 500 m around Lake Magadi to about 2500 m in the Ngong Hills area. Most of the district's area of 21,903 km^2 is classified as arid or semi-arid. The total population of the district, mainly Maasai people, was 406,054 according to the 1999 Census (GoK, 2001), which implies an average population density of 19 people per km^2. The Maasai's livelihoods have traditionally revolved around livestock—primarily cattle, sheep and goats. Increasingly, they are seeking to diversify their livelihoods, and recent surveys show many households also depend to varying degrees upon income from off-farm employment, crops, quarrying, bee-keeping and wildlife/tourism-related activities (Kristjanson et al., 2002).

New "high-resolution" poverty maps for Kenya show high and variable poverty levels across Kajiado District, ranging from sublocations with 11% of the population living below the national poverty line to sublocations with a poverty incidence of 93% (CBS, 2003, Fig. 1). Detailed information on household expenditures (both food and non-food) from a 1997 Kenya Welfare Monitoring Survey and complete geographic coverage provided by a 1999 Kenya Population and Housing Census were combined using a small area estimation technique to derive the poverty estimates. This enabled researchers to reliably estimate measures of well-being (down to the sublocation level) using statistical simulation techniques. Thus the poverty incidence measure used in our analysis is the percentage of the population falling below the rural poverty line, defined as KShs 1239 per adult equivalent per month, or roughly US$0.55 per person per day.

Approach and data sources

The overall approach involved three steps. First, we had to choose a process for deciding which indicators of the five types of capital assets could be mapped. We held a workshop with stakeholders and technical/government experts in Kajiado, resulting in a first "wish-list" of variables that were thought to adequately cover all aspects of the five types of livelihood capital, and determined that these variables would need to be mapped for all 120 sublocations. Second, we collated existing GIS layers from numerous sources[1], involving much effort in collecting, digitizing and creating new data sets. We identified numerous data gaps that needed to be filled. In order to fill these data gaps, we undertook a participatory resource mapping exercise for the entire district in collaboration with a local non-governmental organization, SNV (see www.snvworld.org). The main objectives of the exercise were to:

- Collect baseline data for livelihood mapping, e.g. locating schools and other service facilities, water sources and job opportunities throughout the district;
- Increase the capacity of communities and other stakeholders, such as various Ministry representatives in Kajiado, and to make local communities and government representatives aware of the natural resources that exist within their immediate surroundings; and
- Refine methods and tools for livelihood mapping that involve stakeholders and produce outputs throughout the process (e.g. maps, information) that can be used by different types of stakeholders and inform policy decisions at local to national scales.

The third step involved creating the variables to characterize livelihood assets. Although some GIS layers collected (e.g. simple rainfall patterns and the slope of the terrain) can be used as they are, most layers needed to be translated into some kind of accessibility measure (e.g. how far people or communities are from the resources that provide different livelihood options). In some cases, this involved calculating distance or least-cost-distance surfaces.

For each of the five livelihood asset types, we extracted a number of variables. For the econometric analysis, we aggregated data up to sublocation level (typically by deriving the mean value for the sublocation, e.g. the average long-term precipitation over potential evapotranspiration for the sublocation). For some variables we also derived additional measures, such as the percentage of the sublocation area with suitable soils for agriculture, or per capita water access (number of permanent water sources per 1000 people), or the presence of wetlands (percentage area of a sublocation within 1-hr walking distance from wetlands). With no strong theory and few published analyses at the equivalent of a sublocation level to guide us on the most appropriate livelihood asset variables to include in such an analysis, we brought together a group of researchers experienced in similar types of analyses and chose which variables seemed the best to include (Table 1).

We combined existing data sets and data collected from local communities and decision makers into a consistent spatial database, including many layers that lead to the livelihood assets described in Table 1. Fig. 2 shows one map from each of the five asset categories. The database, together with freeware software to visualize and analyse it, was made available on CD to various organizations and policy makers in Kajiado District. We carried out a GIS training course together with SNV to enable a number of computer-literate people within the district to do their own mapping and analysis of the database. SNV will also be using these data as the basis of their community information system, which they will maintain and update regularly. Alongside the distribution of the digital data set, we produced division-level thematic maps (e.g. natural resources, livestock inputs, social amenities and socio-economic features), following suggestions from local communities regarding the kind of maps that they would find most helpful. The maps were printed out in the form of a District Atlas that was distributed widely around the district (ILRI, 2004).

