SAGA-Bridging Qualitative and Quantitative Methods of Poverty Analysis

Poverty Mapping

The Case of Kenya

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1.0 Introduction

Kenya like many other developing countries is currently refocusing its development policies towards poverty reduction. The emphasis on poverty reduction is primarily a response to the fact that, despite many efforts to improve the well being of the poor in the past, the majority of the people still live in poverty. Hence, finding ways to reduce poverty and inequality in Kenya is a huge challenge facing both local and national policy decision makers. Poverty is a multi-faceted problem and its levels tend to vary considerably over space. Thus, providing information on the spatial heterogeneity of poverty can greatly assist anyone trying to tackle the challenge of identifying who the poor are? Where they live? And what causes their poverty?

A principal development objective of the Government of Kenya currently is to generate a desired pattern of overall and broad based income growth with special emphasis on accelerating the growth of incomes of target poor groups. However, policies intended to help the poor cannot succeed unless the Government together with other stakeholders know where the poor are and how they are likely to respond to different growth strategies.

The poverty mapping work recently launched is the first in a series that are aimed at showing the spatial distribution of the poor in Kenya at various administrative levels namely the national, regional, district, division, location and constituency. Prior to this research, poverty estimates in Kenya were only known at the national, provincial and district level. These earlier survey poverty estimates assumed and treated sub district administrative areas as homogeneous. But generally, Districts in a province are not necessarily homogeneous and similarly within districts, divisions and locations could be very much different. Such aggregated level poverty estimates conceal significant variations in poverty at the lower administrative levels.

2.0 Rationale for poverty mapping

The plight of the poor has brought the issue of poverty to the fore in almost all socio economic and political debates in the world today. The initial and early thinking by development planners was that fruits of economic growth would trickle down to the poor but this has instead resulted to persistent and deepening level of poverty. During the early 70s and up to mid 1990s, the so-called poverty and social services programs in Kenya often missed the poor partly because of the lack of a well-constructed poverty profile.

Measures to improve the quality of life by reducing poverty are therefore receiving greater attention than ever before the world over. This is demonstrated by the recent adoption of renewed poverty reduction strategies under the PRS process. The Poverty Reduction Strategy

process presents a range of challenges, ranging from facilitating and managing effective participation, to identifying policies for pro-poor growth and establishing adequate systems for public expenditure management. The PRS processes are being built on existing national strategies, with serious attention being paid to broadening participation and sharpening poverty diagnosis and monitoring.

Before the research on poverty mapping in Kenya, poverty estimates were available only at the district level. This is because detailed data samples collected through the Welfare Monitoring Survey series were not representative at the sub-district level. This problem has partly been circumvented by applying a statistical approach that enables combination of detailed welfare information from the WMSIII with the complete geographical data coverage provided by the 1999 population and housing census.

3.0 Background of the approach

The poverty mapping research summarized in this paper is a result of a broader collaborative research effort between CBS[1], ILRI[2], and The World Bank under a broader research project started in 2001 to produce high-resolution poverty maps for Kenya, Uganda and Tanzania. The underlying methodological approach was developed at the Development Research Group, Poverty Unit (DECRG-PO) of The World Bank.

The spatial distribution of poverty remains one of the oldest of puzzles and yet one of the most contemporary issues. The incidence of poverty in an area could be attributed by a variety of life style and environmental factors, including where people live. Characteristics of these locations (including socio-demographic and environmental exposure) offer a valuable source for poverty research studies such as the determinants of poverty. Welfare and poverty always have a spatial dimension.

Traditional survey methods, which are generally costly and time-consuming, usually provide information at the regional or national level only. The utilization of small area estimate techniques developed for poverty mapping makes it possible to use small sample surveys and census population data to estimate poverty rates for small geographical areas such as division, location and sub-location. This paper attempts to present some of the results of poverty mapping focusing more on the methodology used.

The results show that there is considerable heterogeneity in poverty levels between districts in the same province, divisions in the same district, and locations in the same division. The results also pinpoint certain areas where the poor are mainly concentrated. While the results do not explain why particular areas are poorer than others, such detailed information can be linked with other socioeconomic and geographic information to make it more useful in targeting the poor. Poverty maps make it easier to integrate data from various sources such as surveys, censuses, and satellites and from different disciplines such as social, economic, environmental data. Researchers can therefore use poverty maps to investigate the relationship between

[1] CBS- Central Bureau of Statistics

[2] ILRI- International Livestock Research Institute

growth and distribution within broad areas such as the province or district. Thus, identifying spatial patterns of poverty using maps provides new insights into the causes of poverty, for example how much are physical isolation and poor agro-ecological endowments impediments to escape poverty. This in turn can affect the type of interventions to consider.

