Analysis of Spatial Determinants of Poverty in Rural Uganda

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X/50/8475/2006

A Dissertation Submitted to the School of Economics, in Partial Fulfillment of the Requirements for the Award of the Degree of Master of Arts in Economics

August 2007

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DEDICATION

To my mother Karungi Scola for her endurance and sacrifice

DECLARATION

This thesis is my original work and has not been submitted for a degree in any other University

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ACKNOWLEDGEMENTS

Writing a dissertation for one year may not be such a long time, but its rather stressing. Writing this thesis sometimes felt like a never-ending project. However most of the time I enjoyed the work and appreciated the opportunity to develop my skills as a researcher. I have to thank many people for that. The struggle to complete this thesis could not have been the fruitful and mostly pleasant experience it was without their support.

First and foremost I am very grateful to *African Economic Research Consortium* (AERC) for offering me sponsorship throughout the whole programme, without which I wouldn't have succeeded. I would like to thank my University supervisors, Professor Wafula Massai and Mr. Jasper Okello. Their guidance was always constructive and inspiring. They took me through the whole research exercise, taught me the relevance of a good research question, clearly defined objectives, and consistence in writing. Dr. Jane Mariara was also very instrumental in helping me come up with a good problem statement, and literature review and her office was always open for consultation.

I also want to extend my gratitude to the management and staff of *International Livestock Research Institute* (ILRI) for all the support during my period of attachment. I am grateful to Adell Veyrl, the manager training department for recruiting me in the graduate fellowship programme, and Ade Freeman, the theme director, targeting and innovations for hosting and granting me access to all the facilities I needed. Special thanks go to my supervisor Dr. Paul Okwi, who tirelessly pointed out the need for methodological precision and gave me guidance in a very new area of Spatial Analysis. Nothing could have been done in chapter four and five had it not been the diligent effort of the GIS experts; Mike Arunga, John Owuor, Abisalom Omolo, Patrick Kariuki, and An Notenbaert, who went through a hard task of extracting spatial variables and providing them in a way clearly understandable to an economist. I therefore owe them a great deal.

Mother, you have been very encouraging and committed to me since childhood. Every time I would think about us, I would go an extra mile. Aunt Theopista and Aunt Mary, I cannot afford to appropriately reward you. You have always been there and sacrificed a lot for the family in all aspects, and mother has been safe in your hands. My brother Ronald, your prayers and love all worked. Abwooli Dinah, the day you drew me close to my people, I started seeing my future. Ever since, my world has been getting better and better. Paul and Darlison, I can't tell it all, in the last seven years, you have made me see the light and helped purge my future. Thanks for being such a wonderful family and role models. To you I must say, I won't let you down. I promise to make a very good economist, but also return the favour. Dorothy and Julius, thank you for all the time, advice and encouragement, not least of all Dorothy's home was full of cups of tea and delicious food.

To you Josephine, thank you for being not only a colleague but also a true friend, a sister. I must say, together we've been through some tough times, but we've made it. The encouragement, the hope you gave me has led me through. It is great friends like you that remind me of the importance of friendship. I'll try my best to return every favour. To Solomon and John Bosco, our friends reflect the choices we make in life. Thank you for keeping my mother and staying in touch.

I thank all my former colleagues in the school of economics; Simon, Joash, Steve, Dikuly, Richard, James, Paul, Fridah, and Nicholas. You made the university more than a place to work.

I sincerely hope that the results of this study will be useful to the government of Uganda, international and non governmental organisations in the design of policies and programmes to reduce poverty in the country.

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August 2007

ABSTRACT

This study sought to examine the spatial determinants of poverty in rural Uganda. It was undertaken based on the theoretically informed expectation that certain spatial characteristics of where an individual or household lives can be important determinants of whether those residents will attain an adequate level of welfare to meet their basic needs. With the aid of small area estimation techniques, and a spatial regression models, the study combined sub county poverty estimates from the 2002 high resolution poverty maps obtained from the most recent Population and Household Census (2002), and the National Household Survey data (2002/2003), with up-to- date spatial data (2000-2006) to analyse the impact of these characteristics on poverty in the country.

We found that the nature of heterogeneity necessitated the specification of different models for specific regions of the country Results indicate that different spatial factors affect certain regions differently, thereby warranting regional specific policy interventions if poverty reduction if to be realized The results indicate that various spatial characteristics of where communities live play a key role in determining whether those communities will attain a given level of welfare.

LIST OF ABBREVIATIONS AND ACRONYMS

CDF	Constituency Development Fund
CSO	Civil Society Organisation
GIS	Geographic Information Systems
IDA	International Development Agency
HIPC	Highly Indebted Poor countries
HIS	Integrate Household Survey
ILRI	International Livestock Research Institute
IMF	International Monetary Fund
LDC	Less Developed Country
MDGs	Millennium Development Goals
MFPED	Ministry of Finance Planning and Economic Development
PEAP	Poverty Eradication Action Plan
SAE	Small Area Estimation
UBOS	Uganda Bureau of Statistics
UNHS	Uganda national Household Survey
USAID	United States Agency for International Development

CHAPTER ONE: INTRODUCTION

1.0 Background

Poverty still persists as a major huddle on the face of the developing world. Apart from the physiological limits it imposes, it still stunts the wishes and aspirations of millions of people, yet given sustainable human development as in East Asia in the last 40 years, its reduction is by no means an impossible task (Bonger 2000). Programmes to cut poverty are at the centre of national and international policy agendas. In its 24th special session in Geneva in 2000, the UN General Assembly expressed the world commitment to "reduce the proportion of people living in extreme poverty by one half by the year 2015 with a view to eradicating poverty". Several mechanisms and frameworks are being utilized and new initiatives explored with a view to promote and implement pro-poor policies and strategies, with emphasis on the Least Developed Countries (LDC's), particularly the Heavily Indebted Poor Countries (HIPCs). It is widely admitted that poverty is a multi-dimensional phenomenon and its eradication is a complex task. It therefore requires a wide range of policy and programme packages necessary to contribute to its reduction in developing countries.

Starting in the 1980s, many African countries attempted the kinds of economic policy reforms that had accelerated growth and reduced poverty in many East Asian developing countries. Similar successes did not reward their efforts: in Sub-Saharan Africa, per capita income declined by 15 percent and poverty rates increased between 1980 and 2000. Uganda was one of the few exceptions to this pattern. After years of civil conflict and failed economic policies, the country was ready to try something different. Starting in 1986, it introduced economic policy reforms that generated rapid economic growth and reduced poverty rates (USAID 2003). Uganda's growth has been rapid and sustained for an extended period of time. Further, this growth has clearly translated into substantial improvement in welfare for all socio-economic groups and in all regions of the country (Appleton, 2001).

In spite of the tremendous achievements, Uganda is still one of the poorest countries in the world, with a per capita income of about $ 338 per annum (DFID Uganda, 2006). Average per capita income levels conceal the extent and depth of this poverty since the country suffers from a skewed distribution of income. There have been wide spread of expenditure patterns and marked differences in expenditure levels between and within rural and urban areas in the country (Okurut et al 2002). Even though evidence of improvement is quite clear, there is concern that living standards are not improving by anything like the quantitative analysis of household expenditures suggests. Both of Uganda's participatory poverty assessments found that focus group participants and key informants were only slightly more likely to say that poverty had declined rather than increased in their community (UPPAP, 2000, 2002). In addition, there is concern among policy makers and stakeholders that non-income measures of well-being such as infant mortality and children's nutritional status are not improving over time despite the substantial increases in income (MFPED, 2002; UBS and ORC 2001) Successful interventions for poverty reduction therefore require clear insight into the problem both at the local and national scale.

For many years, the Government has been allocating resources directly to districts and communities with limited empirical basis for these decisions. For instance, resources are allocated to districts and constituencies in the form of Equalization Grants, Constituency Development Funds (CDF), the Roads Fund, Health Grants, Universal Primary Education Funds, District /Constituency level Bursaries for University education and more recently Micro-finance Funds. Although these disbursements are meant to reduce poverty and improve wellbeing, project implementation has proved difficult to gauge the performance of such programs because reasons why people are poor are not the same across regions.

Evidence from poverty maps for Uganda and other developing countries shows that poverty is not homogenous and tends to show a wide spatial variability (Okwi et al 2006). There are significant differences in poverty and welfare levels between communities living in different geographical areas. Some of these differences are caused by differences in environmental conditions and presence of natural factors (Jalan and Ravallion, 1998). Even though these factors have been identified as the major contributors to the differences in the standards of living of populations in different areas, there has been little empirical work to ascertain the exact causal relationship between the standard of living and these factors. The major problems to this kind of analysis have been data deficiency and the correct application of analytical tools (Birungi et al 2005). However recent advances in Geographic Information systems now allow such analyses to be undertaken. GIS are computer software programs designed to handle geographically referenced data. They are essentially database management systems that use geographic location as a reference for each database record. Location can be used to integrate information from heterogeneous sources, for example to find for each village in a region the mean annual rainfall or soil quality information, and distribution of population density. A GIS can also generate information to test hypotheses about neighborhood relationships. For instance, we can examine whether neighboring farmers tend to share similar household characteristics, which may point to the existence of significant clusters caused by some other factors, diffusion processes or spatial spillovers. It also provides powerful visualization tools that facilitate analysis of geographic data and improve communication of analysis results and policy recommendations. With availability of such and other spatial software, this study is able to investigate how effects of spatial variables explain poverty incidences in the rural areas of the country. This is made possible with the use of recently developed poverty maps for Uganda.

Poverty maps provide a detailed description of the spatial distribution of poverty. Detailed geographic profiles of poverty can be extremely valuable to governments, nongovernmental organizations and multilateral institutions that want to strengthen the impact that their spending has on poverty. For example, many developing countries use poverty maps to guide the division of resources among local agencies or administrations as a first step in reaching the poor. They can also be an important tool for research. Recent theoretical advances have brought income and wealth distribution back into a prominent position in growth and development theories (Demombynes et al., 2002). Detailed information about the distribution of the poor also enables us to investigate whether the spatial disparities in living standards have been caused by geographically defined factors. For instance, agro-ecological resource endowment, access to input and output markets, and availability of educational and health facilities all influence the well being of households. In addition to household survey data, small area data on poverty thus also allows to test hypotheses concerning the cause-effect relationships between geographic factors and the level of well being (Deichmann 1999).

1.1 Background to Uganda

Uganda is located in East Africa. It borders Tanzania and Rwanda in the south, Congo (Kinshasa) in the west, Sudan in the north, and Kenya in the east. The country's population is estimated at 28 million. The total fertility rate (the number of children that, given current age-specific birth rates, women will have in their lifetime) as estimated by the DHS, stands at 6.9, largely unchanged over the past decade and much higher than in neighbouring countries (e.g. Kenya: 4.7; Tanzania: 5.6, see Klasen 2005). Consequently, the population growth rate was about 3.4% per year between 1991 and 2002, which puts Uganda among the countries with the highest population growth rates in the world.

The country has four regions, which vary sharply in agro climatic conditions. The central region is a high rainfall area around Lake Victoria where bananas, Robusta coffee, and food crops are grown. This region is the most developed in terms of social and economic indicators, and includes the capital city, Kampala (Shenggen et al., 2004). It is still generally the least poor region in the country. The western region is the second least poor region and has mountainous areas where the altitude permits cultivation of temperate fruits, vegetables, and some traditional food crops. Infrastructure permitting, this region has the potential to be able to grow high-value crops. The eastern region has two distinct rainy seasons, separated by a four-month dry period, and its main crops include millet, cassava, and cotton. . This region is the second most developed region in terms of its social and economic indicators, but its rural poverty rate is still high. In the north, the rainfall pattern restricts cultivation to one season, with the main crops being cotton, maize, and millet. The northeastern region is included as part of the northern region, where the low average rainfall of 80 mm per year is suitable for pastoralism, sorghum, and millet.

Agriculture is the mainstay of the economy, and employs over 70% of the workforce. Most of the farms are small in size. The chief food crops are cassava, sweet potatoes, plantains, millet, sorghum, corn, and pulses. The principal cash crops are coffee, cotton, tea, tobacco, cut flowers, and sugarcane. There is a sizable fishing industry, and much hardwood is cut. Copper ore, once the leading mineral resource, has been virtually mined out. Other minerals extracted on a small scale include tin and iron ores, and tungsten. Uganda's few manufactures are limited mainly to processed agricultural goods, but they also include textiles, chemical fertilizers, and cement. Activities other than agriculture are gaining importance in the Ugandan economy. In particular, the manufacturing and the trade sectors together employ household heads that represent more than a fifth of the population at present (Kappel, 2001).

The annual value of Uganda's imports is usually considerably higher than the value of its exports. The principal exports are coffee (which accounts for the bulk of export revenues), cotton, gold, and tea. Ugandan exports are mainly composed by agricultural products, like coffee, cotton, tea, and fish. The economy is exposed to external shocks, as world prices for agricultural products tend to be volatile. Until 1994/95, coffee accounted for almost all Ugandan exports but its share declined dramatically thereafter. This was due to falling world coffee prices, whereas the quantity of exported coffee hardly diminished. In contrast, non-traditional exports like fish and fish products, tobacco, flowers, beans, hides & skins, and maize gained more and more weight in Ugandan exports, and fish might even become the country's future main export product. Export shares of cotton and tea grew only slightly in the same period. Generally spoken, the share of traditional agricultural products in Ugandan exports decreased sharply during the 1990s, while non-traditional exports gained higher share (Kappel, 2004). The leading imports are transportation equipment, machinery, consumer goods, chemicals, fuel, and foodstuffs. The main trade partners are the European Union countries, Kenya, and Japan.