Analytical methods

The reduced form model we tested was that poverty depends upon natural, social, human, physical and financial capital assets. Our dependent variable is the estimated poverty incidence in each sublocation, or the proportion of the population falling below the rural poverty line (i.e. the number of poor people in each sublocation divided by the total population for each sublocation). The mean poverty incidence is 0.48 with a standard deviation (SD) of 0.15. We cannot use the number of poor people as our dependent variable directly, because we need to account for the fact that the total population size varies considerably across sublocations. Since our dependent variable is based on a count, and typically counts are assumed to follow a Poisson distribution (which cannot fall below zero), we used a Poisson regression model (Agresti, 2002).

Table 2 gives a description of all the predictor variables considered in the econometric analyses. While many of these variables are exogenous, some could be influenced by community-level actions (e.g. livestock density, number of community groups, likelihood of tick and tick-borne diseases). Thus we are interested primarily in identifying associations or correlates between these factors and poverty, rather than attempting to get at a causal relationship. Given the lack of theory to guide us, a huge challenge in this type of analysis turned out to be narrowing down the choice of independent variables, since we started out with more than 40 possible variables, and many of the candidates were highly correlated with one another (because facilities such as schools, markets, etc. are often found in the same places). Thus we went through a considerable process of testing the relationships between variables[2] and eventually eliminated those variables that had correlation coefficients greater than 0.5, starting with the variables that were correlated with more than one other explanatory variable.

We used a loglinear Poisson regression model (McCullagh and Nelder, 1989) that assumes a linear relationship between poverty incidence and our predictor variables on the log scale. This allows us to work within the familiar linear model framework. The regression model can be specified as:

$$Log(y_i / N_i) = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + ... + \beta_k x_{ki} \qquad (1)$$

where y_i is the number of poor people in each sublocation (*i* = 1, 2,…, n sublocations); N_i is the total population in each sublocation (*i* = 1, 2,…, n sublocations); x_j are the predictor variables; and β_j are the regression coefficients (*j* =1, 2, …, *k* predictors).

The focus of the statistical analysis was to establish the set of predictor (independent) variables that best explained the variation in poverty incidence across sublocations based on the Poisson regression model. As a result, we used a model selection approach, based on information theoretics. In particular, we used the corrected Akaike information criterion (AICc, Burnham and Anderson, 2002) to identify the set of predictor variables that were most strongly related with poverty incidence.

All our 14 predictor variables are spatially referenced, which poses some specific analytical challenges. The first relates to spatial autocorrelation. With these types of data, observations made at sublocations that are closer together may be more similar than sublocations that are farther apart. Therefore, a careful modelling of these data has to consider the possibility that substantial spatial autocorrelation is a problem. Tests of statistical hypotheses would be invalidated if spatial autocorrelation exists and is not accounted for. A second potential problem with assuming a Poisson distribution for these data is that they may have a larger variance than the mean (overdispersion), while a Poisson model assumes that the variance equals the mean.

Thus, we built models that explicitly accounted for overdispersion and spatial autocorrelation (Cressie, 1993) in poverty incidence, and assessed the strength of evidence in the data in support of these models, relative to models that assumed no spatial autocorrelation, using the AICc. Specifically, the full model was a generalized linear mixed model with a Poisson distribution for its error variance, a log link function and the predictor variables as fixed effects. The variation part of the mixed model explicitly incorporated exponential, Gaussian, spherical or power models as candidate models that account for spatial autocorrelation. We modelled overdispersion in the count data by multiplying the variance by a constant term so that it equals the mean, as required by the presumed mean-variance relation in the theoretical Poisson model advocated by McCullagh and Nelder (1989).

On rearranging terms in Eq. 1 as:

$$Log(y_i) = \log(N_i) + \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + ... + \beta_k x_{ki} \qquad (2)$$

where all terms are defined as before, it can be seen that we model the number of poor people, offset by the log of total population size in each sublocation, $\log(N_i)$, as a function of the explanatory variables, following McCullagh and Nelder (1989). We fitted the entire model using penalized restricted maximum likelihood in SAS GLIMMIX MACRO (SAS Institute Inc., 2001).

Model selection proceeded in two distinct steps (Wolfinger, 1993). First, with all the predictor variables included in the model, we used AICc based on penalized restricted maximum likelihood to select between the different candidate models for spatial autocorrelation as well as a model assuming no autocorrelation. It resulted that the data better supported the model that assumed no autocorrelation, based on the relative likelihoods, or Akaike weights (Burnham and Anderson, 2002)[3]. This is probably not surprising, given the scale of this analysis and the fact that we had so many spatial predictor variables.