The allocation of resources can be improved using poverty maps. Poverty maps can assist in where and how to target antipoverty programs. Geographic targeting, as opposed to across the board subsidies, has been shown to be effective at maximizing the coverage of the poor while minimizing leakage to the non-poor. Research examining narrow geographic targeting at the community level can assist in the implementation of antipoverty programs, for example by promoting subsidies in poor communities and cost recovery in less poor areas.

The Bureau expects other institutions to use poverty maps to strengthen the design of poverty interventions in the country. Detailed information on the spatial distribution of the poor will greatly assist policy makers, implementers and development partners to design specific social and geographic based pro poor policies and programs. It is expected that with increasing attention being given to poverty targeting below the district level under the ERS/PRS process, the utilization of detailed poverty maps will provide development planners both in the Government (central and local), private sector NGOs and civil society with a powerful tool to help them achieve their targeting objectives.

4.0 Summary of Major Highlights

The poverty maps themselves provide information rather than answers. Below are some of the major highlights from the **Volume I:**

Pockets of high poverty incidence—that is, relatively small areas with a very high proportion of the population falling below the poverty line—are not concentrated in any one region of Kenya. There are 34 Districts in Kenya that have at least one Location with more than 70% of the population living below the poverty line and a total of 248 Locations (12% of the total number of Locations captured in this analysis) demonstrating this unenviable statistic.

Poverty density 'hotspots'—relatively small areas with very high numbers of poor people—also occur in many areas of Kenya: 60% of the rural poor are found in 35% of the 422 Division and in 31% of the 2,070 Locations included in this analysis.

In Kenya's least-poor areas, the poverty gap is typically around 5% of the poverty line; in the poorest areas, poverty gaps reach 50% .

Central Province, with roughly one million poor people, ranks as the least poor Province, with most Locations having a poverty incidence of less than 40%. One District, Thika, accounts for 43% of the urban poor in Central Province; a second, Nyeri, accounts for another 21%.

Nairobi has 880,000 people living below the poverty line. Poverty rates range from 32% in Westlands to 59% in Makadara across Divisions, and perhaps not surprisingly from 8% in Nairobi West to 77% in Makongeni across Locations. Add more for Nairobi.

Coast Province has a rural poor population of roughly 909,000 people. Two-thirds of the rural poor are found in two districts—Kilifi and Kwale. In the impoverished District of Kilifi, there is a high depth as well as incidence of poverty: three-quarters of the population falls below the poverty line in 24 out of 34 Locations and the Location-level poverty gap ranges from 27 to 44%.

Of the 2.5 million rural poor in Eastern Province, 64% (1.6 million people) live in four Districts: Kitui, Machakos, Makueni and Meru North. Eastern Province has 13 districts.

With a rural poor population of 2.4 million, Nyanza Province has very high poverty rates across most Divisions and Locations. Poverty gaps are also very high here. South Asembo Location in Bondo District, for example, has a poverty gap of 34%, meaning that the average adult below the poverty line would require an additional Kshs.421 per month to get out of poverty.

Rift Valley has the largest population of Kenya's seven provinces. The estimated number of rural poor from this analysis is 2.7 million, plus 450,000 urban poor. Several of the Rift Valley's 18 Districts, with relatively low poverty according to District-level welfare estimates, demonstrate huge spatial variability. Magadi Division is the poorest in Kajiado District, with 57% of the population living in poverty. But even within Ngong Division, its nine Locations have rural poverty rates ranging from 11 to 64%.

Western Province, with an estimated 1.8 million poor people, is fairly uniformly and deeply poor. There are no Divisions or Locations with poverty incidence point estimates of less than 60% and poverty gaps are uniformly high, typically over 35%.

5.0 Overview of the Methodology

The main idea behind the methodology is to apply a regression analysis technique to data from the 1997 Welfare Monitoring to obtain parameter estimates related to household expenditures and associated explanatory variables such as a number of socio-economic variables like household size, education levels, housing characteristics, and access to basic services. While the census does not contain all household expenditure data, it does contain these socio-economic variables. Therefore, we can statistically infer census household expenditures by applying the WMSIII based estimated relationship together with comparable socio-economic variables from the 1999 population census. This in turn allows for estimation of poverty statistics at the sub-district level(s) such as administrative divisions and locations. For details of the methodology refer CBS report[3].