1.2 The Poverty Situation in Uganda

In the 1990s annual GDP growth rose steadily to 6.9 percent from only 3 percent per annum during the 1980s (MFPED 2004). As a result, the share of the population below the poverty line fell from 56 percent in 1992 to 35 percent in 1999. Inflation has been under control and relatively stable at an average monthly rate of approximately 5 percent. The parallel market foreign exchange rate premium fell from over 100 percent in 1986 to less than 0.5 percent by 1994, while the private sector investment GDP ratio has been on a rise. Mean real private consumption per adult equivalent rose at an annualised rate of 4.7 percent for the country as a whole (Appleton 2003). This remarkable turnaround has been achieved through sound policies linked to investments and economic liberalization undertaken by the Government of Uganda with support from several development partners (Benin and Mugarura, 2006).

Despite the substantial progress made, including major developments in social services, several challenges remain in sustaining the momentum by way of reducing poverty, as there is indication that growth in the last few years has not been pro poor. The incidence of poverty increased on average from 35 percent in 1999/00 to 38 percent in 2002/03, with the largest increment occurring in the Eastern Region (Benin and Mugarura 2006). It should also be noted that while important initial steps have been undertaken to implement a broad-based poverty reduction programme, within the context of the Poverty Eradication Action Plan (PEAP) indications are that the recent actions and resultant gains achieved have not consistently improved the well-being of the poorest sections of the population (MFPED 2001). With this trend, there is need to critically examine the poverty situation at both the micro and macro levels of the economy.

Poverty in the country remains a predominantly rural phenomenon and particularly very pronounced among crop farmers. Rural poverty headcount declined from 60 percent in 1992 to 37 percent in 2000 before rising to 42 percent in 2003. The corresponding figures for urban areas are 28, 10 and 12 percent. The disproportionate contribution of rural areas to the national poverty has remained unchanged at about 96 percent. Between 1997 and 2000 consumption expenditure per adult equivalent for the richest 10 percent of the population grew by 20 percent while that of the poorest 10 percent grew by only 8 percent. In the 2000-2003 period the richest 20 percent of Ugandans experienced a 9 percent increase in consumption expenditure while the rest of the population reported a decline in consumption expenditure. This translated into the reported increase in poverty and the rise in welfare inequality from a Gini coefficient of 0.40 in 1999/2000 to 0.43 in 2002/2003 (Okidi et al, 2004). Regional imbalance, especially between Northern and the rest of the country has persisted, with Northern being the only region where consumption expenditure declined between 1997 and 2000. Nonetheless, this region has maintained the highest incidence of poverty of not less than 64 percent

Table 1 Inequality by spatial and welfare groups 1992 2003

	Relative Mean of Expenditure				Gini Coefficient			
	1992/93	1997	1999/00	2002/03	1992/93	1997	1999/00	2002/03
National	1.00	1.00	1.00	1.00	0.36	0.35	0.40	0.43
Rural	0.88	0.88	0.83	0.82	0.33	0.31	0.33	0.36
Urban	1.83	1.78	2.10	2.14	0.40	0.35	0.43	0.48
Central	1.28	1.37	1.41	1.45	0.40	0.36	0.42	0.46
Eastern	0.89	0.84	0.89	0.78	0.33	0.33	0.35	0.36
Western	0.93	0.92	0.96	0.95	0.32	0.28	0.32	0.36
Northern	0.77	0.76	0.58	0.58	0.34	0.31	0.34	0.34
Central Rural	0.99	1.12	1.02	1.06	0.33	0.32	0.33	0.37
Central Urban	2.11	1.98	2.36	2.50	0.39	0.33	0.41	0.48
Eastern Rural	0.85	0.79	0.81	0.72	0.32	0.31	0.32	0.34
Eastern Urban	1.25	1.43	1.57	1.51	0.32	0.34	0.43	0.40
Western Rural	0.90	0.89	0.90	0.88	0.31	0.27	0.29	0.33
Western Urban	1.64	1.57	2.07	1.64	0.35	0.36	0.39	0.44
Northern Rural	0.75	0.74	0.55	0.55	0.33	0.30	0.32	0.32
Northern Urban	1.11	1.17	1.13	1.12	0.39	0.33	0.39	0.41

Source, Okidi et al. 2004

The country has also witnessed substantial movements both into and out of poverty, and a significant minority of households have been persistently poor (Okidi and McKay, 2003). As a result many households have failed to benefit from Uganda's impressive macroeconomic development over this period (Lawson et al 2005).

1.3 Institutional Framework for Poverty Reduction in Uganda

In response to challenges and other general constraints to trickle-down effects of the macroeconomic achievements of reforms, in 1997 the Government launched the PEAP as the national policy framework for medium-term growth and development. The plan, which is Uganda's Poverty Reduction Strategy Paper (PRSP), is a medium term planning tool that describes the county's macroeconomic, structural and social policies and programs to promote growth and reduce poverty. Progress in achieving the goals as stipulated in the Plan are closely monitored and regularly revised in order to update it in a manner that reflects and accommodates changing socio-economic trends, emerging issues and challenges, priorities and achievements in the fight against poverty. The level of effort and input to the PEAP is so diverse and enormous that all institutions, agencies including the Civil Society Organizations (CSO) are consulted during the review process. The consultation process is undertaken at different levels: - Central and local governments; Civil Society Organisations (CSO); private sector; donors; academic and research institutions (Ssewanyana et al, 2004).

To operationalise the PEAP, detailed plans of action and goals for particular sectors are developed in the respective sector development plans, the implementation of which depends on the resources (spending ceilings) provided within the Medium Term Expenditure Framework (MTEF). The MTEF is a three-year rolling spending plan that links priority public spending areas to medium-term development goals.

Since the issuance of the PEAP, the government has been conducting the Uganda National Household Surveys, which measure the living standards of the population. It has also conducted a National Service Delivery Survey to assess the performance of public services. The results of these surveys, in particular the findings of the household survey, are reflected in the progress report and provide a robust basis for evaluating the evolution of poverty in Uganda.

While important initial steps have been undertaken to implement a institutional arrangement for poverty reduction within the context of the PEAP 2004/5-2007/8, indications are that the recent actions and resultant gains achieved have not consistently improved the well-being of the poorest population in the country.

1.4 The Problem

Efforts to reduce poverty at the national level often fail because the reasons people are poor vary from one location to another, and range from household characteristics to environmental covariates. Therefore, research based on spatial information, such as poverty mapping, to pinpoint where the poor are located and why they are poor has come to the forefront in recent years (Benson et al, 2005). In Uganda, various studies have attempted to explain the regional determinants of poverty in a bid to offer a hand in poverty reduction, but their analysis has concentrated on socioeconomic characteristics of households, with no emphasis on the impact of spatial covariates.

Although discrete evidence indicates that poverty is highly connected to poor-quality soils, drought-prone climates, high-altitude residence, absence of natural resources such as forests or water bodies and lack of access to markets, urban areas, public facilities and related services (Elbers et al, 2004, Okwi et al, 2006a), there has been little effort to establish the precise relationship between poverty incidence and these factors. In Uganda a few studies(see for instance Birungi et al (2005), Benson (2005b), and Okwi et al. (2006 b) attempted to incorporate these factors in poverty analysis, but applied data for 1991 that may no longer be relevant for current policy purposes. In addition, the maps they used could not facilitate analysis at sub-county level (the smallest planning level) due to large standard errors, which prompted the studies to base analysis at county level. With the recently concluded census (2002), and the 2002/03

Integrated Household Survey, there have been significant changes in the past decade that are likely to influence the direction of poverty incidences across regions. This study offers an improvement over the preceding studies by employing the 2002 poverty maps that used more recently collected (census and survey) data in addition to most recent spatial data(2002-2006). These maps have high resolution poverty data that facilitates analysis at sub-county-level.

The study attempts to establish the link between people and their local environments by estimating poverty incidence as a function of selected variables representing agro-climatic characteristics and market access to determine which of these factors are significant in explaining spatial patterns of poverty. Similar approaches have been followed by Minot et al (2003), Okwi et al (2006a), Benson et al (2005a), Benson (2005b) and others.

1.5 Objectives of the Study

The general motivation of the study was to investigate the spatial determinants of poverty in rural Uganda. Specifically, the study is intended to:

- explore whether the relationship between spatial factors and poverty differ significantly among regions in rural areas of the country
- explore the impact of spatial factors on sub county poverty incidence[1]
- suggest recommendations for viable intervention by government and other stakeholders

1.6 Research Questions

The key research questions in this study are as follows:

- Does the relationship between spatial factors and poverty differ significantly among regions in rural areas of the country?

1 Note that poverty incidence (used interchangeably with poverty rate in this study) is defined here as the proportion of the population living in household whose per capita expenditure is below the poverty line. This is the Foster-Greer-Thorbecke measure of poverty when $\alpha=0$

- What spatial factors account for the variation in sub county poverty levels across rural areas of Uganda?

1.7 Significance of the Study

The study was undertaken based on the theoretically informed expectation that certain agro-ecological and aggregate socio-economic characteristics of where individual or household lives can be important determinants of whether those residents will attain an adequate level of welfare to meet their basic needs. Such a local-scale understanding of the significant spatial determinants of local welfare, if coupled with knowledge of how individual and household-specific and broader national and sub-national factors affect household welfare, will contribute to the success of poverty reduction efforts.

1.8 Organisation of the report

The report is organised in five chapters .The first chapter is essentially an introduction, chapter two reviews existing literature in the area of spatial analysis, with emphasis on poverty. In chapter three, we highlight the theoretical framework upon which the study is built. Chapter four describes the data and methods used in this study. The fifth chapter explores results of spatial determinants of poverty in rural Uganda, using OLS, and spatial regression analysis, and a set of variables obtained from the Geographic Information System (GIS) database. The last chapter summarises policy implications and areas for further research.

CHAPTER TWO: LITERATURE REVIEW

2.0 Introduction

This chapter explores the studies related to poverty, and its interaction with space. It reviews the theoretical and empirical contributions to the proposed area of study. We review empirical works carried out in different countries in order to find gaps so as to justify the study.

2.1 Theoretical Literature

A focus on location and spatial interaction has recently gained a more central place not only in applied but also in theoretical econometrics. In the past, models that explicitly incorporated "space" (or geography) and therefore applications of spatial econometrics were primarily found in specialized fields such as regional science, urban and real estate economics and economic geography. However, more recently, spatial econometric methods have increasingly been applied in a wide range of empirical investigations in more traditional fields of economics as well, including, among others, studies in demand analysis, international economics, labor economics, public economics and local public finance, poverty analysis, agricultural and environmental economics(Aselin 1999). Of recent analysis has been focused on the spatial interactions of poverty and various environmental processes.

There are many kinds of environmental processes, interacting in elaborate ways with a variety of different aspects of poverty. This makes it very hard to generalize. Even where specific processes are well understood, outcomes and policy implications are often likely to be site-specific because of the sensitivity of the processes to local social, economic, and biophysical conditions. Therefore there is need to progress rapidly beyond the truism that the poor depend on environmental assets, to more rigorous examination of the impact of poverty alleviation policies on environmental conditions, and of environmental conditions on poverty. Environment-poverty interactions are best understood by a systematic examination of agents and impacts. The crux of most environmental issues is that actions by a set of agents have external (usually negative) impacts on a different group (crump. 1997).

A study by Chomitz (1999) points out that environmental interactions differ in regions and therefore influence poverty incidences differently. His analysis seems to suggest that there is an element of heterogeneity in poverty levels across regions, prompting specific policy and programme packages for poverty reduction. In line with this argument, Jalan and Ravallion (1998) note that poverty incidences are highly heterogeneous phenomena showing wide spatial variability. The large differences between the standard of living and of populations in different geographical areas are common in both developed and developing countries. They suggest introduction of spatial heterogeneity for various reasons, including differences in agroclimatic conditions, geographic conditions (particularly access to main urban centres and markets), the presence of natural resources, and facets of public policy. This study attests the likely influence of the above on poverty incidences across regions of Uganda.

In his first law of geography Tobler (1970) states "everything is related to everything else, but near things are more related than distant things". Essentially, the poverty condition of one zone correlates with the poverty conditions of its neighbors. Thus, zonal-based household and poverty are likely to exhibit correlation, even after controlling for observable factors. He points out that models without explicit treatment of these spatial dependencies may result in inappropriate inferences and conclusions.