In the second step, and assuming no spatial autocorrelation, we fitted the model including all 14 predictors to the data and calculated the relative likelihoods or Akaike weights based on penalized maximum likelihood of a series of models obtained by systematically deleting one predictor variable at a time. We also calculated the evidence ratios between the best approximating model and all the other models included in the set of candidate models. Akaike weights can be interpreted as the probability that the selected model is the best if all the candidate models were to be fitted to multiple data sets, while the evidence ratios provide the evidence against a model as being the best compared to another model (e.g. the best model in the set of candidate models). The larger the evidence ratio, the stronger is the evidence against a model relative to the reference model in the pair under consideration (Burnham and Anderson, 2002). We also used likelihood ratio tests to compare the series of nested models to determine which model had the greatest strength of support in the data.

Our approach thus involves explicit modelling of spatial autocorrelation, as part of the variance-covariance matrix of the mixed models, using a number of models for spatial autocorrelation equivalent to semivariograms or covariograms (see for example, Cressie, 1993) and model selection to choose the best semivariogram model from a set of candidates. This approach eliminates the need to first establish if significant autocorrelation exists in the data using tests such as Moran's or Geary's. Also, within the mixed model framework we adopted, model fitting and parameter estimation proceeds via likelihood-based methods, as methods that assume perfect independence, such as ordinary least squares (OLS), are inefficient and therefore inappropriate. As a consequence, only likelihood-based goodness-of-fit statistics (e.g. AICc), but not such commonly used fit statistics produced by OLS as R^2, are available for mixed models.

Empirical results

The model selection approach used resulted in selection of a set of three "best models" (Table 3). A 96% confidence set on models encompassed the three models (calculated by adding up the Akaike weights for each), implying that if we were to select the best models based on many repeat samples, these three models would be selected as best 96% of the time. By dropping the variables included in models other than the final three, we thus suffer negligible loss of explanatory power. Thus lessons can be learned from which variables dropped out and which variables remained in the final three models.

Table 4 shows parameter estimates for the best model overall and *t* tests of the null hypothesis that the estimates equal zero. One of the strengths of this approach is that the results from the set of our three best models also can be used to determine model-averaged parameter estimates that take into account the three best models rather than just one model as is typically done. These are shown in Table 5. Averaging involves computing a weighted sum based on the Akaike weights but with the weights renormalized to sum to 1.

Averaging the parameters over the three models allows our making inferences that are not conditional on any one model and therefore are more robust.

Explanatory variables that dropped out of the final three models included: density of active community groups (social capital); access to health facilities (human capital); distance to Nairobi (physical capital); likelihood of having tick and tick-borne disease problems, wildlife density, access to a permanent water source (natural capital).

Eight explanatory variables remained in the final set of models, i.e. that appear to be strong correlates of sublocation poverty rates (Table 5).

At least one variable from four of the asset categories, with the exception of social capital, emerged in the set of models that were best able to explain the variation in poverty levels across the district. This does not necessarily imply that social capital is unimportant vis-à-vis poverty incidence but could reflect the difficulty in capturing this concept through the use of a proxy such as density of active community groups. We also faced the problem that our social capital variables were strongly correlated to other variables (e.g. the location of important gathering places such as churches and nursery schools tend to be in the same locations as schools, and human population density is highly correlated to livestock density).

Within the natural capital assets, NDVI was a selected variable with a negative sign, so sublocations with a lower presence of green vegetation have higher poverty rates (or sublocations with higher poverty rates tend to be less "green" with lower pasture potential, because we cannot be certain of the direction of the relationship). Thus our results support the hypothesis that people living in areas with access to more or higher quality natural capital will tend to have more livelihood options open to them and be less poor. This relationship can be seen in Fig. 3A and 3B. The dark areas in Fig. 3A show that NDVI is relatively low in many poor sublocations, particularly in western and south-eastern Kajiado. Similarly, in Fig. 3B, in quite a few sublocations throughout central Kajiado, people are less poor with higher NDVI levels.

Livestock density, an indicator of financial capital assets, was included in the final set of models and has a negative sign, implying that in general, sublocations with lower livestock densities have higher poverty rates. It will be interesting to monitor this over time with observed trends of intensification of livestock systems and diversification in livelihood/income sources starting to take place in certain areas. This result could be expected in this district where so many livelihood strategies still rely heavily on livestock. The parameter estimate for livestock density (Table 5) suggests that an increase of 10 TLU/km^2 from the average TLU/km^2 for the district (26) would lower sublocation poverty incidence by 6.3%.

Road density, an indicator of physical capital assets, was a selected variable with a negative sign, suggesting road infrastructure is a correlate of poverty and sublocations with less road infrastructure are poorer. Increasing road density by 100 units from a mean of 152 km/km^2 would lower the poverty rate by 6.4%. Decreasing the distance to a major town by 10 km, from an average of 31 km, would lower poverty incidence by 1.9%.