The poverty mapping analysis is based upon a statistical technique[4], sometimes referred to as small area estimation, that combines household welfare survey and census data (both collected at approximately the same time) to estimate welfare or other indicators for disaggregated geographic units such as communities. This method is elaborated fully in Hentschel et al. (2000) and Elbers et al. (2002), and is briefly summarized here.

The first step of the analysis involves estimating a regression model of log per capita expenditure using the survey data, employing a set of explanatory variables which are common to both the survey (i.e. WMS III) and the census. Next, parameter estimates from that regression are used to predict log per capita expenditure for every household in the census.

[3] Geographic Dimensions of well-being in Kenya Volume1 Where are the Poor: From Districts to Locations-2003 –Republic of Kenya

[4] Hentschel, J. and P. Lanjouw,, "Combining Census and Survey Data to Study Spatial Dimensions of Poverty and Inequality", World Bank Economic Review.

Finally, "welfare indicators" are constructed for geographically defined subgroups of the population using these predictions.[5]

The approach is simplified by breaking it down into three stages. The first stage analysis deals with the survey data and the second stage analysis concerns the census data. In addition, there is a "zero stage" associated with defining and selecting the set of comparable variables common to both survey and census before the 'real' analysis can begin.

5.1 Zero Stage

In the zero stage, variables within the census and welfare monitoring surveys are examined in great detail. The objective of this stage is to determine whether the variables are statistically similarly distributed over households in the population census and in the household sample survey. For example, there are questions in both the population census and in the WM survey about household size, level of education of the household head, and type of housing. However, the exact questions and manner in which the answers are recorded differ in some cases - e.g. the exact number of years of schooling for the household head may be asked and recorded in the survey, while whether they have an education at a primary, secondary, or higher level is what is recorded in the census. In many cases, there are also discrepancies between identically defined variables due to regional variation in interpretation, rendering certain variables comparable in some provinces and not in others (specific examples are given in Box 1.1).

Box1: Variables created from questions regarding source of water and sanitation

Category	**Survey Question**	**Census Question**	**Comparable variable**
Water Questions	A. What is the main source of drinking water During the DRY season? B. What is the main source of drinking water During the RAINY season (The two had the same options)	Main Source of Water	Five new variables based on source of water were constructed
Response Categories	1.Piped into dwelling or compound 2.Public outdoor tap or borehole 3.Protected well, rain water 4.Unprotected well, rainwater 5.River, lake, pond 6.Vendor, truck 7.Other **From Survey** wtriv=(5) wtwel=(3, 4) wtbor=(2) wtpip=(1) wtgod=(1, 2)	1.Pond 2.Dam 3.Lake 4.Stream/river 5.Spring 6.Well 7.Borehole 8.Piped 9. Jabias/tanks 10.Other **From Census** wtriv=(1, 2, 3, 4) wtwel=(5, 6) wtbor=(7) wtpip=(8) wtgod=(7, 8)	wtriv wtwel wtbor wtpip wtgod

For example, during the 1997 WMSIII, respondents were asked to state their main source of water during the DRY and the RAINY season, while in the 1999 census respondents were asked what their dominant source of water was (Box 1.1). The first challenge in constructing comparable water source variables thus arose from the different ways in which the question

[5] We use the term "welfare indicator" to refer to any function of the distribution of expenditure.

was asked. The survey had two questions on water while census had only one. It was necessary to establish which of the two survey questions (RAINY or DRY) was more comparable to the census question. The census was conducted in the month of August, when many parts of the country are dry, while the survey was undertaken from March-July, a time when large parts of the country are generally wet. It was then established that the DRY season prevailed for the longest time in a year in majority of the regions. Thus the survey question on source of water during the dry season was then equated to the census question on main source of water because for the majority of the year, many parts of Kenya experience dry weather conditions[6].

The second challenge in designing comparable variables in this example arose due to the lack of similarity in the design of the pre-coded response categories in the survey and census questionnaires. The response categories were differently coded as shown in Box 1.1. A close look at the response categories in the survey indicated that public outdoor tap water and borehole water together formed one response category, implying that borehole water in the survey could not be compared with that of the census. Further, the category of water from the well in census could not be properly matched with that of water well in the survey because in the survey, well water is represented by two categories (protected and unprotected well plus rainwater). However, five water-related variables were created as shown in Box 1.