The social science literature has three basic ways of thinking about how places affect individual or household poverty. One way of thinking, underlying much of the urban neighborhood poverty literature, is that places (neighborhoods) are sources of information and networks and norms that determine one's aspirations and opportunities to work and prosper. Recognizing that this class of models includes a variety of theoretical frameworks, Weber and Jensen (2004) label these as "social interaction models." A second framework for thinking about poverty and place is the "structuralist" tradition which views "place" as the locus of a set and barriers. Data on rural places usually confirm that rural areas offer barriers to economic success. A third way of thinking about place and poverty recognizes that people and firms make decisions in a spatial context

The "spatial interaction models" explicitly account for residential location and proximity to opportunity or risk factors in explaining an individual's likelihood of being in poverty, and consider the opportunities and barriers in adjoining places as well as in one's own neighborhood Blumenberg and Kimiko (2003) examine two types of spatial interactions in the quantitative studies. "Spatial mismatch" models examine how variations across neighborhoods in job access affect work outcomes of residents. This literature has focused mostly on urban areas and only on work, not poverty per se. "Spatial spillover" models examine the probability of being in poverty as a function of both the characteristics of one's own neighborhood and the characteristics of surrounding neighborhoods.

The issue of poverty and the physical environment also can be well understood when linked with the concept of risk and uncertainty, which are universal characteristics of life in rural areas Sources of risk include natural hazards like drought, commodity price fluctuations, illness and death, poorly functioning or missing input and output markets, sudden changes in price and non-price policies, changing social relationships, unstable governments and armed conflicts. All of these risks can cause losses in household welfare. Some risky events, like drought, simultaneously affect many households in a community or region. Other risky events, like most illnesses, are household specific. Poor households have a limited asset base, and face poorly functioning or missing insurance and finance markets, and a confined risk pool The risk management strategies adopted by rural households thus tend to be inefficient and have negative implications for social welfare and equity (Siegel and Alwang 1999). Private and social welfare losses result both from the risky events and from household strategies to manage the risk.

2.2 Empirical Literature

Many detailed poverty assessments and participatory poverty appraisals are at their weakest when it comes to differentiating between poor groups, except on the basis of income, and provide little information on the correlation between levels of poverty and geographical location of livelihoods and their production systems. Nonetheless, they do provide important insights into who the poor are, and the nature of their poverty. Identifying spatial patterns of poverty can provide new insights into its causes (Henninger, 1998). Spatial determinants are important particularly in the area of natural resources, as natural capital asset holdings (including natural resource stocks and environmental quality) are difficult to characterize with conventional variables, but by definition are spatially distributed. In the absence of reliable information geographic targeting offers several advantages over other methods of targeting. It can provide clear criteria for identifying the target population and avoids the informational constraints that impede most other targeted programs. The basic rationale for targeting programmes aimed at poverty alleviation on the basis of geography is the existence of large differences in living standards between geographic areas and the concentration of poverty in some areas (Bigman & Fofack, 2000).

In developing countries, where the dualism of urban and rural areas is still present and distinctive, a sharp distinction appears, likewise, in the analysis of poverty according to each area. It is stated that rural households are mostly affected by poverty. Indeed, it is in rural areas that poverty is the mostly pronounced with multidimensional aspects (economic, social demographic, and so forth). Poverty in rural areas is not only of chronic nature, but also structural for it found expression in mediocre socio-demographic characteristics. These characteristics engender a weakness of incomes and, even, an absence of steady sources of income (Samir etal, 2001). Nonetheless in many cases these socio-demographic characteristics in one way or the other interact with environmental traits of where individuals live to influence their wellbeing.

Where attempts are made to discriminate between degrees of rural poverty, the 'poorest' are characterised in terms of the (less favourable) agro-ecological conditions in which they must make a living, as in the case of the farmers in 'diverse, risk-prone environments' prioritised by 'Farmer First' approaches to technology development (Chambers et al 1989). This notion that poverty is concentrated in areas with lower agricultural potential has been commonplace in the 'targeting' of international agricultural research to combat poverty, although studies in India in the early 1990s suggested 'the percentage of the total population which is poor is fairly uniform across agro-ecological zones, varying from approximately 25 percent in the 'wet zone' to 39 percent in the 'seasonally dry zone' Even in the parts of India where the green revolution has taken place, the proportion of the population living in poverty is between 30 and 40 percent (Woodhouse, 2002)

Remoteness is also a key factor in explaining concentrations of poverty in Africa as it limits Access to markets, increases the price of inputs and makes both economic and social services less accessible One study in Tanzania has estimated that households within 100 metres of a gravel road, passable 12 months a year with a bus service, earn about one-third more per capita than the (rural) average' (IFAD 2001). There are similar findings from Nigeria (Porter 1997). Research by the UNDP provides evidence of spatial poverty traps in Africa's 'marginal lands (which) include drylands, swamps, saline lands and steep slopes. The areas are often isolated, unreached by well-developed physical and socio-economic infrastructure' (UNDP 1997) They found clear evidence of agro-ecological factors influencing the intensity of poverty:

Nevertheless it should not always be assumed that absolute levels of poverty will always be worse in 'remote' areas than in more economically dynamic, less remote areas Marzetti (2001), comparing more and less remote villages in Morrumbala District, Mozambique, found lower household incomes but also lower levels of child malnutrition in more remote villages than in villages with better market (road) access. This therefore calls for explicit analysis of distance to main centres, but also placing emphasis on access to other public resources that capture wellbeing.

Farrow et al (2002) used statistical and spatial analyses to examine the distribution of food consumption and food poverty and to test and generate hypotheses of food poverty estimates at the district level in Equador. Results indicated that the food poor are concentrated in certain locations with a significant cluster identified in the central Andean region. Geographically weighted regression showed that the processes underlying food poverty in Ecuador are also spatially variable. They noted that improvements in transport infrastructure would likely decrease levels of food poverty country-wide but could be most beneficial in the extreme south. The study however ought to have captured more on the dimension of poverty by considering per capita expenditure. This is because individuals might afford food items, but still remain below the poverty line given inability to spend on other basic necessities.

In attempt to examine the spatial determinants of the prevalence of poverty for small spatially defined populations in Malawi, Benson et al (2005a) used a theoretical approach based on the risk-chain conceptualization of household economic vulnerability to guide selection of a set of potential risks and analytical determinants that could be represented spatially. They used these to develop global and local models of poverty prevalence. In the global spatial error model, only eight of 24 determinants selected for analysis proved significant. These models provided strong evidence of the spatial non-stationarity of the relationship between poverty and its spatial determinants. Their results imply that poverty reduction efforts in rural Malawi should be designed for and targeted at district and sub district levels. It should be noted that, to what extent households or individuals are exposed to risks or shocks is an important consideration in assessing their likelihood of being vulnerable to falling into poverty, to this effect this study applies the risk chain analysis to draw theoretical understanding of poverty determinants.

In the study of Spatial Concentrations of Poverty, and Poverty Dynamics in the United States, Mindy and Bruce (2004) highlighted that poverty in the United States is not evenly distributed across the landscape. Poverty rates were highest in the most remote rural counties and in central cities, and persistent poverty was geographically concentrated in isolated rural regions. The decline in poverty, however, that occurred nationwide between 1990 and 2000 (from 13.1percent of the population to 12.4 percent) made large inroads in persistent poverty areas. This study however did not elaborate whether the tract-level poverty dynamics of the 1990's were affected by spatial concentrations of poverty, neither did it highlight whether the effect of improved economic conditions depended on what happened in neighboring areas.

A household's spatial position also affects its access to both input and output markets necessary for accumulating wealth and benefiting from the opportunities an overall economic upturn provides (Christiaensen 2003). Christiaensen (2003) further agrees with the view that regional differences in living standards are obviously also linked to the agro-ecological characteristics of the environment (temperature, rainfall, altitude, slope, soil fertility, etc) which affect the productive potential of the locality and its inhabitants. And the availability of public infrastructure and services (electricity, sanitation, health and schooling facilities, credit and extension services) often differs considerably across regions. There is a strong expectation, therefore, that growth in Africa is likely to have highly differentiated geographical effects.

Using a relatively new method called Small Area Estimation to estimate various measures of poverty and inequality for provinces, districts, and communities of Vietnam, Minot et al. (2003) found out that the poverty rates were greatest in upland areas and locations distant from urban centres. Agro-climatic and market access variables were able to explain about three quarters of the variation in district level rural poverty. Poverty was higher in districts with sloped land and rock land cover, as well as poor soils. A local regression model in which coeffients vary from one area to another revealed that variables such as rainfall and forest cover were positively associated with poverty in some areas and negatively associates in others.

Okwi et al. (2006a) applied spatial regression techniques to explore the effects of geographic factors on poverty in Kenya, and investigated the link between poverty incidence and geographical conditions within rural Locations of the country. The results showed mixed effects of geographic variables at national versus provincial levels. Slope, soil type, distance/travel time to public resources, elevation, type of land use, demographic and income inequality variables proved to be significant in explaining spatial patterns of poverty. However, differential influence of these and other factors at the Location-level showed that Provinces in Kenya are highly heterogeneous; hence different spatial factors were deemed important in explaining welfare levels in different areas within Provinces. The study highlighted the importance of investments in roads and improvements in soil fertility as potential interventions to reduce poverty rates in the country.

A study by Biringi et al (2005) investigated an approach based on the spatial regression model, for mapping poverty in Uganda and highlighted the importance of wetlands, roads, hospitals, grasslands, farmland, built areas, slopes and rainfall on the probability of sub counties being poor. There results suggested the presence of a poverty environment relationship and hence the impact of environmental factors on the lives of communities in the country. The study stressed the need to consider environmental factors in the design and implementation of effective poverty reduction strategies. However the study would have produced better results for policy design by employing a more recent population and housing census (2002) as well as the 2002/2003 Household survey dataset.

Combining spatially disaggregated poverty and biophysical data for 1991 and for 1999/2000, panel analysis of small-area estimation techniques for rural Uganda was applied in Okwi et al (2006 b) to analyse the relationship between poverty and the environment. The results indicate that poverty is less is in areas that have been degraded, subsistence farm wetlands (reclaimed) and highest in areas with mainly grasslands or woodlands. They also indicate an overall decline of poverty in most areas with an exception of some areas in Northern region. On the other hand, environmental degradation was more visible in areas of eastern, central and western Uganda. The accuracy of these results was however reasonable only up to the county level.

Benson (2005b) analysed the spatial determinants of poverty and inequality in Uganda based on results of the poverty mapping exercise carried out by Hoogeveen, Emwanu, and Okiira Okwi (2003). The poverty maps here were derived by combining the 1999/2000 UNHS, the 1992 and the 1991 Uganda Population and Housing Census in order to predict per capita consumption for each household. Like the previous studies, in addition to using old data, this study was unable to make analysis at sub county level.

2.3 Overview of Literature

Theoretical literature on poverty highlights the importance of space in influencing poverty levels across regions, but less effort is made to evaluate the impact of environmental correlates in detail. On the other hand, most empirical poverty studies surveyed (for instance Mindy and Bruce, 2004, Benson et al. 2003, Okwi et al. (2006a.), Okwi et al. (2006b) Birungi et al. 2005, Chambers et al. 1989) seem to agree with the impact of spatial factors on the incidence of poverty. As earlier noted however, in Uganda analytical work on determinants of poverty is scanty and the few existing studies have focused simply on descriptive and measurement issues. This study attempted to extend the analysis of poverty by modeling the determinants of poverty using spatial data for rural areas of the country. As noted in the previous chapter, it offers offer an improvement over Birungi et al. (2005) and Okwi et al (2006 b), and Benson et al. (2005b) studies by employing the 2002 poverty maps derived from the 2002 population census and the 2002/03 household survey data. An innovative aspect of this study is that it used sub county level poverty rates using spatial regression analytical techniques. This approach models the spatial determinants of Location-level poverty, or the factors that help explain spatial variation in the proportion of the rural population living below the poverty line across the country.

CHAPTER THREE: THEORETICAL FRAMEWORK

3.1. Introduction

This chapter explores the theory on which our study is based. We offer and insight into the concept of vulnerability with more focus on the subject of poverty, and how various spatial factors may act to contribute to the probability of individuals and household becoming poor

3.2 Understanding Vulnerability to Poverty

In this study we adopt an underlying theory that attempts to understand how households cope (or fail to cope) with shocks, called the risk chain theory[2]. Practitioners from different disciplines use alternative meanings and concepts of vulnerability, which, in turn, have led to diverse methods of measuring it. Differences in approaches to vulnerability among the disciplines can be explained by their tendency to focus on different components of risk, household responses to risk and welfare outcomes. In this case we define Vulnerability to poverty as "having a high probability of being poor in the next period" and is determined by the ability of households and individuals to manage the risks they face Vulnerability is an important aspect of households' experience of poverty. Many households, while not currently in poverty recognize that they are vulnerable to events that could easily push them into poverty-a bad harvest, an unexpected expense, an economic downturn, environmental impact.

Literature on vulnerability recognizes explicitly that poverty, as it is usually defined, is a static concept, yet the relationship between outcomes, such as consumption and life-cycle welfare is dynamic. Siegel and Alwang (1999) assert that vulnerability, if it is to be a useful concept, must embody both risk and the household's position relative to the poverty line A household that is well above the poverty line, but who faces a small risk

2 See also Dercon (2001)

of falling below it, cannot be considered more vulnerable than a household with a level of certain consumption that is below the poverty line. Thus, it is important to consider both levels of income (or consumption) and deviations from this expected value.