Access to education facilities and security, both indicators of human capital assets, remained in the final set of models. Access to education, with a positive sign, suggests that in sublocations with better/greater access to education facilities, poverty rates are higher, a somewhat non-intuitive finding. Perhaps education facilities exist in the poorer areas but have not been in place for a sufficient length of time to have an influence on poverty levels. The fact that non-governmental organizations (NGOs) often deliberately establish education facilities in poorer areas may also explain this, thus the observed relationship between access to education and poverty. We have not captured quality of education by our access measure, thus “number of students per teacher” or some other indicator that captures quality of education may in fact be a better measure for human capital vis-à-vis poverty incidence.

Not surprisingly, in this district where livestock theft and banditry still occur, access to security was an important variable, with a negative sign, implying that sublocations with poor access to security are poorer. Our results suggest that increasing access to security by 10%, from a mean of 30% of a sublocation’s area within 1-hour walking distance to a police post, would lower poverty by 2.4%.

Discussion and conclusions

From a starting point of 14 livelihood asset indicators (cut down from an original list of over 40), this analysis further narrowed to eight the list of critical variables, with respect to helping explain sublocation-level poverty incidence. These included NDVI (pasture potential), livestock density, distance to a major town, road density, access to education, access to security, soil fertility, and P/PE (agricultural potential). Thus natural, financial, physical and human capital assets were all shown to be correlates of sublocation-level poverty levels in Kajiado District.

Equally informative are the factors that "dropped out". The fact that access to water was not showing up as highly associated with poverty in this very dry district somewhat puzzled us. However, Bekure et al. (1991) found in the same district that proximity to a water source had a marked effect on the number of livestock owned per household. Households closest to water owned fewer cattle than those further from water, because more feed was available further away from water sources. This suggests that if we use cattle holdings as a proxy for wealth, we would expect to find poorer households closer to water but, with our water access variable dropping out, our findings did not provide support for this.

We also had difficulty capturing the significance of environmental/ecosystem services such as wildlife that indirectly influence people's livelihood options and levels of welfare. This probably reflects the fact that people indigenous to this district are not yet benefiting significantly from wildlife/tourism efforts. The "greenness" index, NDVI, turned out to be a strong predictor of poverty in this district. NDVI has been determined to be a good predictor of forage abundance (Thoma et al., 2002). This finding suggests that more interdisciplinary work is needed towards better understanding the usefulness of such satellite-derived indicators for policy makers and for examining poverty-environment linkages if we want to provide high-value information to local and national policy makers. For example, more in-depth information is now being gathered on soils throughout the district that will allow us to examine in more detail the significance of the finding that NDVI is strongly and positively correlated with poverty.

Our findings are consistent with development priorities recently outlined by the Poverty Task Force for the Millenium Development Goals (see http://www.earthinstitute.columbia.edu/tropag/policy/hunger_task_force.html). For example, Jeffrey Sachs argues in a recent Economist article that investments are badly needed in roads, security and soil fertility (Sachs, 2004). Sachs also points out ample evidence of underinvestment in education and health and the important role they play in helping alleviate poverty in countries such as Kenya. Discussion of our findings with stakeholders suggest that there are probably better measures that capture quality as well as access to education (e.g. teacher:student ratio per sublocation; private, public distinction) and health (doctor:patient ratio, availability of medicine) than the purely distance-defined indicators used in this analysis. The complexities of some of these issues[4] point to some of the limitations of this approach, and the need for linking qualitative and quantitative, as well as micro-, meso- and macro-level, research approaches for improved pro-poor policy and intervention targeting.

Our results also highlight the important role livestock continue to play as a livelihood option that can lead to lower poverty levels. So investment in improved livestock management, health and marketing strategies are pro-poor areas where research and development efforts can be targeted.

We found that a real strength of this approach was that the livelihood framework resulted quite intuitive to local decision makers, and various Ministry officials, NGOs, other researchers, etc. received the maps enthusiastically. Local policy makers and others are already using some of the information to inform decisions. For example, district water officials are using the water access maps to target new interventions, and technical government officers from other districts are asking for training in the participatory land-use mapping approach that we used in this study. The bottom line is that most people absorb and interpret maps (particularly of familiar areas) relatively easily. They help amplify messages to higher-level policy makers (e.g. that the semi-arid districts of Kenya have extremely little infrastructure relative to other areas of the country). Lessons learned from this study will help better select particular indicators in future applications of this approach to other regions and will provide important baseline information for policy makers and planners in Kajiado District as they monitor progress towards poverty reduction goals. At the national level, these results are feeding into the food information and vulnerability information management system (FIVIMS), which has both a technical committee made up of the numerous organizations and researchers involved in food security, and a policy committee.

