Welfare and Environment in Rural Uganda

Results from a Small-Area Estimation Approach

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Abstract

This study combines census, survey and bio-physical data to generate spatially disaggregated poverty/biomass information for rural Uganda. It makes a methodological contribution to small area welfare estimation by exploring how the inclusion of bio-physical information improves small area welfare estimates. By combining the generated poverty estimates with national bio-physical data, this study explores the contemporaneous correlation between poverty (welfare) and natural resource degradation at a level of geographic detail that has not been feasible previously. The resulting estimates of poverty measures were improved by the inclusion of bio-physical information and the poverty estimates appear to be more robust, as the standard errors show a decline of up to 40 percent in some cases. The coefficients of variation (i.e. the ratio of the standard error and the point estimate) decline in general as well. Overall, we conclude that the estimates of the poverty measures are more robust when bio-physical information is taken into account. One of the outputs of this study is a series of maps showing poverty and biomass overlays for Uganda. These maps can be used as a planning tool and for targeting purposes.

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1. Introduction

Attaining sustainable use of bio-physical resources and sustainable growth in agriculture are important for Uganda because the economy is agriculturally based and nearly 90 percent of its 25 million people live in rural areas. Ugandan policy-makers, with few resources at their disposal, must make critical decisions concerning the future land use patterns and, at the same time, focus on alleviating poverty. Unfortunately, information about poverty and land use is often incompatible. For instance, spatially disaggregated bio-physical information is available but disaggregated poverty information is not. As a result, decisions are often made in an 'information vacuum' and there is limited understanding of the dynamic processes linking poverty and land use patterns.

For both researchers and policy-makers alike, various questions need to be answered. Where are the poor located, and what is the state of the natural environment? What is the relation between the location of the poor and the state of the natural environment? What role do initial environmental conditions play in poverty reduction and what is the relevant level of policy intervention: regional, district, county or sub-county level? To answer these (rather basic) questions, high-resolution and comparable data on welfare and bio-physical factors are required. To date, such information has not been available and, as such, none of the research questions formulated above could be addressed.

Recent research on poverty and the environment is either based on case study approaches or on cross-country studies. The former is unrepresentative; the latter is clouded with data incomparability problems (see Atkinson and Brandolini (1999) on the problems associated to use of the Deininger and Squire data set). Other numerous studies have only looked at the theoretical link between poverty and environmental degradation (Ambler 1999; Barbier, 2000 and Roe, 1997). These studies show that the relative strength of links between poverty and environment may be very context-specific (Chomitz, 1999; Ekbom and Bojo, 1999). By providing comparable welfare and bio-physical information for many data points, the proposed database solves these problems. However, the bio-physical information has not been linked to welfare information in Uganda as yet.

For poverty, data below the regional level are often not available. However, Hentschel, Lanjouw, Lanjouw and Poggi (2000) developed an approach to examine the geographic distribution of poverty by combining sample survey information with census data. This approach is elaborated in Elbers, Lanjouw and Lanjouw –ELL, (2003). Their approach generates welfare estimates at low levels of spatial disaggregation, and additionally, it estimates standard errors with the poverty estimates. For Uganda, this approach was taken up and the results show comparable welfare estimates are feasible for rural counties for both 1991 and 1999 (Okwi et al. 2003; Hoogeveen et al. 2004). These estimates only rely on census and household survey data and do not use the available bio-physical information. The ELL approach leads to high precision maps and is more robust than conventional approaches.

This paper builds on an existing effort to generate small area welfare estimates and combines spatially disaggregated poverty and bio-physical data for 1991. We use the detailed information provided in the 1992/93 Integrated Household Survey (IHS) and combine it with the 1991 Population and Housing Census and the 1990-93 biomass data to analyse the links between poverty and bio-physical information at a more disaggregated level. This study has a spatial dimension because environmental problems are inherently geographical. The estimates are based on household per capita expenditure as a measure of welfare. The first step involved using data from the survey of 1992/93 to estimate the relationship between poverty and biomass data. Poverty was measured by household expenditure and other indicators of welfare (including household economic and demographic characteristics, district and regional dummies). The second step involved using the values from the first stage regression for each stratum to get poverty estimates at lower levels (including district, County and sub-county levels). Finally, the third step involved developing poverty–biomass maps (overlays) to show the relationship between poverty and bio-physical data.

