Poverty among Livestock Keepers in Kenya: Are Spatial Factors Important?

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Abstract

This paper explores the spatial determinants of poverty among livestock keepers by taking an econometric approach that combine poverty indices for livestock keeping areas in Kenya as the dependent variable and relating this to a variety of spatial variables likely to contribute to poverty at a local scale. We use both global and local regression models. In carrying out this analysis, elimination of spatial autocorrelation was done by use of the *Moran's* I and *Lagrange* multiplier. The results show different spatial variables to influence poverty at the different scales and to be geographically related at the local scale. Soil quality, agro-climatic conditions, slope, land use and demographic variables are important factors in determining poverty. These variables offer a challenge to policymakers in deciding on the measures to take to enable the reduction of poverty in the rangelands of Kenya. With the establishment of constituency development funds, tackling the problem at the local scale could be the most feasible option for the national government when such information is made available.

Key words- livestock, poverty, rangelands, rural, spatial, Kenya

1.0 Introduction

It is estimated that in the next two decades, the livestock sector will have significantly changed to produce about 30% of the value of global agricultural output and directly or indirectly use 80% of the world's agricultural land surface (World Bank 2001). This would make it the Worlds most important sub-sector in terms of land use. In Kenya, the livestock sector is dominated by small scale producers and is a very important sector for the economy since its products are important commodities both locally and internationally. The livestock is mainly concentrated in the arid and semi-arid lands (ASALs) covering over 75 percent of the country's land surface (FAO, 2005). There, it accounts for 90 percent and 95 percent of employment and family incomes respectively

Despite the growing importance of livestock in the economy, very little is known about the nature and determinants of poverty among livestock keepers. Within Kenya, poverty has been highest in the rangelands, where most livestock keepers are found (CBS, 2003). In 1999, the year with which we are primarily concerned, the incidence of poverty in the rangelands was 56 percent and the Gini–coefficient, which is used to measure income inequalities, was 0.30. Within the rangelands, poverty is particularly severe in rural areas. Interestingly, despite their rural status and poverty, livestock related activities continue to generate the biggest proportion of their incomes.

This paper aims to investigate the nature and determinants of poverty among livestock keepers in the rangelands of Kenya, as well as their distributional profile and poverty impact. The study sets out to answer the following questions. What spatial factors are dominant in influencing variation in poverty among livestock keepers in Kenya? Does the relationship between agro-climatic variables and poverty differ significantly among poor livestock keepers in Kenya? In other words, what spatial factors are important in explaining the level of poverty in livestock keeping areas in Kenya? What are the implications of changes in spatial factors and policies for poverty among livestock keepers in Kenya?

The paper proceeds as follows. Section 2 provides a brief overview of general issues about livestock, poverty and environmental conditions in Kenya. Section 3 discusses the data and presents a brief overview of the analytical methods. Section 4 assesses the impact of geographical conditions on poverty by estimating a global and local model. An illustrative simulation is done in this section. The last section concludes with policy recommendations and some hypotheses about the effects of changes in geographic conditions on the course of rural poverty in the rangelands.

2.0 Poverty, Livestock and the Environment in Kenya

Kenya ranks among the least developed countries where the poverty index shows more than 50% of its population below the global described poverty line (World Bank 2004). Poverty is more pronounced among the livestock keepers (CBS and ILRI, 2003). Since independence, one of the principal goals of Kenya's development effort has thus been to reduce poverty. Successive governments have pursued this through development strategies emphasizing economic growth, employment creation and provision of basic services. In the first decades after independence, Kenya's development strategy was based on the idea that poverty would be alleviated through rapid economic growth, as the poor would benefit from sustained growth. However, poverty reduction was not realized even when the country was experiencing strong economic growth in the 1960s and 1970s. As a result, the growth led poverty reduction approach has been criticized on the grounds that it ignores the non-income aspects of poverty. In a participatory poverty assessment study (AMREF 1998 a,b,c,d), some Kenyan communities claimed that neither their district authorities nor the local governments had initiated effective poverty-alleviation measures. The communities attributed the lack of such to the failure by the administration to involve them in the development process. Thus, the consensus in development is that beneficiaries of anti-poverty programmes should be involved in the design and implementation of such programmes since they have valuable contributions to make in the design of these programmes. They can provide the data and detailed insights into the causes, nature and extent of poverty, as well as on what can be done to effectively tackle it (KIPRRA, 2000). The recently introduced constituency development fund is expected to go a long way in enabling this since it is the stakeholders who determine their development priorities.

The relationship between the incidence of poverty and the livestock sector is often rather subtle. The most direct impact on poverty can be discerned when the sector offers employment opportunities to the poor with remuneration levels that are not sufficient to lift them out of poverty. But the literature on livestock rearing in Kenya describes how heterogeneous livestock activities can be, and suggest that they can be divided into two groups of income sources: high income activities which mainly result from diary farming and low income activities which mainly result from beef production (intensification and extensification). The latter activities can be quite common among the livestock keepers in the lowlands particularly in the Coast, North Eastern and Eastern provinces. The former is mainly found in the highlands and Rift Valley areas. However, even if the 'low income' activities may offer no realistic prospects of lifting communities and households out of poverty, such income sources are clearly very important from a social welfare perspective, since they help reduce the severity of deprivation for many communities and families. In addition, for certain groups of the population who are in the ASAL and are unable to participate in productive farming these livestock keeping activities may offer the only means to some economic security (a safety net).

The Kenyan government has however continued to encourage farmers to engage in commercial livestock farming and today the cattle population (the most popular livestock among the livestock keepers) exceeds ten million heads with the large scale farmers keeping animals both for commercial and subsistence purposes. The government has of late taken steps to improve dairy farming by increasing extension services, extending credit facilities to farmers through co-operatives, investing in research and availing training opportunities. It has also set up demonstration farms and projects which breed high quality bulls (GOK, 2003).