Poverty tends to be an ex post state of being; that is, a household is poor if and only if its consumption (or whatever objective criterion is used for measurement) falls below a level deemed necessary for a minimum level of well-being. A household may move in and out of poverty, but at any point in time, it is classified as poor or not poor. Vulnerability is both an ex ante and an ex post state associated with the probability of falling into a state of destitution. A vulnerable household may have a level of welfare at a point in time that exceeds the minimum level, but under a different state of nature this household would fall below this level.

As an organizing framework, the Social Risk Management (SRM) framework is used to decompose vulnerability into several components. To better understand the literature, Alwang et al (2002) decompose it into several components of a risk chain: a) the risk, or risky events, b) the options for managing risk, or the risk responses, and c) the outcome in terms of welfare loss. The SRM approach uses this risk/vulnerability decomposition to understand means by which society can manage risk at any part of the chain. The SRM search for optimal vulnerability reduction involves understanding the most efficient means of managing this risk and tradeoffs that exist along the chain. Although vulnerability is a dynamic concept since it is concerned with the potential future welfare status of individuals and households, it also provides useful insights accounting for why households and individuals or, as here, aggregations of households are poor or not poor at a particular point in time.

Households are vulnerable to suffering an undesirable outcome, and this vulnerability comes from exposure to risk. Vulnerability begins with a notion of risk. Risk is characterized by a known or unknown probability distribution of events. These events are themselves characterized by their magnitude (including size and spread), their frequency and duration, and their history — all of which affect vulnerability from the risk. Policies and actions can reduce risk or exposure to risk. Risk management can also, however, help households manage risk at other parts of the risk chain. Households can respond to, or manage risks in several ways. Households use formal and informal risk management instruments depending on their access to these instruments. Risk management involves ex ante and ex post actions. Ex ante actions are taken before a risky event takes place, and ex post management takes place after its realization. Ex ante risk reduction can reduce risk or lower exposure to risks. It is also possible for a household to take ex ante risk mitigation actions that provide for compensation in the case of loss such as purchase of insurance. Ex post risk coping activities are responses that take place after a risky event is realized and involve activities to deal with realized losses such as such as selling assets, removing children from school, migration of selected family members. Some governments provide safety nets, such as public works programs, that help households cope with risk. Households often face constraints to adopting efficient risk management practices.

Many times in an attempt to avoid risk exposure, households may take costly preventive measures, which in turn, contribute to poverty. For instance, to avoid extreme income poverty or food insecurity a household may choose to live in an unhealthy or unsafe environment (such as landslides). It is not only exposure to risks that may lead to unacceptable outcomes in well-being. The manifestation of risk (as a shock) also leads to undesirable welfare outcomes (Hoogeveen et al 2003). In this framework, household vulnerability depends upon the degree to which they are exposed to negative shocks to their welfare, and on the degree to which they can cope with such shocks when they occur (Benson et al, 2005a).

To provide a better insight on the concept of vulnerability, we borrow an illustration from Pritchett et al (1999). Here the vulnerability of household h for n periods (denoted as R(·) for "risk") is the probability of observing at least one episode of poverty (in the usual notion that real current consumption expenditures, c, are less than the poverty line) for n periods, which is one minus the probability of no episodes of poverty:

$$R(n,PL) = 1 - \left[(1 - P(e_{t+1}^{h} < PL)) \ldots (1 - P(e_{t+n}^{h} < PL))\right] \tag{1}$$

We have key issues to note here. First, since expenditures at time t are known, it is also known whether a household is currently in poverty or not. In the future, however, many households currently in poverty will rise out of poverty in the next n periods, so the future vulnerability of the currently poor is less than one. Second, the poverty line (PL) is time invariant because the household's total real expenditure e is appropriately deflated, so that a constant poverty line on those expenditure units represents constant levels of welfare over time. Third, by defining the notion in terms of observed expenditures, this measure of vulnerability already incorporates the existence and use of coping mechanisms. Some households may face large income variability and risk but have adequate mechanism to smooth over income changes and maintain expenditures relatively constant (e.g. savings, borrowing, informal). Hence observed expenditure vulnerability reflects both income risk and the utilization of smoothing.

While each household has some vulnerability, we want a more concrete measure of the number of households which are "vulnerable." We define a household as *vulnerable* if the risk in n periods is greater than a threshold probability level p:

$$V_t^{h}(p,n,PL) = I\left[R_t^{h}(n,PL) > p\right] \tag{2}$$

where I[ ] is an indicator function. So, while vulnerability is a risk and comes in degrees (between zero and one), being *vulnerable* is a state (either zero or one).

Taking the first period in the expression for vulnerability, we define the change in expenditures in the natural way as Det+1 = et+1 – et. Suppose that there is a time invariant trend (the expected increase in household h's income in each period, m) and variability of the inter-temporal *change* in expenditures for each household (s) - note this is not the usual variability *across* households. Then the probability of a household with expenditures in the current period of et falling into poverty in next period is just the probability that the negative shock to expenditures is greater than the current amount by which the household's expenditures exceed the poverty line (et – PL) plus the expected change in income (m):

$$P(e^h_{t+1} \angle PL) = P(\Delta e^h_{t+1} \angle -(e^h_t - PL)) or$$

$$P(e^h_{t+1} \angle PL) = P((\Delta e^h_{t+1} - \mu^h)/\sigma^h \angle (-(e^h_t - PL) - \mu^h)/\sigma^h) \tag{3}$$

The latter probability is,

$$P = \int_{-\infty} f((\Delta e^h_{t+1} - \mu^h / \sigma^h) d\Delta e \tag{4}$$

where f( ) is the density function of Δe

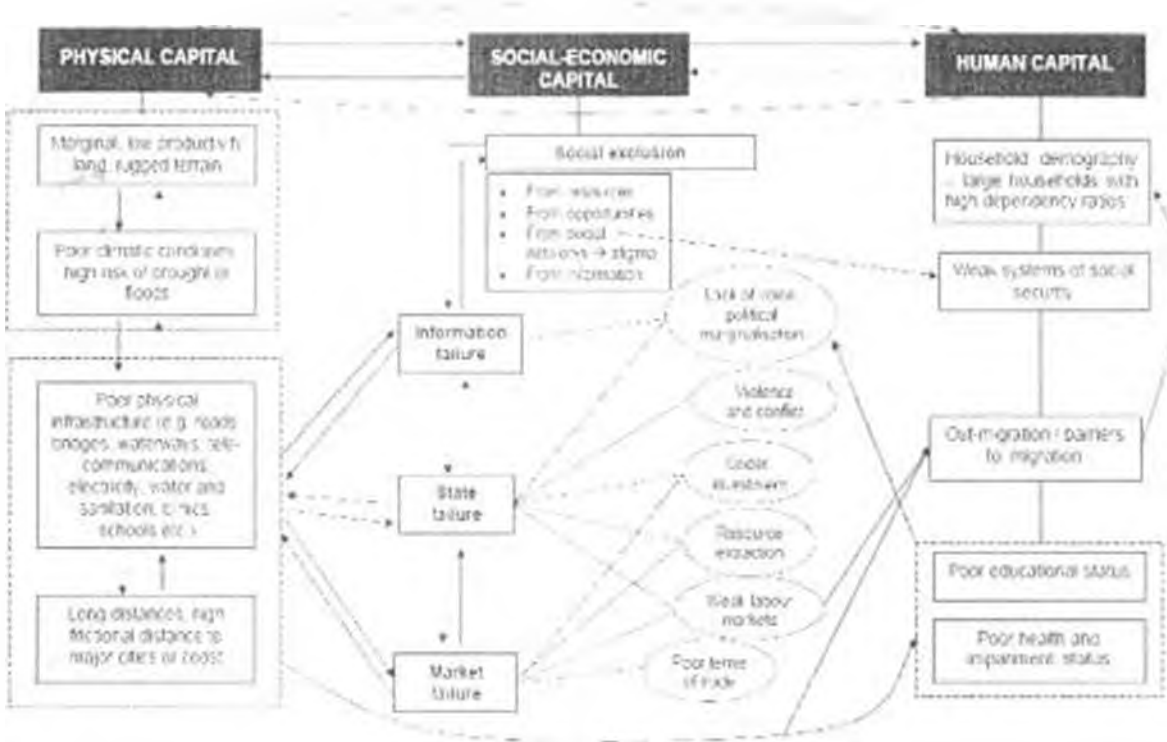
To make more progress we need to make more, and stronger, assumptions. First, assume that household expenditures is expected to be the same in each period so that $\mu = 0$ and $E(e_{t+n}) = e_t$. This assumption has two justifications. First, this is a plausible "base case" as a hypothetical question: If incomes were to remain constant but the household faced the variability of income it currently faces, what is the probability it will fall into poverty? Hence, one should think of the calculations below as answering the question: if the level of income did not change but each household had variability in their expenditures repeated for n periods, what fraction of households would end up having at least one observed episode of poverty? Second, this assumption is easily modified later if one is willing to make clear and explicit predictions about the expected future growth (or fall) in earnings (either on average or for specific households)

We also make the even stronger assumption that Δet is independently identically distributed (iid) in each period and that the distribution of the *changes* in expenditures (not necessary the level) is normal. With these two assumptions we can compute the level of "vulnerability" of a household for any given level of current expenditures (e) as:

$$R(n,PL,e,\sigma)=1-\{1-\int_{-\infty}N(0,1)\}^{n} \qquad (5)$$

To what extent households or individuals are exposed to shocks is an important consideration in assessing their likelihood of being vulnerable to falling into poverty. These risks may be events that affect the population broadly (covariate risks) or those that affect individuals or households in a more random fashion (idiosyncratic risks). Covariate risks that affect specific areas or broad and, ideally, spatially defined segments of the population are the easiest to bring into a spatial analysis. Idiosyncratic risks, in contrast, are less easily managed analytically within a spatial context. The outcome is whether or not the household is poor, which can be measured by a consumption-based welfare indicator (which we use in this study). At the community or Location-level, shocks such as droughts or floods are typically felt by all households, and their access to natural resource assets (soil, water, services, etc.) that help them cope with the shocks are also similar. Thus, the independent variables used in this type of analysis are made up of an array of aggregate spatial characteristics for the small local areas considered, and based on the underlying risk-chain theory, can be considered determinants of the local prevalence of poverty, and not simply correlates

Figure 1 Multiple Vulnerabilities in Remote Rural Areas: Spatial poverty traps based on poor geographic capital and covariant risk



Source Bird et al (2007)

Generally, this study investigates how well spatial variables account for the spatial variation seen in sub-county-level poverty rates across the country. Overall, it is initially expected that the impact of spatial variables and poverty varies significantly from one region of the country to another. The ability of these variables to explain a large portion of the differences in poverty can well indicate that poverty in remote areas may be linked to agricultural potential, natural resource availability and lack of market access. By intuition, access to towns is expected to favor production of high-value products and non-farm activities and should therefore contribute to better welfare or higher incomes. Areas with high agricultural potential (proxied by longer growing period) could also have an absolute advantage in producing high value crops. In terms of the demographic variables, population density is expected have varied directions; i) to influence labor intensity of agricultural production, including the choice of commodities as well as production technologies and land management practices, by affecting the land-labor ratio; ii) Increase pressure on meager resources through say high dependence ratio, and land fragmentation, thereby limiting efforts to improve welfare. Presence of social services such as hospitals, schools and markets may influence welfare in localities by promoting better health, livelihood and other human capital variables. Such an understanding of the determinants of poverty can effectively guide governments' and others' effort to reduce poverty by adopting more location specific and precise policy options. It can also provide valuable policy lessons for other countries in the region

CHAPTER FOUR: METHODOLOGY

4.0 Introduction

Having explored the theory that guided the selection of our independent variables in our study (chapter three), here we examine the methods that were employed to analyse the spatial determinants of rural poverty in the country, and reasons for their adoption. Results of this chapter guide the proceeding discussion in chapter four

4.1 Model Specification

4.1.1 The dependent variable

First, we turn our focus on the independent variable (sub county poverty rate) used in this study. Recall that our interest in this case was to investigate the impact of spatial variables on poverty incidence in various rural sub counties. The poverty estimates here were derived from the recently developed poverty maps for Uganda (2002)[3] which employed household survey data (2002/2003) and census data (2002) to produce poverty estimates for administrative levels (districts, counties and sub counties). These estimates were obtained by applying the expenditure-based Small-Area Estimation (SAE) approach. SAE is a statistical technique that combines household welfare survey and census data (both collected at approximately the same time) to estimate welfare or other indicators for disaggregated geographical units such as communities. It applies parameters from a predictive model to identical variables in a census; the assumption is that the relationship defined by the model holds for the larger population (census) as well as the original sample. This approach was developed by Elbers et al (2003) to analyse the link between poverty and location, and has undergone be refinement with many collaborators[4]. Much as our study made use of the estimates that were ready

3 These maps were develop by UBOS and ILRI. A full report is yet to be published

4 For more insight regarding the approach, review Hentschel et al., 1998, hentschel et al., 2000, Mistiaen et al., 2002

derived, it is important to have an idea regarding the process through which these estimates were obtained.