Such a combination of information is valuable to policy-makers who continue to struggle with the twin objectives of alleviating poverty in the short run and preserving the natural resource base in the long run[1]. This information is also valuable for research analysts who want to better understand the environmental-poverty nexus. From the analysis conducted in this study, we have been able to produce sets of maps (overlays) locating the poor in Uganda. This was done using an integrated database that combines census, survey and biomass information. This paper also refines the methodology of small area estimation by including biomass variables and other GIS environmental information in the first stage regressions for poverty mapping. It then considers how this improves the accuracy of the poverty/biomass maps for Uganda. The first stage regressions results (R-square) improved on average by 2 percentage points over all the rural strata after including biomass data; the point estimates (standard errors) also improved at all levels. The small area estimates were then used to explore several dimensions of the poverty and natural resource relationship in rural Uganda.

This paper is divided into five sections. Section 2 presents an overview of the Ugandan country setting, providing a discussion on the patterns of poverty, natural resource use and the current policy framework. Section 3 describes the data and methods that form the basis for the research reported in this paper. It also provides an overview of the three-stage empirical model that underpins the analysis of the data, drawing exclusively on the existing literature on small area estimation techniques. The results are presented and discussed in Section 4, while the last section concludes and discusses the broader implications of the research.

2. Poverty and natural resources

For many years, the Government of Uganda has been committed to poverty reduction and environmental protection. Government strategies are summarized in the Poverty Reduction Strategy Paper (PRSP) and implemented by the Poverty Monitoring Unit of the Ministry of Finance, Planning and Economic Development, and the National Environment Management Authority (NEMA). With respect to poverty reduction, the Government has been quite successful, although Uganda remains among the poorest countries in

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the world. For instance, during the 1990s poverty in Uganda almost halved from 56% in 1992 to 35% in 1999/2000. At the same time, Uganda has faced a significant change in its landscape. Reliable figures are hard to come by, but the Forest Department (2002) shows that forest cover in Uganda is shrinking at a rate of 55,000 ha per year. This has raised concern about the future supply of fuel wood, other forest products and environmental services. Many of these landscape changes are believed to be linked to conversion of woodlands to agricultural land.

2.1 Poverty

The results from different studies on poverty and inequality (Appleton et al., 1999; Appleton, 2001; Okwi and Kaija, 2000 and UPPAP 2000) in Uganda have wide ranging conclusions and are not easy to compare. This is because either the poverty lines used were not always constant or due to other methodological differences. However, there is little correspondence of results across the studies. The studies based on survey data collected by Uganda Bureau of Statistics show some similarity while the other studies have some contrasting findings. Estimates of the prevalence of poverty range from 66 percent to 44 percent in 1997. Recent results from Ssewanyana and Appleton (2003) show that poverty has risen to 39 percent, and inequality has remained more or less the same at a Gini of 0.38 in 2002/03. All the studies clearly show that rural areas suffer from a higher prevalence of poverty and inequality than do the urban areas. This situation holds even after adjusting for the cost of living differentials. This is not a surprising finding, given that in many other developing countries (like Kenya and Tanzania) the situation is the same. However, there may be some bias in favour of overestimating rural poverty relative to urban poverty in all the studies. The reason is that income and expenditure are more accurately measured in urban areas; in rural areas these variables are systematically under-measured (UBOS, 2002). Without a concerted effort to measure all income and expenditure accurately, the degree of overestimation of rural inequality and poverty cannot be accurately known. Despite this bias, the studies universally conclude that the prevalence, depth and severity of poverty are all greater in rural Uganda.

Table 1 Poverty estimates for Uganda, 1992 –1999.