The common view of the rangelands among policymakers in Kenya is that of a sector driven entirely by livestock keeping, and rural welfare in the rangelands is equated with income. Thus, policymakers view state efforts to combat rural poverty in the rangelands as policies to enhance productivity among livestock keepers.

The issue of poverty among livestock keepers has however received little attention by researchers and policymakers. Most analyses on livestock keeping in Kenya are a by-product of the literature on rural poverty such as Mwabu et al., (2000), Oyugi (2000) and Geda et al.,

(2001) that deal with measurement, profile and determinants of poverty in Kenya using overall expenditures and food expenditures as dependent variables. These studies show that poverty prevalence is highest in the rural areas and that regional disparities are large and increasing. However, they do not include natural endowments in their analyses yet it is likely that certain natural endowments may enhance the opportunities of the rural poor to diversify incomes and at the same time lift themselves out of poverty.

As regards environment, poverty is a major cause and consequence of the environmental degradation and resource depletion where major environmental challenges include deforestation, soil degradation and desertification, declining biodiversity and marine resources (Okwi et al 2005). Others include water scarcity and deterioration of water and air quality. Thus, though the country is implementing new national and multilateral environmental policies, their effectiveness is low. There is growing recognition that national environmental policies are more likely to be effectively implemented if they are supported by an informed and involved public. Thus environmental awareness and education programmes are expanding almost everywhere, while indigenous knowledge receives greater recognition and is increasingly used (UNEP, 2000)[1]

The most pressing environmental health problems worldwide today in terms of their role in causing death and illness, are those associated with poor households and communities. In rural areas and in peri-urban slums in Kenya, inadequate shelter, overcrowding, inadequate safe water and sanitation are by far the greatest threats to human health (Dasgupta and Karl-Goran, 1994). According to World Health Organization (WHO) and the World Bank, environmental improvements at the household and community levels would make the greatest difference for global health. Specifically, the World Bank has calculated that improvements in the local environmental conditions facing the poor can lower the incidence of major killer diseases by up to 40 percent (Eckholm 1976).

By targeting policies that help to reduce environmental threats that contribute to both ill health and poverty, it is possible to produce good health faster than income growth would do on its

[1] http://www.unep.org/geo2000

own. Improving living conditions might itself help reduce poverty. This means that removing the environmental hazards that make people sick could keep people productive, which would in turn raise their incomes. Thus, continued environmental deterioration is a source of continued impoverishment. Livestock keepers depend on natural resources in the most vulnerable areas of Kenya and thus suffer most from deterioration in the environment because of the threat to their livelihoods and aggravation of health risks.

There is a need to understand the interrelationships between poverty, livestock and environment in order to reduce poverty among the livestock keepers. Despite the fact that pastoralism presents a very efficient system to utilizing the heterogeinety of the rangelands, poor livestock keepers are often portrayed as having large numbers of livestock, which in turn contribute to environmental degradation thus compounding the problem of poverty. Pastoral areas are marginal and have largely relied on organized traditional institutions. However un informed government policies and actions that undermine such institutions have made these areas more vulnerable to degradation. Creating a balance in these areas is therefore key to reducing poverty among the pastoralists. Understanding interrelationship between the three is therefore critical as is sought in this article.

Generally, we test the hypothesis that agro-climatic variables and market access explain the variation in poverty among the livestock keepers in Kenya. The ability of agro-climatic variables to explain differences in poverty indicates that poverty in remote areas may be linked to natural resource availability and lack of market access (see also Pender, et al., 1999; Pender, 2001), in this case for animals. Better roads and access to markets are expected to favor better returns among the livestock keepers and should therefore contribute to better welfare or higher incomes (Pender et al., 1999). Presence of social services such as hospitals and, schools may influence welfare by promoting better health, livelihood and other human capital variables. In this study, we investigate the impacts of these spatial variables. Such an understanding of poverty can effectively guide governments' and others' efforts to reduce poverty by adopting more specific and precise policy options specifically targeted to livestock farmers.

3.0 Data and Empirical Implementation

3.1 Data

The data on poverty come from the poverty mapping results that were obtained from the 1997 Welfare Monitoring Survey (WMS) and the 1999 Population and Housing Census. The survey is similar to the LSMS conducted by the World Bank in various developing countries (see Grosh and Glewwe, 1995 and World Bank 1991). The 1999 Population and Housing Census were conducted by the same institution (CBS) and meant to cover the entire population in both rural and urban areas. The census and survey data have several common household variables such as household size composition, education, housing characteristics, access to utilities and location of residences. In this study, the location level poverty headcount estimates that were derived from the poverty mapping study for Kenya (CBS and ILRI, 2003) is used as the dependent variable. This paper uses only the rural sample for the rangelands, comprising of 1159 locations.

The spatial analysis portion of this project uses a variety of spatially referenced variables describing topography, land cover and land use, climate, demography and market/town access derived from GIS data layers. Geo-referenced information from various government departments and institutions is used. Information about vegetation cover such as forests, grassland, wetlands, water resources and land use such as subsistence and commercial farmland, and other landscape aspects were obtained from Multipurpose Africover Database for Environmental Resources (MADE). Data on demographic attributes was obtained from CBS described above. Other natural and physical capital layers were derived from a wide array of local and global layers (for detailed description of data sources, see Table A1 in appendices). The data is extremely rich in bio-physical factors and also includes the distribution of infrastructure such as markets, towns and others. Subsets of these variables are used as independent variables and they are aggregated to the location level.

3.2 Estimation Strategy

Following the description of the data in the previous sub section, we present briefly the empirical model. We adopt the spatial regression approach developed by Anselin (1988) and used by Benson et al (2005) and Minot et al (2003). The analysis is typically divided into three stages:

- a simple ordinary least squares regression;
- a global spatial regression and;
- a local spatial regression analysis.

These regression analyses aim to improve our understanding of how communities might be assisted in reducing poverty by targeting key spatial determinants of poverty.