This approach begins with the nationally representative household welfare survey to acquire a reliable estimate of household expenditure (y). This enables calculation of more specific poverty measures linked to poverty a line. The log linear regressions model per capita expenditure using a set of explanatory variables (x) that are common to both the integrated household survey and the census (e.g. household size, education, housing and infrastructure characteristics, and demographic variables). These first stage regression models are represented at the lowest geographical level for which the integrated household data is representative (region), and a different first stage model is estimated for each stratum (e.g. region, urban, and rural).

Next, the estimates coefficients from these regressions (including estimated error terms associated with these coefficients) are used to predict the log per capita expenditure for every household in the census. These household-unit data are then aggregated to small statistical areas, such as sub counties, to obtain robust estimates of the percentage of households living below poverty line. These poverty rates are used to produce a poverty map showing the spatial distribution of poverty at the sub county level., in the case of Uganda, which represents a significantly higher level of resolution than the regional- level measure obtainable from using the household welfare survey alone.

In the first stage of the Uganda analysis, the variables within the census and household survey were examined in detail. The objective in this case was to determine whether there was as statistically similar distribution of the variables over households in the population census and in the household sample survey.

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 various statistics for east variable obtained from both surveys, which include: the mean, the standard error, and the values for various percentiles.

The modeling step of the analysis involved developing nine models, (four for rural, four for Urban and one for Kampala) using the household survey data in regression analysis. The variable estimated in this case was per capita household expenditure for a household in a particular location. The independent or explanatory variables for the model were those observable characteristics in both surveys.

The estimated first stage parameters were then combined with the observable characteristics of each household in the census to generate the predicted per capita household expenditures (including an error estimate) for every household in the census. For each model estimates, a step wise regression procedure in the SAS software was used to select the subset of variables from the set of comparable variables that provided the best explanatory power for the log per capita expenditure. A significance level criterion with a ceiling of 15-20 comparable variables to be selected was chosen. The authors used variables that were comparable across all the nine strata and in cases where they were less, only those variables that were comparable across only either urban or rural strata were selected. All variables that were significant at the 5 percent level were selected for the regression. The results of the regression analysis show that the models were quite successful at explaining the variation in household expenditures in both urban and rural areas.

4.1.2 Generalised OLS Regression Model

Having traced the origin of our independent variable, it is important to describe the regression techniques that were employed in the study. Preliminary assessment consisted of a simple Ordinary Least Squares (OLS) regression. This takes the form:

$$y = x\beta + \varepsilon \qquad (6)$$

Where

y is a vector of observations on the dependent variable (poverty rate obtained in 4.1.1) taken at each of the locations.

β is the vector of coefficients

ε is a vector of disturbances.

χ is a non stochastic matrix of observations on the explanatory variables for a given region. These vectors may include spatial and non spatial factors.

However, we have two major concerns to be addressed in this case.

i) Heteroscedasticity

Note that one of the important assumptions of the OLS regression model is that the variance of the disturbance term ε conditional on the chosen values of the explanatory variables is homoscedastic, that is, it has a constant variance regardless of the values taken by these variables. However this is not always the case. Many times especially in cross sectional analysis, this assumption is violated leading to heteroscedasticity; a case where the variance of the disturbance term is not constant. In this case for instance, the variance of poverty rate may change with different levels of population density. One of the causes of heteroscedasticity is the presence of outliers. An outlier is an observation that is much different (either very small or very large) in relation to other observations. For instance an observation for distances in one location may be very small or very large compared to observations on the same variable in other locations. Inclusion or exclusion of such observation can alter results of the regression. It could also arise as a result in errors in data collection, transformation and management, and skewness in the distribution of one or more explanatory variables such as population density in this case.

Although OLS remains unbiased and consistent in the presence of heteroscedasticity, the standard errors of the estimates are biased. With biased standard errors, we can not use the usual t statistics, F statistics or LM statistics for drawing inferences. In this case

OLS, even if standard errors could be correctly measured, is no longer efficient. This calls for remedial measures.

In this study we employed the Breutch-Pagan-Godfrey (BPG) test to test for the presence of heteroscedasticity. It follows a χ^2 distribution under the null hypothesis of homoscedasticity (constant variance). The null hypothesis is rejected if the calculated χ^2 value is greater that the critical χ^2 value5.

The most common response to the (potential) presence of heteroscedasticity of an unknown form is to use a heteroscedasticity-robust estimator for the covariance matrix of the regression parameters. Another approach often applied is making log transformation of variables.

ii) Spatial Autocorrelation

Another critical concern with the regression is violation of the OLS assumption that error terms should not be spatially correlated with each other, as evidenced by observations from locations near to each other having model residuals of a similar magnitude (spatial autocorrelation). Spatial autocorrelation is a property of spatial data which arises whenever there is a systematic pattern in the values recorded at locations in a map (Kr¨amer and Hanck, 2006). For instance poverty in one geographical area might be influenced by poverty levels in the neighbourhood. Spatial autocorrelation if not corrected leads to biased OLS estimates.

The presence of spatial autocorrelation can be evidently indicated by the Gi- statistic, Geary's C, and by Moran's I statistic in which case the OLS assumption of uncorrelated and homoscedastic error terms is not fulfilled (Stogbauer 2001). In this study we place emphasis on the Moran I statistic. This statistic is a region wide or global measure of spatial autocorrelation informing us about the extent to which a variable in the

5 This can be obtain from the chi distribution tables appended in most econometrics textbooks

regression is surrounded by similar values of that variable. The statistic is given as:

$$r = \frac{\sum_{i}\sum_{j\neq i} w_{ij}(x_i - \mu)}{s^2\sum_{i}\sum_{j\neq i} w_{ij}} \qquad (7)$$

Where

w_{ij} is the element of the weight matrix that refers to the regions i and j,

x_i is the observed value of the population at location i, and

μ is the mean.

A positive and significant value of the Morans I statistic indicates positive spatial autocorrelation, indicating that areas have poverty incidences similar to their neighbours. The index is analogous to the conventional correlation coefficient, and its values range from 1 to -1.

A negative and significant value of Moran I statistic indicates negative spatial correlation showing that areas have levels of poverty unlike neighbouring locations, and a low value may be surrounded by high values in neighbouring locations, and a low value may be surrounded by high values in nearby locations.

4.1.3 Specification of the Spatial Regression Model

In the even that no spatial autocorrelation is evident, it is imperative to go a step further and consider the OLS regression in equation 6. Otherwise, it necessitates introducing a model that can control for this kind of occurrence. Spatial autocorrelation can be controlled by using the spatial regression model that controls for the dependence with neighbouring observations in the dependent variable. The model is also important in analysing the impact of spatial factors. Spatial autocorrelation can manifest itself either in form of spatial lag dependence or spatial error dependence *i) Spatial Lag Dependence*

The spatial lag case can be interpreted as spatial contagion or spill-over: here the behaviour of one region is spatially explained by similar behaviour in adjacent region For instance in this study spatial dependence could be a result of the level of poverty in a location affecting the level of poverty in the location in question through for example trade or investment linkages Such a relationship can be modeled as a spatial lag model, which is a formal representation of the equilibrium outcome of processes of social and spatial interaction. In the spatial regression equation, this is accomplished by including a function of the dependent variable observed at other locations on the right hand side in equation 1 to obtain:

$$y_i = \rho \sum_j w_{ij} y_j + x_i \beta + \varepsilon_i \qquad (8)$$

Where,

y_i is the dependent variable (as in equation 6) for sub county i, and

x is the usual data matrix containing explanatory variables.

β is the coefficient of the independent variable

ρ is the spatial autoregressive coefficient, and the error term is independent and identically distributed.

w is a spatial weight matrix

The parameter ρ displays the strength of the correlation between the disturbance term and the weighted average of the disturbance terms of the neighbouring areas. It measures the degree of correlation, which can be both positive and negative. y_j is a spatially lagged dependent variable for area j, whereas parameters

w reflects the proximity of i and j. It assumes a value of one in a square matrix with dimension of n, where n stands for the number of spatial units. If they have no common border, the corresponding value of w_{ij} would be zero (Stogbauer 2001). Omitting this adjustment leads to biased estimates.

Equation 8 can be presented in matrix notation as:

$$y = \rho w y + x\beta + \varepsilon \qquad 9$$

The proper solution to the equations for all observations is the reduced form, which no longer contains any spatially lagged dependent variables on the right hand side. After some matrix algebra, this follows as:

$$y = (1 - \rho w)^{-1} x\beta + (1 - \rho w)^{-1} \varepsilon \qquad 10$$

ii) Spatial Error Dependence

This kind of spatial dependence occurs if there are variables that are omitted from the regression model but in fact do have an effect on the dependent variable and they are spatially correlated. For example, the type of administration in an area may affect income and poverty levels, but is not easy to include in a regression model. Since the type of local administration is likely to be spatially correlated (all locations in a given sub county may be affected by poor administration), the error term in each location is likely to be correlated with those in nearby locations. Such a relationship can be modeled as a spatial error model (Okwi et al 2006a)

$$y_i = \beta x_i + \lambda \sum_{j} w_{ij} \varepsilon_j + \varepsilon_i \qquad (9)$$

Where λ is the spatial autoregressive coefficient and the rest are earlier defined

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 the question.

Ignoring substantive spatial dependence results in biased OLS estimates, disregarding error dependence results in unbiased but inefficient OLS estimates (Anselin 1988).

A joint application of the Lagrange multiplier error and Lagrange Multiplier lag tests can be used to determine which of the two (spatial regression) models is appropriate. A positive and significant value of the statistic I statistic indicates positive spatial autocorrelation, indicating that areas have poverty incidences similar to their neighbours, whereas a negative and significant value indicates negative spatial correlation[6]. The Lagrange Multiplier error test (lm_{err}) is χ^2 distributed with one degree of freedom and has the form:

$$lm_{err} = \frac{\left\{e'we / s^2\right\}^2}{tr\left\{ww + w^2\right\}^{-1}} \tag{10}$$

where tr is the trace matrix operator, e is the vector of OLS residuals, $s^2 = e'e/N$ represents the Maximum Likelihood (ML) estimate for the residual variance, and w stands for spatial weight matrix. The Lagrange multiplier lag test (lm_{lag}) has a χ^2 distribution with one degree of freedom and can be expressed as

$$lm_{lag} = \frac{\left\{e'wy / s^2\right\}^2}{\left\{(wxb)mwxb / s^2 tr\left(ww + w^2\right)\right\}^{-1}} \tag{11}$$

Where tr is the trace matrix operator, $m = I - x(x'x)^{-1}x'$ y is the vector containing the dependent variable, e is a vector of OLS residuals, W is the spatial weights matrix, $s^2 = e'e/N$ represents the ML estimate for the residual variance, and b is the vector of OLS estimates. The preferred model in this case is one with highest LM test value

6 For further discussion of this distinction, see Stogbauer (2001)

4.2 Key Independent Variables and Expected Signs of Coefficients

Table 1 shows the key selected independent variables for the analysis and how they were hypothesized to affect poverty incidence. The variables are divided into two categories. Exogenous variables are those variables that are unlikely to be affected by the level of economic activity or poverty. An example of an exogenous variable is rainfall. This variable may influence poverty in an area but cannot be influenced by poverty. On the other hand, endogenous variables are those that may both influence poverty or be influenced by poverty (Okwi et al 2006a).

Table 2. Expected signs of coefficients

Variable	**Expected relationship to Poverty**
Household Size	Positive (high HH size, higher poverty
Rainfall	Negative (Low rainfall, higher poverty)
Elevation	Positive (High elevation, higher poverty)
Slope	Positive (steeper slope, higher poverty)
Distance to towns/municipalities	Positive (Greater distance, higher poverty)
Type of land cover	Not known
Length of Growing period	Negative (Longer LGP, lower poverty)
Population density	Not known

4.3 Data Types and Sources

The central element in this study is the availability of survey, census and spatial data. The poverty mapping portion of this project makes use of two household data sets collected by the Uganda Bureau of Statistics (UBOS): census data for 2002 and sample survey data from 2002/2003 to derive welfare estimates and maps. The Uganda National Household Survey 2002/03 was the eigth in a series of household surveys that started in 1988. The collected information on the economic characteristics of the population and its activity status at the household level. The main objective of the survey was to collect high quality and timely data on population and socio-economic characteristics of households for monitoring development performance. It comprised of four modules namely the Socio-economic, Labour force, the Informal Sector, and Community modules. The survey presented the levels of different indicators and wherever possible, their respective trends over time. Indicators on population characteristics, labour force participation rates, education, health, household expenditure and poverty among others were presented at national, regional and rural-urban levels. The socio-economic questionnaire aimed at collecting information of the following sections: Household identification, including geo-referencing codes, household roster including basic information such as sex, age, marital status of everyone living in the household, and survival of parents for children below 18 years; information related to health; Education and literacy for all household members. Housing and sanitation conditions, migration; household consumption expenditure, and other attributes. The survey was conducted in all districts[3] except Pader, some parts of Kitgum and Gulu which were not included due to insecurity.