It would be easy to say that policy makers are using the results of this type of study because of workshops held, reports delivered, etc. but the reality is that it is only through involving decision makers at various levels throughout the process of research/information generation that people in positions of power will absorb and ultimately use such information (since they have helped define what is "useful"). We undertook this initiative in this light, and stakeholders learned throughout the process. These processes take time. The jury is still out as to whether (and what) policies will change due to improved information such as that generated by this project. But by taking an approach that built strong partnerships with multiple stakeholders, we will be able to monitor the policy changes and ultimate impacts over the next 5 to 10 years.

While our analysis shows that mapping livelihood assets can help us in better understanding spatial patterns of poverty, evidence is ample that household-level factors (size of household, education of household head, etc.) are also critical factors influencing household welfare. There is little empirical evidence, however, showing the relative influence of community versus household-level factors. Thus we will be building upon this study with follow-up research looking at household-level factors influencing relative poverty levels, spatial (e.g. distance from household to nearest market) and otherwise, within Kajiado District. This will provide additional insights into pro-poor investment and policy priorities.

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[1] Particularly useful data sources included the International Livestock Research Institute GIS database, Africover, Kenya Wildlife Service, Ministry of Land Reclamation, Regional and Water Development, the Department of Remote Sensing and Resources Survey and the Central Bureau of Statistics.

[2] We also tried a principal components approach to come up with indices of each asset category but since we only had one measure for some of the asset categories (financial, social) this was not successful.

[3] This was supported by running the regression with sublocation poverty rate as the dependent variable with all 14 explanatory in Stata and generating a spatial weights matrix to define the "neighbourhood" for each sublocation (using the *spatwmat* module in Stata). We tested spatial autocorrelation for using the Moran's I test, which showed lack of significant *p*-values for both spatial lag and spatial error types of potential autocorrelation problems.

[4] For example, how much time is required to see poverty impacts of investments in education or livestock health; what are the potential poverty impacts at the household, community and national levels of particular interventions.

Figure Legends

Fig. 1. Sublocation-level poverty incidence across Kajiado District, Kenya: percentage of population falling below the rural poverty line

Fig. 2. Livelihood asset maps showing one measure of each of the five types of capital: (A) human, (B) financial, (C) natural, (D) physical and (E) social

Fig. 3. Relative normalized difference vegetation index (NDVI) levels for (A) poor versus (B) less poor areas of Kajiado District, Kenya

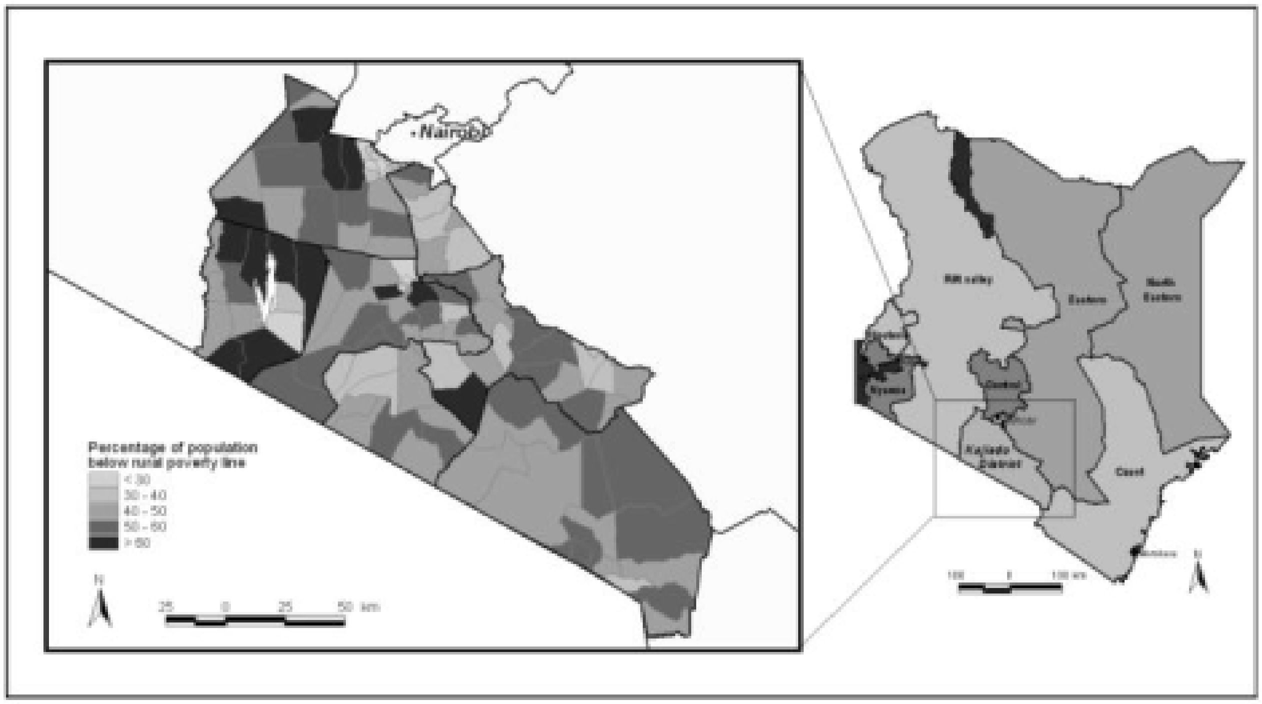
Nairobi
Percentage of population below rural poverty line
< 30
30 - 40
40 - 50
50 - 60
> 60
N
25 0 25 50 km
Rift valley
Eastern
North Eastern
Central
Nyanza
Kajiado District
Coast
100 0 100 km
N