3.2.1 Generalized OLS regression model

Applied to this context, we estimate the OLS regression model as:

$$y_i = \beta X_i + \varepsilon_i \qquad (3)$$

where *Y* is a vector of observations on the dependent variable; *X* is a matrix of independent variables; *ß* is a vector of coefficients, and *e* is a vector of random errors. Despite the popularity of this approach, problems of spatial autocorrelation limit its application in analyzing spatial relationships. Spatial autocorrelation occurs if variables in one area are affected by the value of that variable in a neighboring area. Spatial autocorrelation can also manifest itself through the correlation of error terms. One way in which the error terms may be correlated is spatially, as evidenced by observations from locations near to each other having model residuals of a similar magnitude. Therefore, unless we correct for spatial autocorrelation, the assumptions of OLS regression are violated and thus the estimates derived from this method are likely to be biased. To assess spatial autocorrelation, the clustering of the residuals from the OLS model will be examined using the Moran's *I* statistic and the Langrange multiplier index.

3.2.2 Global spatial regression model

The literature on spatial econometrics identifies two types of spatial dependence[2]. First, the spatial dependence could be a result of the level of poverty (in this case our dependent variable) in one location affecting the level of poverty in another location, through for

[2] See Anselin 1988, 1992 for detailed discussion of how to correct for spatial autocorrelation

example, trade or investment linkages. Such a relationship is modeled as a *spatial lag model* as follows:

$$y_i = \delta \sum_{j \neq 1} w_{ij} y_j + \beta X_j + \varepsilon_j \qquad (4)$$

Where y_i is the dependent variable for area i
δ is the spatial autoregressive coefficient
w_{ij} is the spatial weight reflecting the proximity of i and j
y_j is the dependent variable for area j
β is a vector of coefficients
X_j is a matrix of explanatory variables, and
ε_j is the error term.

The spatial weights matrix, *w*, represents the degree of proximity between each pair of spatial observations. It is usually a binary variable based on whether the two areas are contiguous or a continuous variable based on a function of distance between the two areas or locations. Omitting this adjustment will result in the coefficients being biased and inconsistent.

A second type of spatial dependence can be attributed to the error term of the model (see Anselin, 1992). This kind of spatial dependence occurs if there are variables that are omitted from the regression model but do have an effect on the dependent variable and they are spatially correlated. Such a relationship can be modeled as a *spatial error model*:

$$y_i = \beta X_j + \lambda \sum_{j \neq 1} w_{ij} y_j \varepsilon_j + \varepsilon_i \qquad (5)$$

Where y_i is the dependent variable for area i
λ is the spatial autoregressive coefficient
w_{ij} is the spatial weight reflecting the proximity of i and j
y_j is the dependent variable for area j
β is a vector of coefficients
X_j is a matrix of explanatory variables, and
ε_j is the error term.

Here, the error term is disaggregated into the spatial lag of the error term of neighboring locations and the residual error term for the spatial unit in question. When there is spatial error dependence, OLS coefficients will be unbiased but not efficient (the standard errors will be larger than if there were no omitted variables) (Anselin, 1992).

In order to select which model to use, a Lagrange Multiplier test and Morans I is used to assess the statistical significance of the coefficients in each model, respectively. Where spatial autocorrelation is likely, usually the result of the test on each will be significant. The preferred model in such a case is the one with the highest Lagrange multiplier test value (Anselin & Rey, 1991).

3.2.3 Local Spatial Regression Analysis: Geographically Weighted Regression

The models described above are referred to as global models because they assume that the relationship between poverty and the geographic factors is the same across the country. That is, the relationship is *spatially stationary*. Such an assumption might be reasonable when one is considering physical processes that are governed by universal physical relationships. However, at least at the generalized level of our analysis, few social processes will be found to be constant over space (Fotheringham, et al., 2002, p. 9). The generalized regression models described earlier will hide this potential heterogeneity, or *spatial non-stationarity*, in the determinants of the prevalence of poverty (Benson, 2005).

Local spatial regression analysis does not make this assumption and examines spatial variations in the relationship between poverty and geographic factors. A moving window regression framework, in which numerous regression models are estimated, each centered on a "regression point" and including nearby observations defined by a "kernel bandwidth" is used. Localized coefficient estimates are generated for each regression point.

Using this method, which is closely related to the OLS, the results will be the usual standard regression output. This allows the regression output (including coefficients and R^2) to be mapped, showing their variation over space. This makes this technique particularly useful for analyzing relationships in spatial data (see Brunsdon, *et al*., 1996, for details of this method).

A standard global regression model, written as:

$$y_i = a_0 + \sum_j x_{ij} a_j + \varepsilon \qquad (6)$$

can be extended to a local regression model, written as:

$$y_i = a_0 + \sum_j x_{ij} a_{ij} + \varepsilon \qquad (7)$$

where y is the dependent variable,
x is the independent variable,
a_{ij} is the regression coefficient,
a_0 is a constant,
i is an index for the location,
j is an index for the independent variable, and
ε is the error term.

For each local regression at a regression point *i*, the observations are weighted depending on the distance from the regression point to the observation *j*. The size of the neighborhood to which the spatial weight matrix applies can be a fixed distance (bandwidth) or, alternatively, can be based on *k*-nearest neighbors with a varying, adaptive bandwidth applied to the weighting function. Finally, we should point out that the distance between spatial units is the distance between the center points of locations.

Tests can also be done to determine whether a local model describes better the relationships than a global model by comparing global and local values of R^2. Furthermore, Fotheringham et al., (2002) proposed a Monte Carlo test of whether spatial variations in the estimated coefficients are statistically significant. The test involves randomly adjusting the geographic location of the observations numerous times, running a GWR on each, and then comparing statistically the parameter estimates for the randomly distributed observations with the parameter estimates of the actual geographic distribution (Minot et al., 2003).