The set of common variables was initially identified by systematically comparing the questionnaires (and using the interviewer manuals) of the census and survey. Four main qualitative criteria were used: (a) are the questions and answers identically worded? (b) Are the criteria pertaining to the questions and answers identical (e.g. employment questions are asked of people 10 years and older in both data sets)? (c) Are the answer options identical? (d) Are the interviewer instructions pertaining to the questions identical? In some cases, common variables were constructed by combining information from several questions. In those cases, the criteria were critical towards determining how the variables could be constructed.

The next step was to investigate whether these common variables were statistically similarly distributed over households in the population and those sampled by the survey. This assessment was based on the following statistics for each variable obtained from both the survey and the census for each stratum: (i) the mean, (ii) the standard error. First, the census mean for a particular variable was tested to see if it lay within the 95% confidence interval around the household survey mean for the same variable. Second, for dummy variables, means were checked to ensure they were not smaller than 3% and not larger than 97%, so that the variables constructed contain some variation across households.[7]

5.2 Harmonizing Sampling frame differences

The 1997 Welfare Monitoring Survey was designed to be representative at the District Level. The 1997 WMSIII survey was based on a frame that was designed using the 1989 census. As of 1999, more Districts had been created and the clusters used in the survey in 1997 no longer belonged to the same districts, divisions or locations. This problem was compounded by the fact that the 1997 survey had no identifiers at the division, location and sub location level. Thus an effort was made by the research team to rematch the clusters by identifying their

[6] Obviously this is not as true for areas such as the Coastal belt and the Lake Region and a few highland areas where the DRY season might not exactly correspond to the non-long rainy season.

[7] Such variables generate observations with high leverage in the first stage regressions, such as being the only household sampled in a stratum to have access to electricity.

current districts, divisions, locations and sub-locations. In addition, the WMS survey had only collected data by rural or urban strata, while the census had two additional more categories, i.e. peri-urban and forests or national parks. A comparison of the census means indicated that the peri-urban areas were much more like rural areas than urban, and thus they were merged with rural areas in the analysis.

5.3 First Stage

The first stage estimation involves modeling per capita household expenditure at the lowest geographic level for which the survey is representative. In Kenya, this is at the District level, broken down into urban and rural sectors. But due to small sample sizes at the district level models were run only at the provincial level. The first stage begins with an association model of per capita household expenditure for a household *h* in location *c*, where the explanatory variables are a set of observable characteristics:

$$(1) \qquad \ln y_{ch} = E[\ln y_{ch} | \mathbf{x}_{ch}] + u_{ch} .$$

The locations correspond to the survey clusters as they are defined in a typical two-stage sampling scheme. These observable characteristics must be found as variables in both the survey and the census or in a tertiary data source that can be linked to both data sets.[8]

Using a linear approximation to the conditional expectation, we model the household's logarithmic per capita expenditure as

$$(2) \qquad \ln y_{ch} = \boldsymbol{x}'_{ch}\boldsymbol{\beta} + u_{ch} .$$

The vector of disturbances, $\boldsymbol{u}$, is distributed F (0,$\boldsymbol{\Sigma}$). The model in (2) is estimated by Generalized Least Squares using the household survey data. In order to estimate the GLS model, we first produce an estimate of $\boldsymbol{\Sigma}$, the associated error variance-covariance matrix. We model individual disturbances as

$$(3) \qquad u_{ch} = \eta_c + \varepsilon_{ch} ,$$

where η_c is a location component and ε_{ch} is a household component. This error structure allows for both spatial autocorrelation, i.e. a "location effect" for households in the same area, and heteroskedasticity in the household component of the disturbance. The two components are independent of one another and uncorrelated with observable characteristics.

In order to estimate $\boldsymbol{\Sigma}$, we proceed as follows. The model in (2) is first estimated by simple OLS, weighted with the survey sampling weights. The residuals from this regression serve as estimates of overall disturbances, given by $\hat{u}_{ch}$. We decompose these into uncorrelated household and location components:

$$(4) \qquad \hat{u}_{ch} = \hat{\eta}_c + e_{ch} .$$

[8] The explanatory variables are observed values and thus need to have the same definitions and the same degree of accuracy across data sources. Note that these variables need not be exogenous.

The estimated location components, given by $\hat{\eta}_c$, are the within-cluster means of the overall residuals. The household component estimates, e_{ch}, are the overall residuals net of location components.