	Poverty incidence FGT(0)		Poverty gap FGT(1)		Poverty gap squared FGT(2)	
	1992	1999	1992	1999	1992	1999
Urban	27.8 (2.4)	10.3 (1.6)	8.3 (0.8)	2.2 (0.3)	3.5 (0.4)	0.7 (0.1)
Central rural	54.3 (2.2)	25.7 (1.4)	18.7 (1.2)	5.9 (0.4)	8.8 (0.7)	2.0 (0.2)
East rural	60.6 (2.3)	38.4 (1.6)	23.0 (1.3)	10.5 (0.6)	11.4 (0.8)	4.2 (0.3)
North rural	73.0 (2.9)	67.7 (3.8)	29.0 (2.0)	26.4 (2.9)	14.8 (1.3)	13.3 (2.0)
West rural	54.3 (2.4)	29.5 (1.9)	19.2 (1.3)	7.0 (0.6)	9.3 (0.8)	2.4 (0.2)

Notes: The 1992 estimates are derived from the Integrated Household Survey (IHS). The 1999 estimates are from the Uganda National Household Survey (UNHS). Standard errors are in parentheses.

On average, between 1998-2002 (Table 2) Uganda registered a GDP growth rate of 6.1 percent (UBOS, 2003). Previously, the country had experienced GDP growth rates of about 7.2 percent (between 1991-1997) but the slack in GDP growth started in the fiscal year 1999/2000 due to a fall in world coffee prices, droughts, civil wars, the war in the

Democratic Republic of Congo (DRC), increases in pests and diseases and a rise in world prices of oil (UBOS, 2001). These shocks affected the expansion of the productive sectors and the economy's position in relation to the rest of the world. Infant mortality stood at 88 per 1000 live births, while maternal mortality was at 504 per 100,000 live births in 2001.

Table 2 Uganda: Key economic and social indicators.

Indicator	Year or period	Index
Surface area ('000 of Km squared)	2002	241.0
Population (millions)	2002	24.7
Population (Annual growth rate)	1991-2002	3.4%
GNP per capita (US $)	2002	320
GDP annual growth rate	1998-2002	6.1%
Agriculture (percent share in GDP)	2002	44.0%
Agriculture (percent annual growth rate)	1998-2002	3.7%
Deforestation (percentage of total area)	1990-1995	0.9%
Labour force (millions)	1999	11.0
Average annual growth of labour force (percent)	1990-1999	2.6%
Infant mortality (per 1,000 live births)	2001	88
Maternal mortality ratio (per 100,000 live births)	2001	504
Life expectancy (number of years)	2002	
• Male		48.1
• Female		45.7
Total fertility rate	2001	6.7%
HIV/AIDS prevalence	2001	6-7%
Nutrition (stunting)	2001	39%

Source: Word Bank (2002) and UBOS (2001, 2003).

2.2 The state of the natural environment

Uganda occupies an area of 241,038 square kilometres. Of this, 43,941 square kilometres is open water and swamps, and the rest is land. The population of Uganda was estimated at 24.7 million in 2002, with an annual growth rate of 3.4 percent during 1991-2002, and a population density of 126 people per square kilometre (UBOS, 2002). The settlement patterns in the rural areas vary, depending on whether areas have consistently good rains, good soils, are free from disease agents or have high and rising population densities. Areas with less rain, less fertile soils and which are not free from disease agents have low population densities. Security is another major factor that determines settlement patterns in Uganda: for instance, the serious security problems in the northern region since the 1980s are one reason for its low population density.

Besides other land uses (like pasture), farmland constitutes the biggest proportion of land use in Uganda (36 %), see figure 1. The average landholding size in Uganda ranges from 0.4 to 3 hectares per typical 7-person household. This landholding size has been declining over the years due to population pressure (UBOS, 2002). The climate of Uganda is more or less 'equatorial'. It has two wet seasons, with intervening short dry seasons of one to three months. The vegetation is typically savannah, though there are some forests on the mountain ranges, and riparian vegetation in river valleys. There is a wide range of savannah woodland. This savannah is usually interspersed by perennial grasses (Forest

Department, 2002). Figure A1 in Appendix A shows how land use cover is divided within Uganda at county level.