Uganda Population and Housing Census was conducted in September 2002. The survey presents the results in broad categories of population and household characteristics and housing conditions. The population characteristics covered include spatial distribution of the population, age and sex composition, religious and ethnic composition, education and literacy, economic activity, orphanhood and disability. The household and housing conditions include socio-economic amenities available to households and quality of housing. The country's 56 districts as at September 2002 were grouped into four regions namely Central, Eastern, Northern and Western. These are statistical groupings of districts without administrative or political status. In order to show a clearer trend, the 1980 and 1991 censuses data was redistributed according to the current district boundaries and other lower administrative units.

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3 At the time of the survey Uganda was divided into 56 administrative districts

The spatial analysis portion of this project used a variety of spatially referenced variables describing topography, land cover, agro climatic, and demographic variables. Geo-referenced information from the National Biomass Study of the Ministry of Water, Lands and the Environment was used. We also data from Africover[8] multipurpose database which availed information on land cover variables woodlots, forests, grassland, wetlands, and water. Data on slope and elevation was obtained from NASA database. Some of these variables were used in the development of poverty maps for 1992. All the data from these sources was combined using GIS techniques in order to manage the spatial dimension, and analysis was made using GeoDa[9] statistical package and STATA 9/SE[10].

4.5 Limitations of the Study

The practical application of the spatial determinants of poverty analysis presents a number of econometric and computational limitations. In this case challenges included issues relating to data processing, spatial autocorrelation, and heterogeneity. However with the recent introduction of GeoDa software, variables from various sources (census, and environmental data) are well handled through. However, STATA version 9.1 (SE) also provides significant modeling components to handle this kind of analysis. The study complemented the analysis done in GeoDa with STATA. A diagnostic selection of appropriate spatial regression models catered for spatial autocorrelation. While there can be different levels of heterogeneity, an argument can be made that, in particular, the regions of Uganda (Eastern, Central, Northern and Eastern) are sufficiently different that they warranted different models. The study used separate models for the different regions because there are a number of geographic and community-related variables that are more relevant for certain regions that may not be relevant for others.

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8 Africover is a FAO environmental database for environmental resources. More info at http://www.africover.org/system/area.php?place=1

9 This software is available as a free download at http://sal.agecon.uiuc.edu/geoda_download.php

10 Features in this updated version can handle spatial regressions unlike the previous versions

CHAPTER FIVE: RESULTS OF THE ECONOMETRIC ANALYSIS

5.0 Introduction

In this chapter we present results obtained from the analysis, having carried out the preceding methodology. The findings are evaluated against the expectations earlier made about the impact of the spatial factors on poverty

5.1 Regression Results at the National Level

5.1.1 Least Squares (OLS) Estimation

We first undertook an OLS regression of sub county level poverty rate [11] on a set of independent variables (see table A2)[12]. Recall that selection of these variables was guided by the vulnerability risk chain theory described in chapter three. The regression was made on a total of 856 rural sub counties as of 2002. As earlier noted, heteroscedasticity is a key aspect in cross-sectional analysis. A Breustch-Pagan test in this case suggested the rejection of the null hypothesis of homoscedastic. To fix the problem, we took the log of population density to make the distribution normal. The adjusted R^2 of the model indicated that the explanatory power of the selected variables was quite reasonable, describing 73 percent of the in poverty in the country.

However as noted in 1.1.2, a critical concern with the OLS regression is violation of the assumption that the error terms cannot be correlated with each other. To assess the nature of spatial dependence, the extent of spatial clustering of the OLS regression residual at sub county level was examined. Table 3 shows the tests which were conducted for spatial dependence using distance band weights. The subsequent results

11 This is the proportion of individuals falling below the regional rural poverty line. Regional poverty lines as prescited in UBOS and IIRI (2007) are given in Uganda shs as, Western 20,308, Central 21,332, Eastern, 20 652, and Northern, 20,872

12 We developed this and all other regressions as well as the diagnostics for spatial dependence using GeoDa statistical 0.9 software(Anselin,2003), and results were compared for accuracy using STATA9/SE software.

of the Moran I statistic (t=34.52485) and the Langrage Multiplier tests suggested the rejection of the null hypothesis of no spatial dependence. Following Anselin (1988), we chose to estimate the spatial error model given a high robust langrage multiplier statistic. This indicated spatial autocorrelation in the error terms, meaning that some spatial variables not in the model were causing the error terms in neighbouring sub counties to be correlated. Consequently the model parameters from the OLS regression in Table A2 should be viewed as invalid and should not be given weight in understanding the patterns of welfare in rural sub counties of the country.

Table 3 Diagnostics for Spatial Dependence for national regression

FOR WEIGHT MATRIX : distwghtnational.GWT (row-standardized weights)		
Test	Statistic	Probability
Moran's I (error)	34.525	0.000
Lagrange Multiplier (lag)	99[illegible].838	0.000
Robust LM (lag)	65.124	0.000
Lagrange Multiplier (error)	1015.125	0.000
Robust LM (error)	86.411	0.000

5.1.2 Spatial Error Estimation

For spatial error estimation, we first run an inclusive model of all initial independent variables, and 6 out of 19 variables were significant (Table A3). We then turned to a more selective model of rural poverty, using intuition to eliminate or combine variables from the inclusive model. To reduce the effect of multicolinearity, we dropped distance to nearest primary school, distance to town of 25,000 people, and distance to town of 100,000 inhabitants. Travel time to municipalities, and city ware dropped because they are correlated with distance variables. Percentage of land under shrub, and urban were also dropped. This left us with 12 explanatory variables in the national regression (Table A2). The same intuition was applied to come up with the regional models in tables A5-A9.

Table A4 presents the results of regressing sub county level poverty rate on a number of selected independent variables, five of which are significant. The spatial autoregressive coefficient (lambda) in the model has a positive sign in the spatial error model, indicating positive spatial dependence between the sub counties. We discuss each of the results below.

Demographic Factors

Population density (a measurement of population per unit area) was found to be statistically significant. It is evident from the results that population density is able to explain poverty incidences. We note that higher population density is associated with low poverty rates. The results are intuitive given that, in many less-favoured rural areas, low population densities drive up costs of both extending physical infrastructure and providing basic services in comparison with densely populated urban areas where there may also be more a effective political lobby for investment, innovations spread very slowly, there is little contact between population groups (allowing ethnic diversity to persist for longer), and interaction with the world economy is difficult and costly. High population densities also influence labour intensity of agricultural production, production technologies as well as market access.

Distance Variables

Among the distance variables, focus was put on distance to nearest town of 10,000 people, 50,000 people, municipality, and to nearest secondary school. Only distance to the nearest town of at least 50,000 people has a significant coefficient (at 5 percent level). Towns with such population are ranked as town councils according to the local government act of 1997. The results imply that: a Sub County that is distant from such a town is more likely to be poorer than one that is closer. This is possibly because, being close to towns can also be taken to imply better infrastructure a community enjoys. The level of infrastructural development usually has a positive effect on the incomes of the poor and their welfare. Communities with better roads are likely to have higher rates of economic growth than others, and result in a substantial and strongly significant increased consumption and welfare. Improvement in the lives of the rural poor can be highly associated with good links between rural areas and urban markets. Longer distance to towns experienced in remote rural areas, restricts local access to these markets, but also maintains spatial, political, and social marginality. In addition towns are associated with various sources of employment and income generation for individuals in neighboring locations. Our results also provide evidence that closeness to small towns rather than municipalities is important in reducing poverty

Slope

As we initially predicted, and following the studies review earlier (Minot 2003, Okwi et al 2006a) the results reveal a strong relationship between poverty rates and slope. Areas located on steep slope exhibit high poverty rates. Slope is an important physical property and affects many properties such as erosion, stability, velocity of flows and others. One would observe more erosion and lower degree of stability at steep locations than flat locations. On steep land, given evidence of erosion and other attributes, one expects poor quality soils, and low agricultural activity, resulting in low earning by farmers. It can be intuitively argued that the further one moves from the extremely steep conditions to relatively flat areas , the problem of soil erosion, limited mobility, lack of tertiary social services and non-diversified livelihood become less pronounced. Subject to empirical analysis, the problem of poverty is likely to be lower in areas with favourable topography

Length of Growing Period

In the absence of high resolution data for rainfall, we opted to consider length of growing period as a proxy. Length of growing period refers to the number of days within the period when moisture conditions are considered adequate. Under rain-fed conditions, the beginning of the length of growing period is linked to the start of the rainy season. The growing period for most crops continues beyond the rainy season and, to a greater or lesser extent, crops mature on moisture stored in the soil profile. It can be deduced that an area with a longer growing period is more likely to receive more rainfall. Given that agriculture is the back-bome of the Ugandan economy, it is not surprising that the length of growing period has an impact on poverty. The results support studies which show that sub counties with longer growing periods are likely to be less poor than their counterparts with short periods (see Okwi et al 2006a). This is possibly because most income generating crops like maize and beans require more days to mature. Therefore locations with shorter growing period are likely to have few income generating products.

5.2 Regional Specific Estimation.

In chapter 4, we pointed out the issue of regional heterogeneity. In this section we investigate the evidence of regional heterogeneity on poverty. We test for equality of parameters for all regions and in effect reject the null hypothesis of homogeneity. Using the Central region as our reference, it was discovered that with exception of the Western region, the other regions are greatly associated with high poverty incidences relative to the central region. It should be noted that regional dummies may be capturing various factors influencing poverty incidences in certain locations that may not be captured by other spatial variables (such as security, administration, culture, e.t.c.). This kind of heterogeneity therefore necessitates the specification of different models for specific regions in the country. In this regard we estimate four main regressions based on regions

5.2.1 Western Region

A test for spatial dependence justified the use a spatial regression rather than an OLS model for the Western region. Much as both the lag and error tests were significant, a large statistic for robust langrage multiplier lag test justified the selection of a spatial lag model (Table 4). The results of this regression (Table A5) indicate a significant improvement in the explanatory power of the selected independent variables, compared to the OLS regression in which the variables were able to explain only 28 percent of poverty incidence.

Table 4 Diagnostics spatial dependence for western regression

FOR WEIGHT MATRIX : **westerndistwgt.gwt** (row-standardized weights)		
Test	Statistic	Probability
Moran's I (error)	16.503	0.000
Lagrange multiplier (lag)	187.481	0.000
Robust lm (lag)	17.174	0.000
Lagrange multiplier (error)	177.345	0.000
Robust lm (error)	7.038	0.008

The regression was run on 233 rural sub counties in the region, and five independent variables are significant. Two distance variables; distance to nearest secondary school, and distance to nearest town of 100,000 inhabitants were significant. The results reveal that locations that are closer to secondary schools are likely to be less poor. This is mostly evident in communities that are close to major towns where most schools are concentrated. Conversely, communities whose secondary schools are associated with longer distances are less likely to take the initiative to educate their children added to the fact that other domestic activities compete against the decision to go to school, and therefore miss out on the returns from education. This is common with sub counties that are distant from major towns and therefore have few and sparsely distributed schools. This has a strong implication for education as an important driver if poverty reduction is to be realized in the region. Proximity to urban centres is also an important aspect in this analysis. Results reveal that locations that are distant to towns of 100,000 inhabitants were poorer than their counterparts in nearby locations.

Just like in the studies reviewed earlier (Okwi et al 2006a and Minot et al 2003), the results point out that locations with steep slopes are associated high poverty incidences. This is true given that such areas are faced with difficulties in cultivating steep land, as well as problems linked to erosion and infrastructure. High elevation (measured in meters above sea level) is seen to be related to lower poverty levels, possibly because of fertile soils in the region. Ideally height above sea level mostly reflects an increased productivity due to expected higher precipitation. It should therefore ideally result in lower poverty levels other things constant

Length of growing period also has a significant and negative coefficient. As in the national regression, this suggests that a longer growing period is seen to lead to low poverty incidence in the region. Several locations in the region benefit from normal rainfall patterns throughout the year, providing favourable conditions for crops such as maize which require adequate moisture. Rainfall distribution in the southern parts is bimodal, allowing two crops annually, and adequate grazing for livestock throughout the year relative to other areas of the region. This partly explains why poverty rates are lower in southern locations like Mbarara and higher in upper districts such as Masindi.

5.2.2 Northern Region

In this case, a spatial lag model was identified as a suitable solution to spatial dependence considering the test statistics in table 5. The model was estimated on a total of 203 rural sub counties, improving the explanatory power from 67 percent points in the linear regression model, to 80 percent in the new model, and four explanatory variables were significant (see table A6)

Table 5 Diagnostics for Spatial Dependence Northern Region

FOR WEIGHT MATRIX : **notherndistwgt.**GWT(row-standardized weights)		
Test	Value	Probability
moran's i (error)	8.176	0.000
lagrange multiplier (lag)	84.175	0.000
robust lm (lag)	47.737	0.000
lagrange multiplier (error)	39.797	0.000
robust lm (error)	3.358	0.067

Population density demonstrated a significant and negative relationship with poverty. Out of the four selected distance variables, only distance to nearest town of 50,000 inhabitants was significant. As expected, the coefficient of this variable was positive, indicating that locations far from towns of 50,000 tend to be poorer than closer locations. This is in line with results of the national regression.