Fig. 1

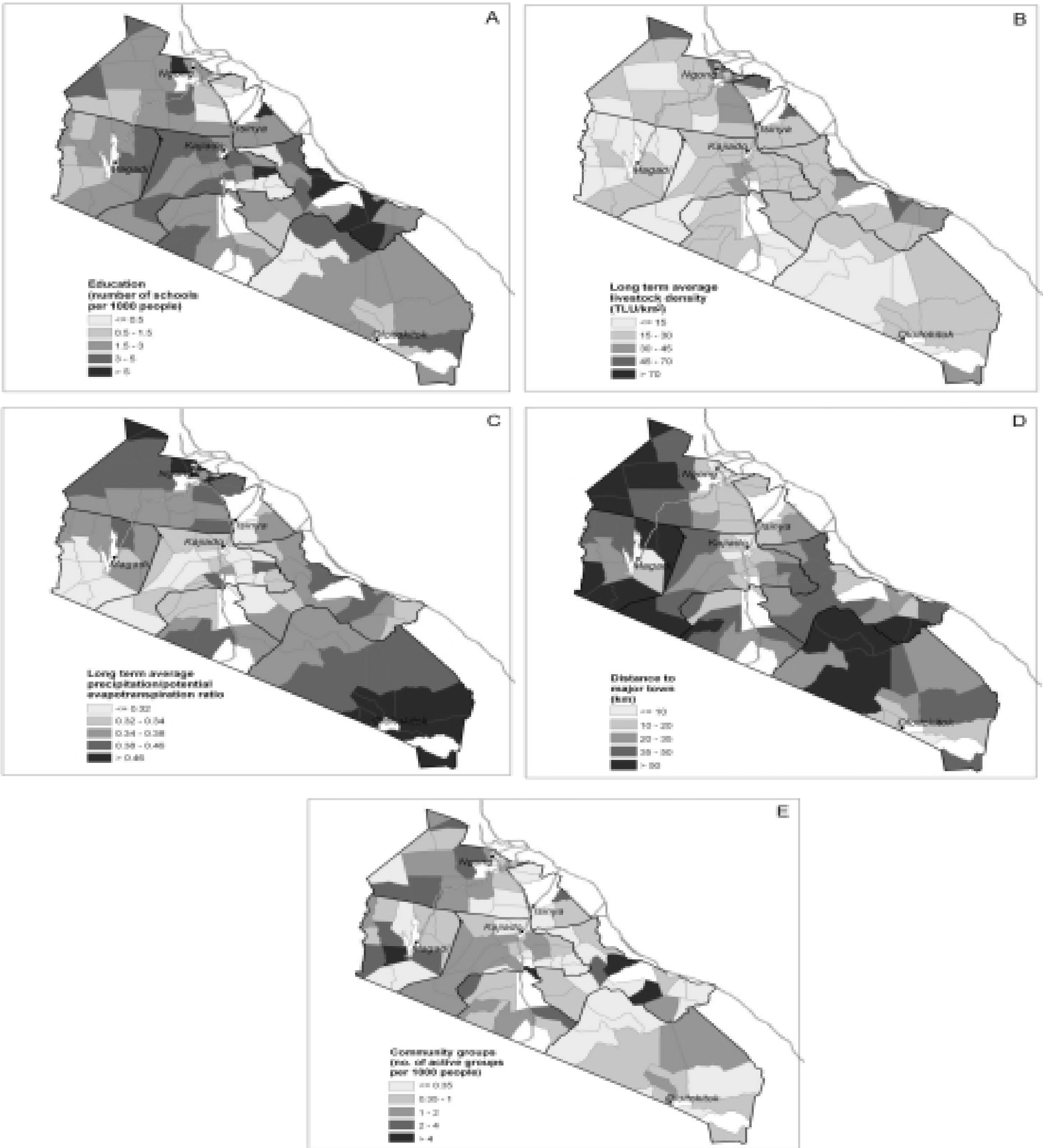
A
Education (number of schools per 1000 people)
B
Long term average livestock density (TLU/km²)
C
Long term average precipitation/potential evapotranspiration ratio
D
Distance to major town (km)
E
Community groups (no. of active groups per 1000 people)