We allow for heteroskedasticity in the household component, modeling e_{ch}^2 using a selection of variables that best explain its variation. We choose variables, $\mathbf{z}ch$, that best explain variation in e_{ch}^2 out of all potential explanatory variables, their squares, and interactions.

For the main regression, given by equation (2), a stepwise regression procedure in SAS was used to select a subset of variables from the set of "comparable" variables, which provided the best explanatory power for log per capita expenditure. All household survey variables that were significant at the 5% level were selected for the regression. The details will be contained in a forthcoming technical working paper documenting the actual details and procedures[9].

The regression models for the urban areas are more successful in explaining the variation in household expenditures than those for the rural areas. The adjusted R2 ranges from .32 to .49 urban areas and .31 to .49 in rural areas. The explanatory power is highest in Nairobi[10]. Only Coast Province had over .40 R^2, the rest of the rural areas had an R^2 of less than .36.

In general, household size, education of household members, sex and the marital status of the household head, and some variables concerning housing characteristics (such as floor and wall materials) and access to services (such as principal source of energy and water) are key variables chosen in most regressions. We note that, on average, household size and head of household being female have a negative correlation with per capita household expenditure. Education has positive association with household expenditures. Walls of brick and cement floors in main rooms, cooking with electricity, roof of iron and connection to main sewer are associated with increased expenditures in urban areas. Lighting with kerosene, cooking with wood, using well water has a negative association with expenditures. There are also few parameter estimates, the signs of which depend on region or whether the model is for rural or urban areas. For example, in urban roofing with iron is negatively associated with expenditures in some regions and positive in others. We remind the readers here that our regressions are association models, and hence the parameter estimates of the independent variables cannot be interpreted as causal effects.

5.5 Second Stage

The second stage has been automated using estimates produced in stage zero and one. In the second stage analysis we combine the estimated first stage parameters with the observable characteristics of each household in the census to generate predicted log expenditures and simulated disturbances. We conduct a series of simulations, where for each simulation *r* we draw a set of first stage parameters from their corresponding distributions estimated in the first stage. We simulate a value of expenditure for each household, $\hat{y}_{ch}^r$, based on both predicted log expenditure, $\boldsymbol{x}'_{ch}\tilde{\boldsymbol{\beta}}^r$, and the disturbance terms:

$$\hat{y}_{ch}^r = \exp\left(\boldsymbol{x}'_{ch}\tilde{\boldsymbol{\beta}}^r + \tilde{\eta}_c^r + \tilde{\varepsilon}_{ch}^r\right). \tag{7}$$

[9] Poverty Mapping in Kenya Technical Paper (CBS/World Bank forthcoming)

[10] In comparison, the adjusted R2 ranges from 0.27 to 0.55 in Mozambique, 0.45 to 0.77 in Ecuador, and from 0.445 to 0.638 in urban areas and 0.239 to 0.460 in rural areas in Madagascar (Mistiaen et al., 2002).

Finally, the full set of simulated per capita expenditures, $\hat{y}_{ch}^{r}$, are used to calculate estimates of the welfare measures for each spatial subgroup.

We repeat this procedure 100 times drawing a new $\tilde{\boldsymbol{\alpha}}^{r}$, $\tilde{\boldsymbol{\beta}}^{r}$, $(\tilde{\sigma}_{\eta}^{2})^{r}$ and disturbance terms for each simulation. For each subgroup, we take the mean and standard deviation of each welfare measure over all 100 simulations. For any given location, these means constitute our point estimates of the welfare measure, while the standard deviations are the standard errors of these estimates.

There are two principal sources of error in the welfare measure estimates produced by this method.[11] The first component, referred to as *model error* in Elbers et al (2002), is due to the fact that the parameters from the first-stage model in equation (2) are estimated. The second component, termed *idiosyncratic error*, is associated with the disturbance term in the same model, which implies that households' actual expenditures deviate from their expected values. While population size in a location does not affect the model error, the idiosyncratic error increases as the number of households in a target subgroup decreases.

6.0 Conclusion and Way Forward

The poverty mapping estimates and their corresponding poverty maps do not explain why particular areas are much poorer than others or even what might be done about it. This information can however be linked with other information to make it much more useful and powerful for addressing critical issues of targeting facing policy makers and planners. Combining location-level poverty estimates with more in-depth household and community-level data opens up opportunities for examining the relative contribution of spatial/community level factors (such as market access or agricultural potential) to relative poverty levels compared to household –level factors such as level of education or household size. Such an analysis can lead to much more specific, targeted poverty policies and ideas towards new community level approaches for tackling the root causes of poverty and ultimately for designing and implementing pro-poor development strategies that are both effective and inclusive.