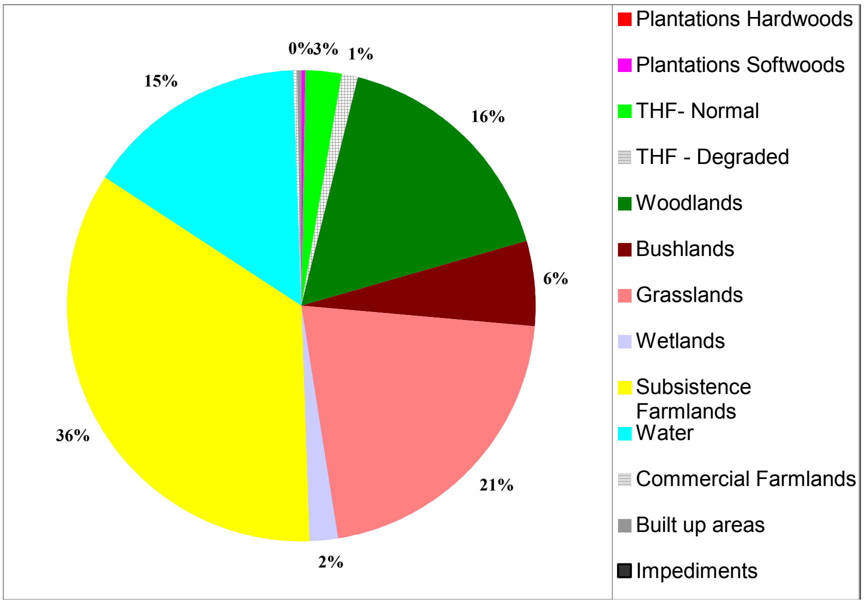

Figure 1 Relative Land Cover Distribution.

Source: Forest Department (2002).

2.3 The institutional and policy framework

Since 1987, the Government of Uganda has been implementing an economic reform program supported by a large number of donors (like the World Bank, International Monetary Fund (IMF) and United States Agency for International Development (USAID)). This reform program aims to promote fiscal and economic management, develop human capital through investment in education, health and other social services, reform the regulatory framework and improve incentives for the private sector. The result of this program has been macroeconomic stability and the continued growth of GDP, on average about 5 percent per annum since 1987. Some studies have found that policy reforms including the current economic policy of liberalization and adjustment efforts may increase the pressure on forests (Jones and O'Neill 1995, Angelsen and Kaimowitz, 1999). For instance, Kant and Redantz, (1997) found a positive correlation between external indebtedness and deforestation. However, some of these empirical studies are based on poor quality data; the analytical models make very simplistic assumptions about government objectives and policy formulation, which limit their relevance.

There are two major players in the use and conservation of natural resources: individuals/households and government institutions. In Uganda, the Government has more power in terms of the conservation and use of natural resources. The Government plays two main roles in the management of natural resources. Firstly, they often own these resources. Secondly, they influence their allocation through policies to which resource users respond. The natural environment is managed by the Department of Forestry, in conjunction with the National Environment Management Authority (NEMA). Tropical forests are almost invariably publicly owned. Equally, the infrastructure of water resources is often developed and owned by the public sector. It is important to note that the natural resource property rights system is often unclear to local communities. The reason for government management of natural resources is that the Government is best placed to pursue multiple objectives - environmental protection, economic growth, regional development and support of indigenous people and cultural heritage. But government ownership and management of resources in pursuit of such public objectives needs to be effective if it is to overcome the incentives for private gain.

In Uganda, government stewardship of resources has shown a mixed record of successes and failures (NEMA, 2002). The failures are basically bureaucratic. The institutions are often inefficient and overstaffed with unqualified personnel. The other related problem is that under-priced natural resources put additional pressure on resource management agencies. By creating opportunities for corruption and personal gain, under-pricing makes the agencies vulnerable to the influence of politically powerful groups. For instance, forestry departments come under pressure to provide low-cost materials to industries, and allow encroachment into gazetted areas so as to serve politically important areas and people. Meanwhile, essential tasks with little political appeal, such as maintenance and regeneration, are overlooked.