Fig. 2

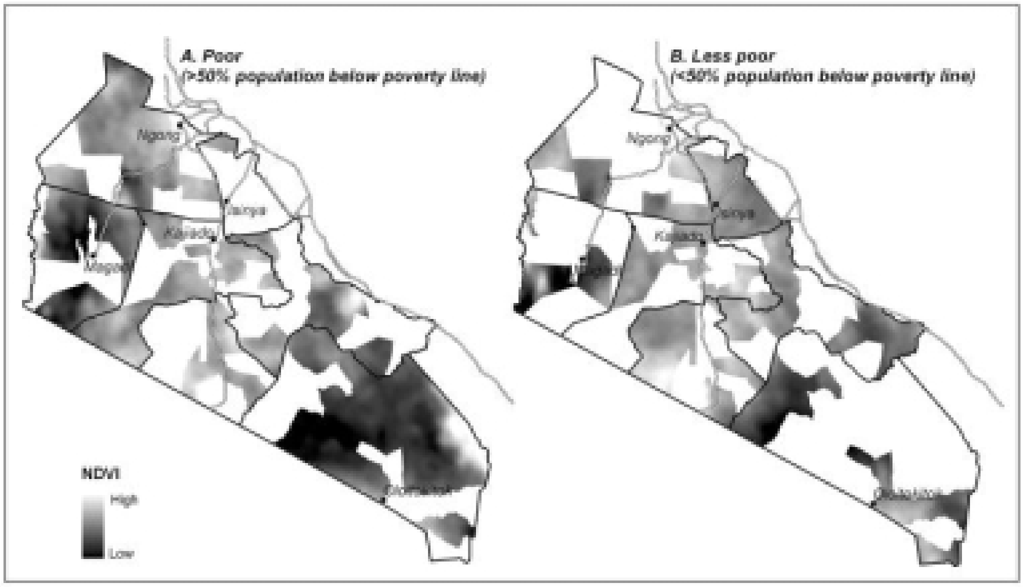
A. Poor
(>50% population below poverty line)
B. Less poor
(<50% population below poverty line)
Ngong
Isinya
Kajiado
NDVI
High
Low

Fig. 3

Table 1
Livelihood asset factors that may affect poverty rate, with examples from the literature

Variables	Expected relationship to poverty
Natural capital[a]	
Rainfall (precipitation/potential evapotranspiration)	Higher rainfall → lower poverty
Wildlife density	Higher wildlife density → lower poverty (if communities receiving benefits from wildlife tourism)
Soil fertility	Higher soil fertility → lower poverty
Access to water	Better access to water → lower poverty
Vegetation cover	More vegetative cover → lower poverty
Likelihood of having tick and tick-borne disease problems	Lower likelihood → lower poverty
Financial capital[b]	
Livestock density	Higher livestock density → lower poverty
Physical capital[c]	
Road density	Higher road density → lower poverty
Distance to nearest major town	Less distance → lower poverty
Distance to Nairobi	Less distance → lower poverty
Human capital[d]	
Access to education	Better access → lower poverty
Access to health services/facilities	Better access → lower poverty
Access to security	Better access → lower poverty
Social capital[e]	
Density of active community groups	More groups → lower poverty

[a] Minot and Baulch, 2002, Place et al., 2002, Minot et al., 2003.
[b] Bebbington, 1999.
[c] Grootaert et al., 1995, Pender et al., 1999, Staal et al., 2002.
[d] Feder et al., 1985, Handa and Simler, 2004, Benson et al., 2005.
[e] Putnam et al., 1993, Fukuyama, 1995, Putnam, 1995, 1996 (as cited in Krishha, 2002), Narayan and Pritchett, 1997, Krishna, 2002, Winkel and Adger, 2002.