4.0 The Determinants of Poverty among Poor Livestock Farmers (rangelands) in Kenya

Tables 1 to 4 present the results from the estimation models for the rangelands, estimated separately from the other areas. The rangelands provide an interesting case for analysis given that they account for a large proportion of poverty in Kenya and have specific features which make them unique from the other areas of Kenya. For example, these areas have inadequate infrastructure and are very remote. Moreover, these areas are typical livestock rearing areas and provide substantial supplies of beef and milk to the other areas of Kenya. Livestock, as we know, is a vital component of well being and provides a pathway out of poverty. Therefore, specific analysis of the determinants of poverty among poor livestock farmers could provide practical intervention areas if poverty is to be reduced in these areas and the role of livestock enhanced.

The dependent variable used in the regressions is the poverty rate for each of the rural locations in the rangelands of Kenya. The explanatory variables included are listed in Table A1 in the appendices. About 1159 locations are used in the estimation.

Table 1 below presents the tests for spatial dependence when an OLS model was estimated with location level poverty rate as the dependent variable against the variables listed in Table A1. Row-standardized weights are used to test for spatial dependence. According to the results, the tests for spatial dependence are all highly significant and the spatial error model should be used to correct for spatial autocorrelation.

Table 1. Diagnostics for spatial dependence

FOR WEIGHT MATRIX :(row-standardized weights)

TEST	Value	Probability
Moran's I	33.5100	0.0000
Lagrange Multiplier (lag)	738.6246	0.0000
Robust LM (lag)	88.3999	0.0000
Lagrange Multiplier (error)	849.5040	0.0000
Robust LM (error)	199.2792	0.0000

Source: Authors computations

4.1 Spatial Error Model

Table 2 below shows the results of the spatial error model based on a regression of a set of unrestricted exogenous variables on poverty rate. The model explains more than 60 percent of the variation in rural poverty and 14 of the 22 coefficients are statistically significant. Based on the preferred parameter estimates shown in Table 2 below, the following points about the determinants of poverty among livestock keepers are notable.

Table 2. Results of the spatial error model

Dependent Variable	Poverty incidence		
Variable	Coefficient	Std.Error	Probability
CONSTANT	0.9318	0.0552	0.0000
Demographic			
POPDEN	0.0000	0.0000	0.7967
Provincial dummy variables			
reg3 (Coast)	-0.1070	0.0396	0.0069
reg4 (East)	0.0218	0.0262	0.4065
reg5 (North Eastern)	0.0716	0.0379	0.0587
Reg7 (Rift Valley)	-0.0344	0.0190	0.0704
Distance and travel time			
Average travel time to Type 1 or 2 Road (minutes)	0.0000	0.0000	0.1501
Mean distance to town 50,000 people	0.0001	0.0002	0.4458
Mean distance to town 200,000 people	0.0000	0.0000	0.1096
Land use			
Percent of location under grass	-0.0006	0.0004	0.1240
Percent of location under farmland	-0.0005	0.0002	0.0474
Percent of location wooded	0.0001	0.0002	0.6391
Percent of location under wetland	-0.0013	0.0006	0.0347
Natural Factors			
Average Elevation (meters above sea level)	-0.0001	0.0000	0.0004
Percent of location with 4 - 8% slope	0.0018	0.0003	0.0000
Percent of location with 8 - 15% slope	-0.0025	0.0005	0.0000
Percent of location with 15 - 30% slope	0.0022	0.0006	0.0004
Percent of location with over 30% slope	0.0015	0.0005	0.0024
Percent of location with LGP less than 60 days	0.0002	0.0002	0.3523
Percent of location with LGP 180 days	-0.0007	0.0001	0.0000
Good soil (dummy)	-0.0146	0.0074	0.0491
LAMBDA	0.8559	0.0260	0.0000
Observations	1159		
Adjusted R-squared	0.6069		
Log likelihood	1089.3881		

Source: Authors computations

Soil

The coefficient for the variable good soil has a significant negative effect on community level welfare in the rangelands. The inverse relation between good soil and poverty, while an expected finding, is critically linked to the issue of agricultural potential or production. This result points to the ability of communities with better soils to compliment their earnings and livelihoods through farming unlike those with poor soils. Another reason for this inverse relationship could be that good soils lead to higher quality pasture and therefore increased animal production. Given the strength of this result and its dependence on other variables such as rainfall or irrigation, much gain can be obtained from this result. This result is not surprising and strongly justifies the need for diversification of income activities in these areas through farming and where possible attempts should be made to improve soil and irrigation in these areas.

Agro-climatic variables

Another result that is noteworthy is the length of growing period. Length of growing period refers to the period when temperature and moisture conditions are such to allow crop growth. To interpret the results, note that in rural areas, the longer the growing period the better the conditions for farming and the less likely the area is to be poor. Keeping in mind these facts, the findings can be explained as follows. It is not surprising the LGP affects rural poverty because poverty in rural areas is closely associated with agriculture. Locations in the rural areas of Kenya that have longer growing periods are capable of growing a variety of crops including perishable vegetables, maize, beans and even cash crops such as tea and sugar cane. It is therefore common that for rural locations that have longer growing periods, the rates of poverty are likely to be lower, ceteris paribus. A similar argument can be made regarding locations that have shorter growing periods. The implication of this result is rather direct and can be a point of emphasis in poverty alleviation programmes. These areas have the potential of both crop and livestock production.

Wetlands and grasslands

Water points and wetlands are important determinants of poverty among poor livestock farmers or in the rangelands. The effect of having larger water points and wetlands is negative and significant. Similarly, more grassland in the location is related to lower levels of poverty. This obviously reflects the effects of greater dependency of these communities on pasture for their livestock and water for their livestock and themselves. This result is not surprising given that about 90% of the population in the rangelands depend on pastoralism for their livelihoods.

The fact that locations with larger areas under wetlands will tend to have lower poverty rates is also not surprising. These results agree with those for the national model for Kenya (see Okwi et al., 2005), which show that larger areas of the location under wetlands means less poverty.