3. Data and methods

3.1 Data

The central element in this study is the availability of survey, census and biomass information. For the purposes of this project, we used census data for 1991 and data from the Integrated Household Survey (IHS) 1992 to derive welfare estimates and maps. The surveys are multi-purpose household and community surveys (in the same vein as the World Bank's Living Standard Measurement Study (LSMS) surveys) and were designed and implemented by the Uganda Bureau of Statistics (UBOS). The IHS used a stratified sample of 10,000 households in both rural and urban areas. The survey questionnaire collected information on household and demographic characteristics, education, assets, employment, income and expenditure (UBOS, 1993). The sample was designed to be nationally representative, as well as representative of the four regions divided into rural and urban strata. In this study, we only used 4 rural strata; as for these strata we can include bio-physical information in the update of welfare estimates (using a sample of households present in the IHS).

The second data source is the 1991 census, which was conducted by the same institution (UBOS) and was meant to cover the entire population in both rural and urban areas. Two forms of questionnaires were used, a short and long form. The short form of the questionnaire covered mainly information on household members and education, and was administered to all households in the country. The long form of the questionnaire covered housing characteristics and access to basic utilities and was administered to only 10 percent of rural areas (UBOS 1991). The 10 percent is representative at district level. Although the census did not collect information on income and expenditure, it provided information on a number of characteristics likely to be correlates of poverty. The census and survey data had several common household variables, such as household size composition, education, housing characteristics, access to utilities and location of residences. With this method, it is important that the survey and census are almost contemporaneous. This is because a main assumption of the method is that the parameters estimated from the survey data are almost equally applicable to the period covered by the census.

To capture the environment aspects, we used geo-referenced information from the National Biomass Study of the Ministry of Water, Lands and the Environment. The project developed its own classification system, which was based on a combination of land cover and land uses. This information covered changes in land cover, such as broad-leaved tree plantation or woodlots, coniferous plantations, tropical high forests (normal and depleted/encroached), woodlands, grasslands, wetlands, water resources and land use (such as subsistence and commercial farmland) as well as changes in landscape among other aspects. The biomass indicators varied at the cluster level. To capture some of these variables, the proportion of the parish under each land use type was used. For example, to capture wetlands, the proportion of the parish that is covered by wetlands was used. Similarly, for subsistence farmland, the proportion of the parish under subsistence farms was used. This criterion was used for all the land use types. Figure A1 show eight types of land use cover at county level in Uganda in 1991.

Table 3 The distribution of land cover and land use.

Stratum	Area (Ha)	Percentage
Plantations Hardwoods – deciduous trees/broadleaves (hardwood)	18,682	0.1%
Plantations Softwoods- coniferous trees	16,384	0.1%
Tropical high forest (THF)- Normally stocked	650,150	2.7%
Tropical high forest (THF) – Degraded/depleted	274,058	1.1%
Woodlands – trees and shrubs (average height > 4m)	3,974,102	16.5%
Bush lands - bush, thickets, scrub (average height < 4m)	1,422,395	5.9%
Grasslands –rangelands, pastureland, open savannah including scattered shrubs and thickets	5,115,266	21.2%
Wetlands – wetland vegetation; swamp areas, papyrus and other sedges	484,037	2.0%
Subsistence Farmlands –mixed farmland, smallholdings in use or recently used, with or without trees	8,400,999	34.8%
Commercial Farmlands – mono cropped, non seasonal farmland usually without any trees for example tea and sugar estates	68,446	0.3%
Built up areas – urban or rural build up areas	36,571	0.2%
Water – Lakes, rivers and ponds	3,690,254	15.3%
Impediments – bare rocks and soils	3,713	0.0%
Total	24,155,058	100.0%

Source: Forest Department (2002).

In the National Biomass Study (NBS) project, the country was split into 9,000 plots with 3 sample plots at each intersection. However, due to influences of population density and agro-ecological zones on land cover and tree growth, some adjustments were made on the overall total sample plots. Topographic maps, land cover maps (1:50,000) and Global Positioning Systems (GPS) were used to locate the field plots on the ground. There were four categories of data capture and processing: i) mapping (spatial and its attributes), ii) biomass survey (filed plot measurements), iii) monitoring of biomass and iv) land cover change. This information details the woody biomass stock for each plot and it can be used to assess the relationship between tree cover and poverty. The data was extremely rich in bio-physical factors and also included the distribution of infrastructure like markets, roads, schools and others. In addition, the GIS format of the data allowed us to explore the possibilities of merging the data sets using GIS variables.