Elevation also met our initial expectation. The results point to the fact that areas on high elevation are poorer compared to those on low elevation. The elevation of a geographic location refers to its height above a fixed reference point, often the mean sea level. It is a proxy for temperature and management constraints on agricultural productivity. It is usually expected ha locations on in high zones have low agricultural potential and are therefore associated with high concentrations of poverty.

The coefficient of length of growing period also followed the same trend as in the preceding regressions. The rainfall in this region is less pronouncedly bimodal with about 800 mm annually. Rainfall in the far north and north-east of the country (Kotido and Moroto) is unimodal and too low and erratic for satisfactory crop production. Mixed cropping is common with a wide variety of crops. The dry season is so severe that drought tolerant annuals are cultivated: these include finger millet, simsim, cassava and sorghum. Tobacco and cotton are major cash crops. With this it suggests that areas that receive relatively more rainfall (and therefore have longer growing period), experience lower poverty levels compared to those that have low rainfall, mostly in the Karamoja region, where inhabitants are forced to rely on normadism for a living. It is no doubt that such locations are most times affected by food shortage.

5.2.3 Eastern Region

Following a test for spatial dependence (Table 6), a spatial lag regression was run for the Eastern region on a total of 248 rural sub counties. The explanatory power of the variables was quite high, and six variables were to be significant determinants of poverty (table A7). Note that this time we included some few household variables.

Table 6 Diagnostics for Spatial Dependence Eastern region

FOR WEIGHT MATRIX : easterndistwgt.GWT(row-standardized weights)		
Test	Value	Probability
moran's I (error)	7.869	0.000
lagrange multiplier (lag)	111.209	0.000
robust lm (lag)	66.802	0.000
lagrange multiplier (error)	45.4631	0.000
robust lm (error)	1.055	0.304

The results appeared to indicate that sub counties with high population density are negatively correlated with poverty. This is true with districts like Mbale, Kapchorwa, and Jinja where population density is quite high and poverty rates are low relative to other districts in the region.

All the three household variables included in the model appeared significant. Larger households were associated with higher poverty incidences. This is given that the dependency ratio tends to be high, putting a strain on the already meager resources that individuals in the active age-group possess. Using charcoal as the reference variable, households that used fuel wood were found to be poorer than those with charcoal, whereas sub counties that had households with electricity were found to be less poor

Surprisingly none of the distance variables was significant. Intuitively one might expect longer distances to towns of varying sizes to be positively correlated with poverty rates.

The impact of elevation on poverty incidence was significant and negatively related to poverty incidence. The result suggests that locations with higher elevation led to low poverty rates. This is true with highland areas of Mbale and Sebei associated with high production, fertile soils and better climate yields. Much as such areas are located on high elevations, they are enriched with very fertile soils which support agricultural production for income generation. It is therefore not surprising that such locations are associated with lower poverty levels compared to their counterparts in the same region.

As in the preceding discussion, length of growing period was significant and negatively related to poverty in the region. This region receives bimodal rainfall, with a longer dry season, from December to March. Rain fall coupled with fertile soils enable high crop yields in districts such as Mbale, contributing to lower poverty rates.

5.2.4 Central Region

Like for all the other regional models, the OLS regression could not be considered for the Central region due to spatial dependence. The robust langrage multiplier lag statistic (36.76) justified the application of a spatial lag regression for the central region. The regression (See table A8) was run 172 rural sub counties. Here we see an improvement in the explanatory power over the OLS regression.

Table 7 Diagnostics for Spatial Dependence Central region

FOR WEIGHT MATRIX distwgtcentral GWT (row-standardized weights)		
Test	Value	Probability
moran's i (error)	6.253	0.000
lagrange multiplier (lag)	11.649	0.000
robust lm (lag)	20.279	0.000
lagrange multiplier (error)	21.599	0.000
robust lm (error)	0.229	0.632

The impact of population density still appeared highly significant and negative, explaining the significance of labour intensity on productive land, and more importantly the role of markets in the region. The impact of household size was significant and positive, suggesting that households in many cases contribute to resource constraints and welfare loss. Among the distance variables, only distance to nearest secondary school, and to town of 100,000 people were significant

Slope exhibited a positive relationship with poverty. Elevation and length of growing period were equally significant. From the foregoing, it can be postulated that locations with a longer growing period are associated with lower poverty rates. In the same trend, areas at high elevation were seen to portray lower poverty rates. The latter is true with districts such as Wakiso.

Unlike the preceding regressions where none of the land use variables was significant, here percentage of land under grasslands was significant. Results reveal that the bigger the proportion of grassland, the lower the poverty rates. This may seem unrealistic as one would expect higher poverty rates since less of agriculture is taking place. Nonetheless, the result could be posing the idea that such areas are sparsely populated

CHAPTER SIX: CONCLUSIONS AND POLICY IMPLICATIONS

In this analysis we have attempted to improve our general understanding of the impact that various spatial factors can have on poverty in rural areas of the country, but also gone ahead to make a regional comparison to investigate whether specific interventions are justifiable. Our approach to modeling the spatial determinants of poverty employed small area estimation and spatial regression techniques to investigate the impact of the environmental variables.

The tests for spatial dependence show that there is significant spatial autocorrelation. Therefore, ignoring the spatial component of the regression analysis, may lead to wrong inference. Both small area estimation and spatial analysis presented in this study suggest that environmental factors in rural areas of Uganda are correlated with poverty attributes of individuals and communities

On the role of access to services and infrastructure (towns in this case) as a spatial determinant of poverty in the country were less clear than earlier expected. The most important determinants were distance to nearest town of 50,000 inhabitants, distance to nearest town of 100,000 inhabitants, and distance to nearest secondary school. Enhancing services especially at town council level is an important policy recommendation emerging from this observation. In this analysis also supports human capital development though secondary school education. This is because for most sub counties where communities were closer to secondary schools, poverty rates were low. This implies that returns to secondary education are relatively high, necessitating further investment in this line. Government effort to provide free secondary education to rural communities should therefore be expedited. In so doing however, there is need to also need to consider socio-cultural dimensions to ensure community approval.

Recall that in some regions, inhabitants in locations with steep slopes and higher elevation (for instance in western Uganda) appeared to be poorer that their counterparts. Note that it may not be possible to design policy interventions that directly influence the impact of such factors. However, we realize that these are only limiting factors to the extent that people cannot migrate. To the extent that migrants are able to raise their living standards without creating a negative impact on others, migration can be a successful instrument to reduce poverty.

Longer length of growing period, if well taken advantage of can help expedite efforts to reduce poverty levels. Areas that have longer growing periods can be relied on to achieve increased agricultural production, especially in products that fetch higher incomes in the markets. This however can be done without neglecting disadvantage areas. Research is needed in crops that mature in shorter growing periods so that such areas can also benefit from the ever increasing demand for agricultural products.

Also note that our results revealed that different spatial factors affect certain regions differently. This therefore warrants regional specific policy interventions if poverty reduction is to be realized. For example, while in some regions access to secondary school education does not seem a potential factor, in other regions, attempting to bring schools closer may have a tremendous improvement on welfare. This realization is sufficient to lend weight to the arguments for decentralisation of government services in the country.

In making use of the results, inferences should not be made about smaller analytical units from the aggregate characteristics of groups of those units. This analysis is mostly intended for actions targeting a broad community level. In using this analysis to plan poverty reduction activities, we should not assume that the nature of relationship observed here will be replicated at the level of the household or individual.

6.1 Areas for Further Research

Due to time[13] and data limitations, the study could not consider using some other variables that are relevant in explaining poverty incidence in the rural locations of the country. Inclusion of explanatory factors such as rainfall variation, travel time to different road types, livestock, and soil quality could have given us more insight in this analysis. Given more time, there is need to extract and incorporate such factors to provide a wider scope in the analysis.

With addition of more factors, we can consider simulating the impact of various public and private investments on poverty rates in rural areas. This can be possible only in the event that some of these factors are amenable to policy change. For instance government can in some way reduce the time it takes to certain facilities if it improves on road network. In addition, the quality of the soil can be influenced through fertilizer application, and better soil conservation practices even in areas that are located on higher slopes.

Having seen a related study in Kenya, and added to this study, there is a need to move from analysis based on one country, and focus our attention to inter-country investigation for the east African region. The countries are unlike each other with different geographics, stages of development, quality and types of data, and so on. There is need to design a methodology that works well in all three settings and produces valuable information about the spatial determinants of poverty and inequality within those countries. Results thereof can provoke policy attention aimed at poverty reduction in the region that is currently aiming at achieving full integration.

In this study we only focused our attention on poverty incidence defined as P0, which captures the proportion of people below the poverty line. It is imperative to extend analysis by considering how other poverty measurements e.g P1 and P2 can be

13 Extraction of spatial variables is a tedious task, and involves spending a lot of time combining various GIS techniques, and transforming data in a way that more understandable in the economics sense

influenced by spatial factors. P1: depth of poverty or poverty gap takes in to account not just how many people are poor, but how poor they are, on average[14]. P2: severity of Poverty or poverty gap squared considers not just how poor the individuals are, on average, but the distribution of income among them[15]. Much as this was captured in Benson (2005b), they were not based on recent data sets.

The government has in the past few years created many more new districts. This simply suggests that the number of administrative units has been scaled up. By the time of this study, data on the new administrative units was not yet documented. Analysis was therefore made only for the 856 rural sub counties as at 2002. In case more information is availed for the new locations, it will be essential to conduct a new study to capture the dimension that the spatial factors will take in these areas.

14 It is equal to the proportion of the population who are poor multiplied by the percentage gap between the poverty line and the pr capita expenditure of the poor

15 It is equal to the incidence of poverty multiplied by the average squared percentage gap between the poverty line and the income of the poor.

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APPENDIX: ADDITIONAL TABLES

Table A1: Descriptive Statistics

Variable	Mean	Std. Dev	Min	Max
Population Density	214.450	201.721	6	2569
Distance to nearest primary school	2.188	2.200	0	23
Distance to nearest Secondary school	5.910	5.364	1	43
Distance to nearest town of 10,000 people	26.243	17.557	5	120
Distance to nearest town of 25,000 people	40.027	23.062	5	142
Distance to nearest town of 50,000 people	69.492	43.885	5	220
Distance to nearest town of 100000 people	167.373	82.825	6	377
Distance to nearest municipality	52.223	31.632	3	165
Travel time to municipality	43.225	84.674	11	7505
Travel time to City	344.788	486.733	11	7483
Slope	4.216	5.406	0	38
Elevation	1230.581	266.242	621	2470
Length of growing period	335.340	35.490	240	365
Percent under farmland	25.781	30.875	0	100
Percent under woodlot	10.179	16.046	0	94.565
Percent under urban	0.190	1.327	0	24.828
Percent under shrub	17.306	20.874	0	92.797
Percent under grassland	2.064	5.537	0	58.156
Percent under forest	2.620	7.992	0	67.085

Table A2 Summary Of (OLS) Ordinary Least Squares Estimation

Dependent Variable Poverty Incidence

Variable	**Coefficient**	**t-Statistic**	**Probability**
Population Density	-0.814	-1.488	0.137
Distance to sec school (Km)	0.411	4.131	0.000
Distance to town of 10000 pple (Km)	0.012	0.177	0.633
Distance to town of 50000 pple (Km)	0.068	6.264	0.000
Distance to municipality (KM)	0.032	2.111	0.035
Slope	0.186	2.318	0.021
Elevation	-0.001	-0.651	0.515
Length of growing period (days)	-0.116	-5.441	0.000
Percent_farmland	-0.060	-4.489	0.000
Perent_woodlot	-0.137	-5.725	0.000
Percent_grassland	0.058	0.899	0.369
Percent_forest	-0.129	-2.869	0.004
Eastern region (Dummy)	17.207	14.290	0.000
Northern region (Dummy)	23.509	12.929	0.000
Western region (Dummy)	1.813	4.168	0.000
constant	70.112	8.913	0.000

Number of observations:	856
Adjusted R-squared :	0.728
Sum squared residual:	76735.641
Log likelihood	-3116.659
Akaike info criterion :	6265.314

Table A3. Inclusive National Regression

Dependent variable: Poverty Incidence

Variable	Coefficient	z-value	Probability
Population density	-1.146	-2.387	0.017
Distance to nearest pri sch	-0.220	-1.161	0.245
Distance to nearest sec sch	0.247	2.713	0.007
Distance to town of 10000 pple	0.052	1.378	0.168
Distance to town of 25000 pple	0.051	1.347	0.178
Distance to town of 50000 pple	0.062	2.065	0.039
Distance to town of 100000 pple	0.005	0.266	0.789
Distance to municipality	0.028	0.753	0.452
Travel time to Municipality	-0.415	-0.665	0.506
Travel time to city	-2.631	3.215	0.001
slope	0.147	2.690	0.007
elevation	0.001	0.438	0.661
Length of growing period	-0.148	-4.644	0.000
Percent under farmland	-0.005	0.741	0.740
Percent under woodlot	-0.008	-0.355	0.722
Percent under urban	-0.859	-4.074	0.000
Percent under shrub	-0.012	-0.632	0.527
Percent under grassland	-0.047	-0.849	0.396
Percent under forest	-0.019	-0.518	0.604
Eastern region (Dummy)	7.629	3.227	0.001
Northern region (Dummy)	13.178	4.609	0.000
Western region (Dummy)	0.011	0.005	0.996
constant	98.789	8.485	0.000
lambda	0.859	38.373	0.000