Farmlands

With respect to the share of land under farmland, the results are as expected. An increase in the area of a location under farmland reduces the location's poverty rate. This implies that an additional increase in farming area spurs significantly the location's participation in farming. This implies diversification of activities from the traditional livestock rearing hence less reliance on livestock income. Diversification into farming activities increases the locations potential to earn agricultural income.

Elevation and Slope

An increase in elevation of the location by one meter has a significant negative effect on poverty. In other words, high elevations contribute negatively to rural poverty. This result is not consistent with the national model. This may be due to the fact that livestock producing areas in the high lands are the real agricultural high-potential areas and are therefore likely to be less poor compared to the flat areas of the rangelands. Another result that is noteworthy is the association between the slope variables and poverty. All the slope variables (share of land with a slope of 4-8 percent, 8-15 percent, 15-30 percent and above 30 percent) are statistically significant. With the exception of locations with 8-15 percent slope, the rest are positive and statistically significant. The results indicate that the amount of slope strongly explains the poverty levels in a rural location and locations with larger area of sloped land will have higher poverty rates than those with more flat area of about 8-15 percent slope. The negative effect could be due to some collinearity between these variables. Again, this result is not surprising given the difficulties associated with cultivation on sloped land. This results points to the need to introduce better farming methods like terracing and grazing in these areas.

Demographic variables

Among the demographic related variables, only the level of income inequality is negatively significant. The results arising from this variable agree with those from CBS and ILRI (2003) which show that areas with higher inequality tend to have lower poverty rates. This result captures the variation in poverty levels as it is often true that there is a tendency for poor communities to locate themselves together hence the inequality levels are not very high among the poor communities. Like in the (ILRI and CBS, 2005) study, this result is capturing the cases of areas with high potential and probably urban growth. Finally, among the rangelands, the location variables or provincial dummies variables are important, though the levels may be different. When dummy variables for the provinces where rangelands are found are included in the rural poverty model, they are jointly significant. Relative to the other regions, Coast, North eastern and Rift Valley are among the significant location variables.

Our results concerning the determinants of poverty among poor livestock farmers in the rangelands provide very interesting findings. The soil quality, agro climatic conditions, land use under wetlands and farming, slope and elevation, income inequality and location specific variables have direct effects on rural poverty. All these variables have the expected sign although the magnitude of the coefficients varies and is in some cases very small. It is not surprising that these variables explain more than 60 percent of the variation in location level poverty in the rangelands of Kenya. The experience from the rangelands suggests that it is possible to isolate general factors affecting poverty in the rangelands. These results are important as they provide specific information about the pattern and spatial determinants of poverty in the rangelands of Kenya, which is of importance in designing effective poverty alleviation policies.

4.2 Spatial Variation in Poverty Determinants

In this section, we present the results of an analysis of the spatial variation in relationships between poverty and a number of agro-ecological variables (Table 3). The Geographically weighted regression technique is used. This method allows for spatially varying relationships between rural poverty and the determinants across the rangelands. The model does not control for spatial autocorrelation. Instead, the GWR analysis attempts to explain the nature of spatial dependence as part of the local analysis. Therefore, the spatial autocorrelation becomes part of what the local GWR model explains.

A global model is first estimated. The same regression is then re-estimated using a local model based on the geographically-weighted regression technique. First, we present the results of the global model. More than 32 percent of the variation on global poverty in the rangelands is explained by the variables. Most of the variables have the expected correct sign and are significant. These variables show consistency with those from the earlier model. Slope, soil quality, length of growing period and land use for farmland and wetlands are significant. However, we do not repeat the explanation of these variables here. Instead, we attempt to explain whether a local model would bring improvements in the explanatory power of the model and whether there are significant spatial variations in the relationship between poverty and the independent variables.

Table 3. Summary results of global model

Variable	Parameter Estimate	Standard Error	T
Intercept	1.13193	0.04556	24.84479
gini	-1.89441	0.11599	-16.33279
pden	0.00002	0.00004	0.49258
elev	-0.00005	0.00001	-5.41664
pcfrm	0.00042	0.00029	1.46745
pcgrs	-0.00142	0.00044	-3.19560
pc48sp	0.00310	0.00038	8.12871
p815sp	-0.00210	0.00063	-3.32066
p1530s	0.00136	0.00078	1.72895
pc30sp	0.00137	0.00057	2.38402
trod12	0.00000	0.00001	-0.27440
lgp60	0.00048	0.00016	3.03990
gdsoil	-0.02892	0.00865	-3.34254
dst502	-0.00020	0.00008	-2.58885
dt2002	0.00001	0.00001	1.28147
pcwod	0.00040	0.00021	1.94122
pcwtld	-0.00182	0.00073	-2.49048
lgp180	-0.00041	0.00013	-3.25238
Adjusted	R-square..	0.321775	
Number of	observations	1159	

Source: Authors computations

The local model explains 69 percent of the variation in location level poverty in the rangelands. However, these variables do not include the location dummy variables. The implication of this result is that the local model presents a better fit by about 37 percentage points. Likewise, the residual sum of squares for the local model is about 3 times less than for the global model (6.2 compared to 16.9 for the global model). From these diagnostics, it is clear that the local model has smaller errors and a better fit than the global model.

Figure A3 shows the local values of the adjusted R-Square for each rural location in Kenya. The expectation from this kind of exposition is that examining the pattern of areas with low R square statistics will enable the determination of any missing variables in the model. It is evident that in all the locations, the value of the R-square from the local model is higher than the global model score of 0.32.

The results of the GWR model can be useful in for those interested in a particular location or area in the rangelands of Kenya and can be used to obtain a multivariate understanding of the important location level determinants of poverty. An assessment of the maps provides a clear view of which locations have stronger explanatory power from the selected variables.