Table 2
Sublocation level analysis: description of independent/explanatory variables (n = 105)

Type of capital	Description[a]	Mean	SD
Natural			
Precipitation/potential evapotranspiration (P/PE)	An index combining avg. rainfall, altitude and sun radiation and a likely indicator of agricultural potential or available rainwater. Long-term avg. calculated for each sublocation.	0.394	0.102
Wildlife density	Wildlife density calculations based on aerial animal counts by DRSRS during wet seasons in 1977-78, 1980-82, 1986, 1990-92, 1994, 1998 and 2000. Wildlife includes eland, elephant, giraffe, Grant's gazelle, greater kudu, gerenuk, impala, kongoni, lesser kudu, ostrich, oryx, rhino, Thomson's gazelle, waterbuck, warthog, wildebeest and zebra. Total no. of animals converted to an avg. annual TLU per km^2.	4.33	4.06
Soil fertility index	Percentage of area with highly suitable soil types for agriculture calculated for each sublocation.	52.38	31.50
Access to water[b]	Percentage of area within 1-hr walking distance of a permanent water source (borehole, tank, well, spring, pan, dam, rain catchment or permanent river).	8.36	8.36
Normalized Differential Vegetation Index (NDVI)	An indicator of presence and condition of green vegetation (grazing/pasture potential). In areas where livelihoods depend so much on livestock, potential for pasture is extremely important. 2002 average NDVI (avg. year for precipitation) used.	0.614	0.045
Likelihood of having tick and tick-borne disease problems	Probability of finding ticks is between 0.25 and 0.75 (range where tick-related problems most likely to occur; <0.25 probability of finding ticks is very low; >0.75 and cattle are likely to build resistance). Percentage of area within the sublocation calculated that is within 0.25-0.75 range.	38.69	28.69
Financial			
Livestock density	TLU/km^2 used to measure livestock density. Avg. livestock density calculated for each sublocation.	26.51	19.31
Road density	A measure of accessibility/availability of road infrastructure within a sublocation. Calculated as total km of all kinds of road per km^2 of each sublocation.	152.22	145.61
Distance to nearest major town	Distance from shopping centre in each sublocation to nearest major town by road (km).	30.71	19.20
Distance to Nairobi	Distance from shopping centre in each sublocation to Nairobi by road (km).	117.69	57.75
Human			
Access to education	Access to education facilities (primary, secondary schools and training centres) defined as no. of facilities per 1000 people within each sublocation.	2.59	1.95
Access to health services/facilities	Defined as no. of health facilities in sublocation per 1000 people.	0.340	0.444
Access to security	Percentage of area within 1-hr walking distance of a chief's office or a police post.	29.71	33.11
Social			
Density of active community groups	No. of active community groups per 1000 people for each sublocation.	1.11	1.51

[a] DRSRS, Department of Remote Sensing and Resources Survey; TLU, Tropical Livestock Unit.
[b]Since some water points are man made, this variable is a combination of natural and physical capital.

Table 3
Model selection statistics for the three best models[a] constituting the 95% confidence set on models

Model	QAICc	-2ll	Change in QAICc (Δ_i)	Akaike weight (w_i)	No. predictors
Best	36.6	19.1	0	0.59	6
Second best	38.1	18.2	1.5	0.28	7
Third best	40.5	18.2	3.9	0.08	8
Total				0.96	

[a] QAICc, quasi-likelihood corrected Akaike information criteria; -2ll, minus two times the maximized likelihood; Akaike weight is a measure of the relative likelihood of each model contained within a set of candidates.

Table 4

Estimates of regression coefficients of the best model overall and *t* tests of the null hypothesis that the estimates equal zero

Variables	Estimate	SE	T	P│T│e
Intercept	0.004	0.348	0.011	0.992
Normalised Differential Vegetation Index	-0.996	0.566	-1.759	0.082
Livestock density	-0.006	0.001	-4.609	0.000
Distance to a major town	0.002	0.001	1.292	0.199
Road density	-0.0006	0.0002	-3.009	0.003
Access to education facilities	0.035	0.015	2.281	0.025
Access to security	-0.002	0.0009	-2.646	0.009

Table 5.
Model-averaged parameter estimates.

Variables[a]	Mean	SD	Estimate	SE	Exponent of the estimate	Base change	PCPI[b]
Intercept			0.014	0.349	1.014		
NDVI	0.61	0.05	-0.978	0.569	0.376	0.1	-6.24
Livestock density	26	19	-0.006	0.001	0.994	10	-6.34
Distance to a major town	31	19	0.002	0.001	1.002	10	1.89
Road density (total km of all kinds of road per km^2)	152	146	-0.0006	0.000	0.999	100	-6.40
Access to education facilities (no. of facilities per 1000 people)	2.6	2	0.034	0.016	1.035	1	3.50
Access to security (and of area within 1 hr walking distance to a chief's office or police post)	30	33	-0.002	0.001	0.998	10	-2.36
P/PE ratio[b]	39	0.1	-0.048	0.097	0.952	0.1	-0.475
Soil suitability for agric. (% area with highly suitable soil types)	52	31	-0.000	0.000	0.999	10	-0.01

[a] NDVI, Normalised Differential Vegetation Index; P/PE, precipitation/potential evapotranspiration.
[b] Percentage change in poverty incidence corresponding to the base change from the mean for each predictor variable.