Number of observations:	856
R-squared:	0.879
Log likelihood:	2833.617
Akaike info criterion:	5713.23

Table A4. Results of the spatial error model for the national regression

Dependent Variable: Poverty Incidence			
Variable	**Coefficient**	**z-value**	**Probability**
lnp_dens	-1.289	-2.903	0.003
Distance to sec school	0.128	1.548	0.122
Distance to town of 10000 pple	0.043	1.234	0.217
Distance to town of 50000 pple	0.064	2.231	0.026
Distance to municipality	0.041	1.234	0.217
slope	0.132	2.397	0.017
elevation	0.001	0.537	0.591
Length of growing period	-0.148	-4.593	0.000
Percent- under farmland	-0.007	-0.505	0.614
Percent under woodlot	-0.006	-0.265	0.791
Percent under forest	-0.046	-1.237	0.216
Percent under grassland	-0.036	-0.645	0.519
Eastern region (Dummy)	7.015	2.939	0.003
Northern region (Dummy)	13.114	4.541	0.000
Western region (Dummy)	-0.263	-0.120	0.904
constant	84.913	7.671	0.000
Lambda	0.859	38.422	0.000

Number of observations:	856
R-squared:	0.874253
log likelihood :	-2848.813705
akaike info criterion :	5729.63

Table A5 Spatial lag Regression for Western Region

Dependent Variable: Poverty Incidence

variable	**coefficient**	**z-value**	**probability**
constant	22.905	1.400	0.161
Population Density	1.394	1.729	0.084
Dist to nearest Sec School	0.499	2.197	0.028
Dist to town of 10,000 pple	0.064	1.565	0.117
Dist to town of 50,000 pple	0.017	1.588	0.112
Dist to town of 100000 pple	0.025	2.257	0.024
Slope	0.237	3.155	0.002
Elevation	-0.004	-2.105	0.035
Length of growing period	-0.084	-2.033	0.042
Perc under farmland	-0.009	-0.557	0.577
Perc under grassland	-0.031	-0.286	0.775
Per under forest	0.086	1.585	0.113
Rho	0.786	14.492	0.000

Number of observations:	233
R-squared:	0.594
Log likelihood:	-766.704
Akaike info criterion:	1559.416

Table A6 Spatial lag regression Northern Region

Dependence Variable: Poverty Incidence Variable	Coefficient	z-value	Probability
Population Density	-2.029	-2.494	0.013
Household Size	0.021	0.027	0.978
Dist to sec school	0.049	0.491	0.624
Dist to town of 10,000 pple	0.032	0.877	0.381
Dist to town of 50,000 pple	0.031	2.699	0.022
Dist to town of 100,000 pple	-0.019	-1.089	0.276
slope	-0.034	-0.236	0.814
elevation	0.011	3.006	0.003
Length of growing period	-0.123	-2.548	0.011
Perc farmland	-0.001	-0.046	0.963
Perc grass land	0.160	1.091	0.275
Perc forest	0.466	0.892	0.372
Constant	52.834	3.230	0.001
Rho	0.654	10.489	0.000

Number of Observations.	203
R-squared:	0.801
log likelihood	-679.055
akaike info criterion -	1386.11

Table A7: Results of the Spatial Lag regression Eastern region

Dependent Variable: Poverty Incidence Variable	Coefficient	z-value	Probability
Population Density	-0.010	-4.104	0.000
Household size	3.796	4.555	0.000
Cook using wood	11.788	3.987	0.000
Use Electronics	-4.082	-4.046	0.000
Dist to town of 10,000 pple	-0.013	-0.434	0.664
Dist to town of 50,000 pple	0.010	0.491	0.623
Slope	0.027	0.333	0.739
Elevation	-0.007	-3.597	0.000
Length of growing period	-0.032	-2.356	0.018
Perc under forest	0.117	1.682	0.093
Perc under grassland	-0.011	-0.174	0.862
Perc under farmland	0.013	0.988	0.323
constant	10.124	1.446	0.148
Rho	0.631	12.774	0.000

Number of Observations	248
R-squared:	0.857
log likelihood	-736.622
akaike info criterion :	1501.241

Table A8 Results of the spatial lag model for central region

Dependent Variable: Poverty Incidence Variable	Coefficient	z-value	Probability
Population density	-0.008	-5.286	0.000
Household Size	1.436	4.678	0.000
Dist to sec school	-0.678	4.497	0.000
Dist to town of 10000 pple	-0.001	-0.021	0.983
Dist to town of 10000 pple	0.056	3.218	0.001
Slope	0.284	2.089	0.037
Elevation	-0.018	-2.488	0.013
Length of Growing Period	-0.193	-3.201	0.001
Perc under forest	-0.005	-0.156	0.876
Perc under farmland	-0.012	-0.625	0.532
Perc under grassland	-0.154	-3.007	0.003
Constant	-51.286	-2.375	0.018
Rho	0.537	7.043	0.000

Number of observations:	172
R-squared:	0.728
log likelihood :	-508.891
akaike info criterion :	1043.78

Table 49: Summary of Regional Determinants of rural poverty

Variable	Region				
	National	Central	Western	Eastern	Northern
Population density	NS	***	NS	***	**
Household Size		***		***	NS
Distance to nearest primary school					
Distance to nearest secondary school	***	***	**		NS
Distance to nearest town of 10,000 pple	NS	NS	NS	NS	NS
Distance to town of 25000 pple					
Distance to nearest town of 50,000 ppl	***		NS	NS	**
Distance to nearest town of 100,000pple		***	**		NS
Distance to nearest municipality	**				
Slope	**	**	***	NS	NS
Elevation	NS	**	**	***	***
Length of growing period	***	***	**	**	**
Percentage of location under farmland	NS	NS	NS	NS	NS
Percentage of location under Forest	NS	NS	NS	NS	NS
Percentage of location under Grass land	NS	**	NS	NS	NS
Percentage of location under Shrub					
Percentage of location under woodlot	NS				

Notes

*** Significant at one percent

** Significant at five percent

* Significant at ten percent

NS Not Significant

Table A10 Description of Variables used in the Analysis

Short description	Source	Explanation
Population density	2002 Population and housing census results, UBOS	Obtained from the census results at sub county level
Household Size	2002 Population and housing census, UBOS	Aggregated at sub county level
Mean distance town nearest of 10,000 people	Towns UBOS, Admin map UBOS	Derived from calculating the euclidian distance from the location to the nearest town with a population of at least 10,000. The distances were averaged for the sublocation
Distance to nearest town of 25,000 people	Towns UBOS, Admin map UBOS	Derived from calculating the euclidian distance from the location to the nearest town with a population of at least 25,000. The distances were averaged for the sublocation
Distance to nearest town of 50,000 people	Towns UBOS, Admin map UBOS	Derived from calculating the euclidian distance from the location to the nearest town with a population of at least 50,000. The distances were averaged for the sublocation
Distance to nearest town of 100,000 people	Towns UBOS, Admin map UBOS	Derived from calculating the euclidian distance from the location to the nearest town with a population of at least 100,000. The distances were averaged for the sublocation
Distance to nearest municipality	Municipalities UBOS, Admin map UBOS	Derived from calculating the euclidian distance from the location to the nearest municipality. The distances were averaged for the sublocation
Distance to nearest water source	Water sources (WRI), Admin map UBOS	Derived from calculating the euclidian distance from the location to the nearest water. The distances were averaged for the sublocation
Distance to nearest health Facility	Health facility, Admin map UBOS	Derived from calculating the euclidian distance from the location to the nearest health facility. The distances were averaged for the sublocation.
Length of growing period	Jones P.G. 2004. Report on preparation of growing season days coverages for Hadley 3 scenarios A2 and B2, Consultant's report International Livestock Research Institute	The length of growing period is calculated as the number of days in a year with an actual to potential evapotranspiration ratio greater than 0.5

Land use	Africover aggregated data	
Percentage of location under farm land	Derived from overlay between Africover landuse map and sub county map	Derived percentage of land within a sub county with the type of landuse
Percentage of location under Forest	Derived from overlay between Africover landuse map and sub county map	Derived percentage of land within a sub county with the type of landuse
Percentage of location under wood lot	Derived from overlay between Africover landuse map and sub county map	Derived percentage of land within a sub county with the type of landuse
Percentage of location under grassland	Derived from overlay between Africover landuse map and sub county map	Derived percentage of land within a sub county with the type of landuse
Percentage of location under water	Derived from overlay between Africover landuse map and sub county map	Derived percentage of land within a sub county with the type of landuse
Percentage of location under town	Derived from overlay between Africover landuse map and sub county map	Derived percentage of land within a sub county with the type of landuse
Percentage of location under shrub	Derived from overlay between Africover landuse map and sub county map	Derived percentage of land within a sub county with the type of landuse
Elevation (meters above sea level)	SRTM data obtained by NASA at the 90m resolution	The average elevation in meters above sea level within the location
Slope in degrees	Calculated from the elevation data	Slope in degrees reflect the average steepness of the sublocation

Figure 2: Percent of population Below Poverty Line (2002)

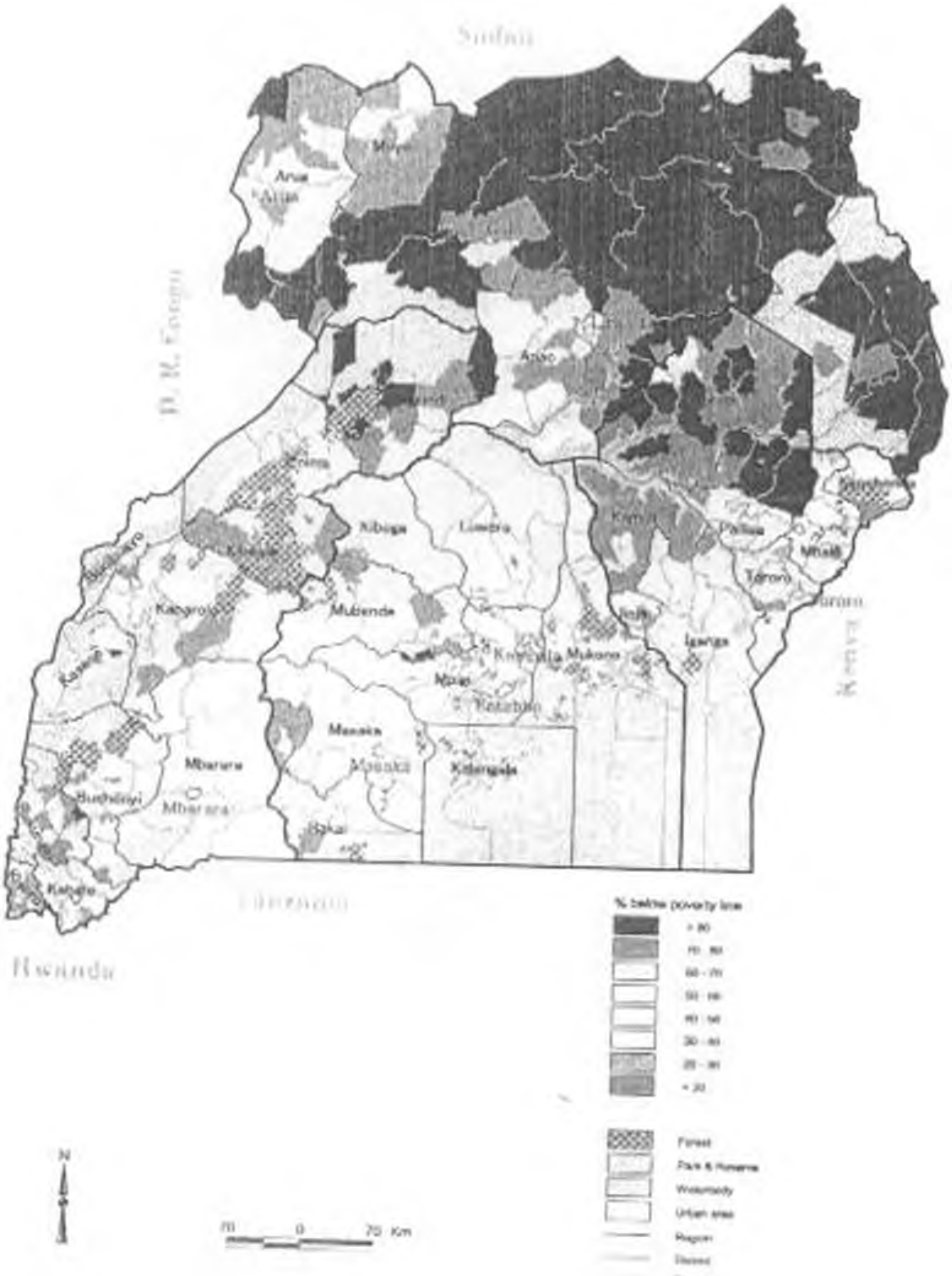

Figure 3 Inequality in Uganda (2002)