The spatial variation in the variables used is presented in Table A2 below. From this result, a clear variation is observed over space in all the variables that were used in the regression.

5.0. Poverty Simulations

In this section we test the effect of different policy initiatives on the proportion of the poor in the rangelands. Clearly, there are an infinite number of permutations of policy changes that can be considered, and we limit our results to a few indicative cases. The effects of a policy change are simulated by changing the values of one or more of the explanatory variables in accord with the policy in question. The changes in explanatory variables result in changes in the predicted probabilities, and these are taken to be the effect of the policy. However, the results of the simulations should be treated as suggestions that are plausible but not real, and therefore treated with caution.

The simulation study in this case is defined by interventions aimed at improving welfare. Our desired result is to reduce the percentage of poor people in the Locations. We therefore suggest interventions in soil improvement in areas where the rainfall is above the rangelands mean of

810m and a reduction in non monetary access costs. In our model non-monetary access costs are measured by travel time. The simulation assumes that improvements are made to roads in these areas so as to reduce every ones travel time to the nearest road (tarmac or murram) to within one hour or less (i.e. to reduce the probability of traveling more than one hour to the nearest road to zero). This is a fairly egalitarian change because our data show that the median travel times are similar for most of the areas in the rangelands.

Table 4 below presents the results of the soil and travel time simulations. They report the expected change in poverty due to improvement in soil conditions (in areas with relatively higher rainfall than the rangeland mean of 810mm. The results show that improving soils in this area alone can generate substantial improvements in welfare by reducing poverty rates from 56 percent to 50.4 percent, but, of course holding other variables constant. Even though the aggregate changes in poverty appear to be modest, the effects may be larger if other variables are included in the model. At this point, the focus should be more on the direction of change rather than the magnitude. Under the travel time scenario, a reduction in travel time to less than an hour reduces the poverty from 56 percent to 48. Therefore, improving road infrastructure in the Rangelands will pay off in terms of improved overall welfare at the Location level. The missing comparison of this simulation is the imputed cost of soil improvement and road construction in these areas. The study also does not provide options to cover costs of road construction and soil improvement. Generally, there would be relatively large welfare improvement among the communities of the rangelands if there are interventions in these two areas.

Table 4. Impact of changes in soils and market access: An Illustrative Simulation

Variable	Obs	Level	Std. Dev.
Base Poverty Rate before soil improvement	1159	55.9	0.147
Poverty rate after soil improvement	1159	50.4	0.126
Poverty rate after road improvement	1159	48.3	0.144

6.0 Conclusions and Implications for Policy

Rural poverty in the rangelands, where most livestock farmers are, remains a crucial part of the poverty story in Kenya as a whole. Kenya is largely a rural based country and poverty in the rural areas is so widespread and persistent that more than half of the country's poor are found in the rural areas. Add this to the fact that rural poverty itself appears to be concentrated among the livestock farms in the rangelands, and it seems clear that the economy of the rangelands must remain a central focal point for policymakers aiming to alleviate poverty.

We investigated the determinants of poverty in the rural rangelands of Kenya. Our approach to modeling the determinants of poverty is to model the determinants of the location level welfare indicator, namely poverty incidence. Three different models are estimated, the OLS, global and local regression models. A number of geographic variables are included in the model as explanatory variables. We use rural regression models to predict changes in poverty levels from simulated policy changes.

A key conclusion of our study has to do with the important instrumental role of geographic conditions in determining poverty rates. The results show the need to take into consideration spatial variables when undertaking such studies with likelihood to influence policy. The results also give an indication of the need to base conclusions on multistage analysis since different factors were found useful at the various scales.

There are several geographical factors influencing poverty among the livestock keepers in Kenya. The magnitude, however, changes with the different variables. Soil quality, agro-climatic variables, wetlands and farmlands, proportion of the location under slope, elevation and income inequality variables tend to have significant effects of poverty. The latter result implies that the higher income households tend to be very concentrated in the main economic centers where many of the productive activities are based, hence they have low poverty in those locations. Levels of poverty are high in the low inequality areas, reflecting less economic opportunities available to households in these areas.

Besides identifying some of the key contributory causes of poverty in rangelands of Kenya at location level, the other objective of this paper was to carry out simulation analysis. This has been considered at two levels, first looking at the factors which can be influenced by policy or area amenable to change. Within this framework, poverty is seen to rise or decline if either (a) a change in the conditions due to a policy effect can lead to a rise or fall in poverty at the location level; or (b) analysis of changes in either direction of certain important geographic conditions that have significant effects on the level of poverty. We can observe that improvements in soil and road infrastructure will reduce poverty by 5 and 7 percentage points, respectively. Broadly therefore, this analysis provides important spatial information about the determinants of poverty and how changes in policy can affect location level poverty in the rangelands of Kenya.

7.0.References.

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Appendices.