In addition to the land uses derived from the GIS information, we also had a 'distance to road' indicator as well. For each geographical area (districts, counties, sub-counties or even parishes), and for three different types of roads (main road, tarmac road and track) we calculated the total amount of area within the range or buffer of the road. We calculated five buffer zones ranging from 5 kilometres down to 1 kilometre. Figures A2 to A4 in Appendix A present the buffer zones for main roads, tarmac roads and tracks respectively. As the buffer zones declined from 5 to 1 kilometre, the percentages of total land area decreased. In particular, in North Uganda, the areas were less close to any type of road than in other parts of Uganda.

3.2 Overview of the analysis

In Uganda, the availability of high-resolution data sets was a strong foundation for us to produce and use poverty-biomass maps. Although several approaches have been developed to design poverty maps, there has been less effort to develop poverty/biomass maps. The Ugandan situation is unique because two decades ago, the country was faced with deteriorating economic, social and environmental conditions. Although today, these social and economic trends have been greatly reversed, it is not clear what the implications of these changes are for the natural resource base. The approach we used to link these problems uses statistical estimation techniques (small area estimation) to overcome the typical limitations in the geographic coverage of household welfare that surveys provide, and the lack of welfare indicators in the census data. It also included biomass information to assess these changes.

Our approach to the analysis of the links between poverty and biomass using maps began with the construction of a poverty map. We adopted the approach developed by Elbers et al. (2003). First, we selected variables based on comparable variables found in the survey and census data sets. The variables were derived from the comparable questions in the questionnaires. This was done because the empirical modelling of household consumption is limited by the set of variables that is common between the two data sets. A test was done to compare the means for the survey and census variables, and the variables that pass the significance test were considered for the regression analysis. Close examination of the data showed that several variables that appeared to be the same in the two data sets were really quite different. Reasons for these differences could be attributed to the fact that the two exercises measured distinctly different aspects of these variables or that the survey was simply not representative of the population for these variables.

The logical next step was to make a connection between welfare and bio-physical information. However, obtaining information on biomass use for administrative units was not straightforward, because of confidentiality, different data formats, the intricacies of geo-analysis and because environmental conditions did not follow administrative boundaries. There have been attempts to link poverty to other socio-economic factors that do not follow administrative boundaries (e.g. Thornton et al 2002), suggesting that combining poverty with other information (in this case on livestock) is key for a convincing integrated framework to address poverty issues for pastoralist populations.

Once the census and bio-physical data sets were integrated, ELL welfare estimates could be improved (see for instance Mistiaen et al. 2002 for Madagascar). The preliminary poverty estimates for rural Uganda were controlled for spatial autocorrelation solely by relying on PSU means calculated from the census. By controlling for bio-physical characteristics at the estimation procedure, the efficiency of the derived poverty estimates may be improved, leading to more precise estimates and enhancing the level of spatial disaggregation that is attainable.

In the regression analysis, we used household survey data to estimate per capita expenditure as a function of a variety of household characteristics. This estimation takes the form:

$$\ln y_{ch} = \chi_{ch}\,\beta + \eta_c\,(Z_c) + \in_{ch} \qquad (1)$$

Where y_{ch} is the log of per capita consumption expenditure of household (h) residing in cluster (c), X_{ch} are the household characteristics that are observable in both the survey and census data sets, and β is a coefficient vector. In our household survey, the clustering is done at regional (disaggregated into rural and urban) areas. The error term is composed of two parts. On the one hand, η_c (Z) applies to all households within a given cluster (location effect), which is a function of the biomass conditions Z_c, which are cluster specific On the other hand, $\in_{ch}$ is the household specific component of the error term (heteroscedasticity). These two error components are uncorrelated with one another and independent of the regressors. This specification of the error term allows for heteroscedasticity of the household specific error component. It also allows for the possibility of spatial autocorrelation (that is, location specific effects that are common to all households within a cluster).