The CBS is currently working on a Volume II. The volume will attempt to present some of the results already produced in volume one this time by Constituencies. There will be in addition some socio economic profiles by Constituency using all other variables included in the population and housing census data. Our hope is that the emerging results will stimulate and ignite the debates on why poor people are found where they are and also provide the foundation for more detailed analyses.

No doubt the information on the spatial distribution of living standards provided by these poverty maps is crucial to both Kenyan policymakers and researchers. "Poverty mapping – the spatial representation and analysis of indicators of human well-being and poverty – is becoming an increasingly important instrument for investigating and discussing social, economic and environmental problems in many countries of the world" (Henninger and Snel,

[11] A third potential source of error is associated with computation methods. Elbers *et al.* (2002) found this component to be negligible.

2002). The Henninger and Snel review of the uses and impacts of poverty maps in other parts of the world concludes that:

- Poverty maps have become important tools in **implementing poverty reduction programs**, including international efforts (such as the World Bank-initiated poverty reduction strategies for Highly Indebted Poor Countries) as well as purely national initiatives. One such example comes from Nicaragua, whose poverty reduction strategy relies heavily on poverty maps to allocate US$1.1 billion in capital spending over five years.

- Poverty maps help **improve targeting of public expenditures** by identifying where the neediest populations are located. For instance, in Guatemala, poverty mapping is being used to restructure the National Public Investment System to improve geographic targeting of hundreds of millions of dollars (US$576 million in FY 2002) of annual expenditure.

- **Emergency response and food aid programs** are beginning to make use of newer, more data-intensive mapping methods. In South Africa, information from a poverty mapping initiative was combined with data on sanitation and safe water supplies to create a geo-referenced strategy for containing a cholera outbreak in KwaZulu Natal province in early 2001. Implementation of this strategy effectively contained the disease in three months, with one of the lowest fatality rates (0.22%) ever recorded. Cambodian poverty maps are being used to identify the poorest communities for distribution of US$50 million in World Food Program food aid, especially "food for work" interventions.

- In several countries, high-resolution poverty maps are contributing to **state- and local-level decision-making**. Brazil's largest state, Minas Gerais, is using poverty maps to redistribute statewide tax revenues totaling US$1 billion annually toward poorer municipalities that are making an effort to invest in health, education, sanitation, and environmental conservation.

- In the cases studied, the production and distribution of poverty maps resulted in **increased transparency of public decision-making**, by raising awareness of poverty, igniting policy debates at local and national levels, and encouraging broader civil society participation in decision-making. One such instance was reported from Panama, where officials of the Social Investment Fund indicated that the use of poverty maps in decision-making helped them resist pressure from politicians to alter funding allocations once they had been made (Henninger and Snel, 2002).

High resolution poverty maps also provide important tools for researchers interested in poverty, allowing them to investigate the relationship between growth and distribution inside a country and the spatial factors behind differential poverty levels. In particular, poverty mapping provides a means for integrating biophysical/environmental information with socio-economic indicators to provide a more systematic and analytical picture of human well-being and equity. For example, such high resolution data for a welfare measure will allow an iinvestigation of the links between geographic characteristics and poverty; an analysis that needs to be done at a scale that provides enough variation in critical spatial variables such as temperature, altitude, access to markets, ethnicity, etc. to examine the importance of these factors in determining land-use patterns and relative poverty levels. Thus, if such 'mapable' geographic and socioeconomic factors are in fact largely determining the degree of

expenditure/welfare levels, this might not show up in the results of typical household-level studies that are confined to a small area – simply due to lack of variation.

At the same time, household-level census or survey data that can be aggregated to the same broader level of observation (e.g. Location) can be used to capture "traditional" determinants of poverty, such as level of education. The premise behind a spatial analytical approach, therefore, is that apart from traditional household-level factors, spatial factors are likely to be crucial in understanding levels of poverty at the broader landscape or community-level. Using GIS, it will be possible to examine climatic characteristics (both level and variability for rainfall), as well as soil and slopes, allowing a more in-depth examination of the linkages between poverty and environmental degradation than was previously possible.

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