Table A1. Description of Variables

Short description	Source	Explanation
Agroclimatological		
Annual Rainfall (mm)	The WorldClim interpolated global terrestrial climate surfaces. Version 1.3.	The average annual rainfall within the location boundaries, calculated as the sum of all the monthly rainfall figures derived from the original Worldclim1.3 dataset of monthly layers.
Rainfall coefficient of variation	The WorldClim interpolated global terrestrial climate surfaces. Version 1.3.	The average coefficient of variation (CV) of rainfall between the months within 1 year within the location boundaries. This variable was derived from the worldclim1.3 dataset of bio-climatic information, which describes the "rainfall seasonality".
Distance and Access to services		
Travel time to municipality	- Africover landcover multipurpose database (FAO) - NASA, Shuttle Radar Topography Mission (SRTM) - World Database on Protected Areas (WDPA - sea.unep-wcmc.org/wdbpa) - Roads - ASARECA - Settlements - CBS	This variable represents the average travel time from any place within the location to the nearest municipality (according to definitions of CBS). Travel time is a function of slope, road type and "impediments" (i.e. wetlands, water bodies and natural parks). The table below summarizes the travel times:
Travel time to town	Idem above	This variable represents the average travel time from any place within the location to the nearest town (according to definitions of CBS).
Travel time to trade centre	Idem above	This variable represents the average travel time from any place within the location to the nearest trade centre (according to definitions of CBS).
Travel time to market centre	Idem above	This variable represents the average travel time from any place within the location to the nearest market centre (according to definitions of CBS).
Travel time to type 1 road	Idem above	This variable represents the average travel time from any place within the location to the nearest road of type 1. *Type 1: Tarmac/All Weather Bound* *Type 2: Murram/All Weather Loose* *Type 3: Earth/Dry Weather*
Travel time to type 1 or 2 road	Idem above	This variable represents the average travel time from any place within the location to the nearest road of type 1 or 2.
Travel time to type 1, 2 or 3 road	Idem above	This variable represents the average travel time from any place within the location to the nearest road of type 1, 2 or 3.
Travel time to type 1, 2 or 3 road	Idem above	This variable represents the average travel time from any place within the location to the nearest road of type 1, 2 or 3.
Land use		
Percent of location under Protected Area	World Database on Protected Areas (WDPA - sea.unep-wcmc.org/wdbpa)	This variable represents the percent of location that is under the Protected Area.
Percent of location under Wetlands	Africover landcover multipurpose database (FAO)	The original land cover was produced from visual interpretation of digitally enhanced LANDSAT TM images (Bands 4,3,2) acquired mainly in 1999. Wetland areas are extracted on the basis of code1 of the original layer (considered to be wetland areas)

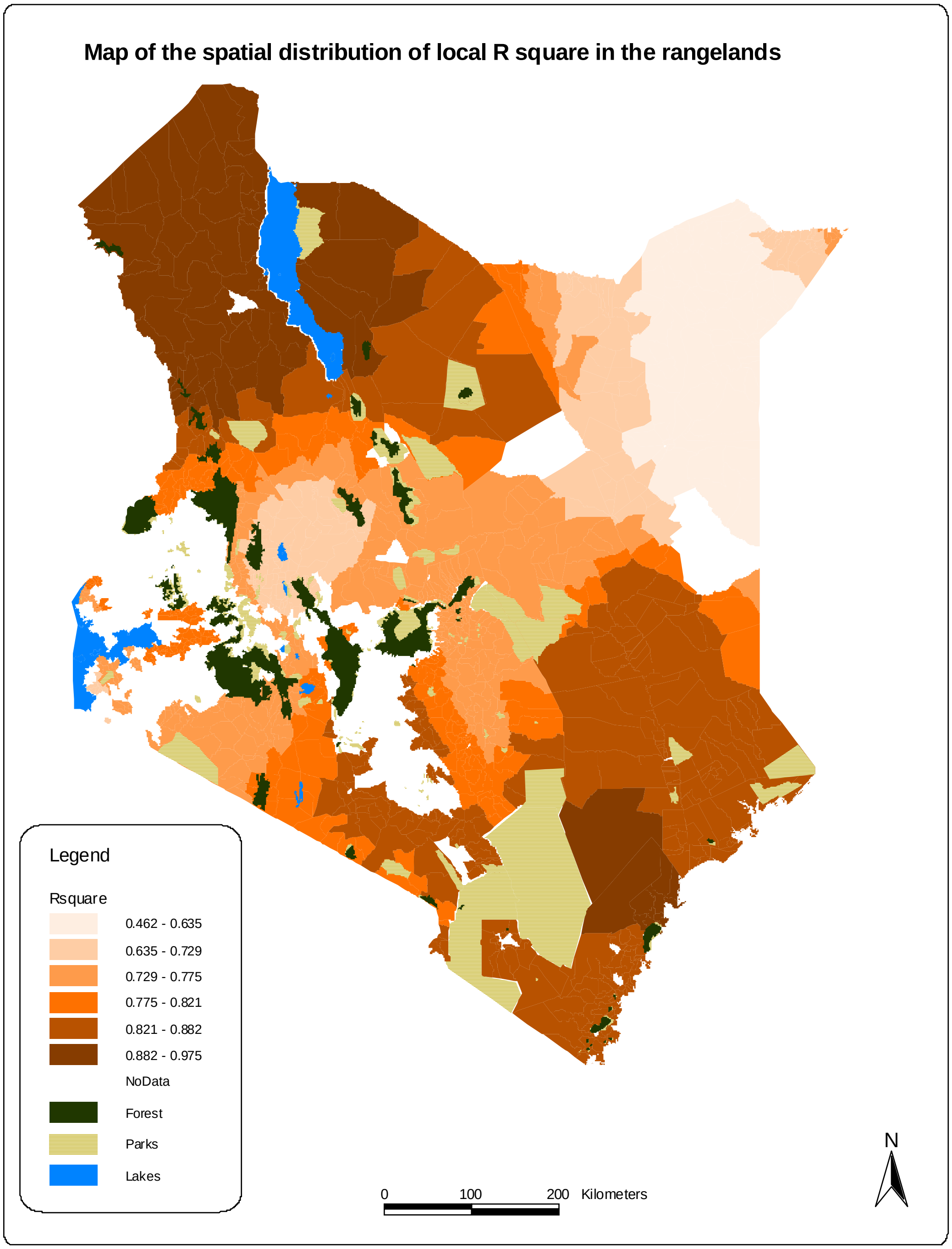
Percent of location Arable land (I.e. LGP > 60 days)	Jones P.G., 2004. Report on preparation of growing season days coverages for Hadley 3 scenarios A2 and B2, Consultant's report, ILRI	The variable describes the percentage of the location that is arable. Arable land was defined as land with a length of growing period of more than 60 days per year.
Arable land between 30 and 60 % (1=yes ; 0=no)	Jones P.G., 2004. Report on preparation of growing season days coverages for Hadley 3 scenarios A2 and B2, Consultant's report, ILRI.	This variable takes a value of 1 if the arable land is 30-60% of the location's area, and 0 otherwise. Arable land was defined as land with a length of growing period of more than 60 days per year.
Percent of location under water	Africover landcover multipurpose database (FAO)	The original land cover has been produced from visual interpretation of digitally enhanced LANDSAT TM images (Bands 4,3,2) acquired mainly in 1999. Water areas extracted on the basis of code1 of the original layer (considered to be water bodies: 7WP, 7WP-Y, 8WFP).
Percent of location that is Built-up	Africover landcover multipurpose database (FAO)	The original land cover has been produced from visual interpretation of digitally enhanced LANDSAT TM images (Bands 4,3,2) acquired mainly in 1999. Build-up areas extracted on the basis of code1 of the original layer (considered to be build-up areas: 5U, 5UC, 5UR, 5I, 5A).
Percent of location under forest	Africover landcover multipurpose database (FAO)	The original land cover has been produced from visual interpretation of digitally enhanced LANDSAT TM images (Bands 4,3,2) acquired mainly in 1999. Forest areas extracted on the basis of code1 of the original layer (considered to be forested areas). The resulting shapefile was converted to a raster with the following values: 100 = forest (covering about 100% of the area); 65 = mixed forest (covering approx. 65% of the area; 0 = non-forest
Percent of location under farmland	Africover landcover multipurpose database (FAO)	The variable contains the percentage of the location's area that is under agricultural land. The original land cover has been produced from visual interpretation of digitally enhanced LANDSAT TM images (Bands 4,3,2) acquired mainly in 1999. Farming areas were extracted on the basis of code1 of the original layer (considered to be agricultural areas). The resulting shapefile was converted to a raster with the following values: 100 = agriculture (covering about 100% of the area); 65 = mixed agriculture (covering approx. 65% of the area); 0 = non-agriculture
Percent of location under grass	Africover landcover multipurpose database (FAO)	The original land cover has been produced from visual interpretation of digitally enhanced LANDSAT TM images (Bands 4,3,2) acquired mainly in 1999. Grass areas extracted on the basis of code1 and code2 of the original layer (considered to be grassland areas)
Natural factors		
Arable land more than 60 % (1=yes ; 0=no)	Jones P.G., 2004. Report on preparation of growing season days coverages for Hadley 3 scenarios A2 and B2, Consultant's report, ILRI.	This variable takes a value of 1 if the arable land is more than 60% of the location's area, and 0 otherwise. Arable land was defined as land with a length of growing period of more than 60 days per year.
Percent of location with Arid or Semi-Arid land (i.e. LGP <= 180 days)	Jones P.G., 2004. Report on preparation of growing season days coverages for Hadley 3 scenarios A2 and B2, Consultant's report, ILRI.	This variable describes the percentage of the location that is arid or semi-arid (ASAL). ASAL was defined as land with a length of growing period of less than 180 days per year.

Elevation (masl)	NASA, Shuttle Radar Topography Mission (SRTM)	The average elevation in meters above sea level within the location.
Percent of location Steep land (I.e. > 10%)	NASA, Shuttle Radar Topography Mission (SRTM)	This variable represents the percentage of the location's area that is defined as steep. Steep land was defined as having a slope of more than 10%. The slope was calculated based on the elevation and can be expressed in degrees or percent.
Percent of location with 0 - 4% slope	NASA, Shuttle Radar Topography Mission (SRTM)	The percentage of the location's area with a slope between 0 and 4 %.
Percent of location with 4 - 8% slope	NASA, Shuttle Radar Topography Mission (SRTM)	The percentage of the location's area with a slope between 4 and 8 %.
Percent of location with 8 - 15% slope	NASA, Shuttle Radar Topography Mission (SRTM)	The percentage of the location's area with a slope between 8 and 15 %.
Percent of location with 15 - 30% slope	NASA, Shuttle Radar Topography Mission (SRTM)	The percentage of the location's area with a slope between 15 and 30 %
Percent of location with over 30% slope	NASA, Shuttle Radar Topography Mission (SRTM)	The percentage of the location's area with a slope of more than 30 %.

Table A2: Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
avg_fgt0	1159	0.56	0.15	0.13	0.91
avg_gini	1159	0.30	0.04	0.19	0.55
popden	1159	86.81	128.35	0.12	1318.44
Elevation	1159	1012.18	646.15	2.82	3087.83
perc_farmlandd	1159	14.62	20.87	0.00	97.95
perc_grass	1159	24.80	13.38	0.00	82.11
perc_wetla~s	1159	1.74	5.41	0.00	51.67
perc_wooded	1159	22.75	22.19	0.00	93.09
perc4_8slop	1159	18.73	14.90	0.00	60.31
perc8_15slop	1159	11.45	11.32	0.00	56.74
perc15_30s~p	1159	8.82	11.02	0.00	59.20
perc30_abo~p	1159	5.72	10.41	0.00	70.87
goodsoil	1159	0.39	0.49	0.00	1.00
lgparids~180	1159	38.54	46.28	0.00	100.00
lgp60days	1159	91.45	25.99	0.00	100.00
t_trav_ro~12	1159	261.26	383.81	7.21	4275.04
d_dist_200k2	1159	2224.22	1831.33	96.19	7982.93
d_dist_50k	1159	117345.30	133542.50	2708.51	547139.10
reg3	1159	0.12	0.33	0.00	1.00
reg4	1159	0.25	0.43	0.00	1.00
reg5	1159	0.17	0.38	0.00	1.00
reg7	1159	0.37	0.48	0.00	1.00

Figure A1



Map of the spatial distribution of local R square in the rangelands
Legend
Rsquare
0.462 - 0.635
0.635 - 0.729
0.729 - 0.775
0.775 - 0.821
0.821 - 0.882
0.882 - 0.975
NoData
Forest
Parks
Lakes
0
100
200
Kilometers
N