To reduce the magnitude of the unexplained location specific component, we estimated a separate model to explain the cluster specific error terms. As regressors, cluster means of the household specific variables were obtained from the census at enumeration area level, and merged into the survey data set. This is a common procedure in poverty mapping. It amounts to explaining spatial autocorrelation between factors common to a household in a given Population Sampling Unit (PSU) - enumeration area. To the extent that households attend the same school, make use of the same source of fuel wood or water, and have similar access to markets, this procedure was likely to go a long way in explaining spatial autocorrelation. Yet, various (rather obvious) determinants of spatial autocorrelation could not be obtained from the census. Population and tree density, soil type and quality, and access to infrastructure were examples of such information. By building an integrated data set with census and biomass information, we were able to include such bio-physical information in explaining spatial autocorrelation. We estimated equation (1), taking into consideration the location and heteroscedasticity component of the disturbance term. Survey weights were included in some of the regressions, depending on the Hausman test (see Deaton 1997) results for whether the regressions should be weighted or unweighted.

Separate regressions were estimated for 1991, for each of the 4 rural strata of the survey data set. For 1999, only one model was estimated. We considered the set of variables that passed the test (zero stage) selection process, and the final selection of variables was determined by a stepwise procedure.

The next step (second stage) was to apply the estimation results of the coefficients from survey equation (1) to the census data. Since we were using household level census data, the combination produced estimates of per capita expenditure for each household. We simulated the level of consumption for each household based on Elbers *et al.* (2003).

4. Empirical Implementation

4.1 Zero Stage: Selection of Variables

The first step is known as the "zero stage". In this stage, we compared variables from the survey and census, and we selected potential ones. These were then used later in the regression models described in the methods above. Principally, the idea was to obtain variables from the household survey, which were comparable to those in the census. The initial step was to look at the question in both the survey and census. This should provide a clue as to whether the responses might supply similar information. However, it was not usually typical for identical questions to yield similar responses for several reasons. For instance, the way the question was asked, the local translation of the question, the ordering of the questions or even variations in the interpretation of the questions may cause major differences in responses. To verify that the questions yielded similar answers, we conducted an assessment to determine whether the variables were statistically distributed in similar ways, over the households in the survey and census. This statistical assessment was done for each of the four strata (i.e. the four regions focusing only on rural strata).

After a comparison of wording, coding and instructions in the enumerator manual, we constructed a more disaggregated total of 161 potentially identical variables, which sometimes involved interactions among some variables.[2] Then, using statistical criteria, we compared the stratum level means of the variables to assess the level of similarity. We did this by testing whether the survey mean for a particular variable lied within the 95 percent confidence interval around the census mean for the same variable. The third and final step was to do a comparison of the variables across the two categories of strata (rural and urban) to assess the level of uniformity in comparability. The selection of variables used in the first stage was based on criteria that picked all the continuous variables found to be comparable. For the dummy variables, we tested whether the census and survey means were identical[3].

4.2 Re-weighting

Despite being identified as potentially identical, household size did not pass the distribution comparison test. It differed consistently between the census and the survey in that small households were under-represented in the survey. For instance, in Central rural areas, the census mean for one-person households was 18.4 percent but the corresponding figure in the survey was 16.3 percent. As household size is crucial when deriving per

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[2] More detailed information on the variables and the zero-stage comparison can be obtained from Okwi *et al*. (2005), which is the supplementary report of this study. The definitions of variables are listed in Chapter 2, while Chapter 3 presents the results of the zero-stage comparison.

[3] For a full list of zero-stage comparisons, we refer to Chapter 3 of Okwi *et al*. (2005).

capita welfare estimates, it was less of an option to drop it from the common set of variables. And concerned that small households might be under-represented because of non-response and improper replacement (Hoogeveen, 2003) we decided to reweigh the survey.

The re-weighting strategy followed is known as a 'post-stratification adjustment' (Lessler and Kalsbeek, 1992). It ensured us that the weighted relative frequency distribution among mutually exclusive and exhaustive categories in the survey corresponded precisely to the relative distribution among those same categories in the census. In total, 13 different household size categories were distinguished. This reflected households of size 1-12, with category 13 reflecting households of size 13 and over. Re-weighting was done at the stratum level. One danger of re-weighting along one dimension (household size in this case) is that survey variables that were representative using the 'old' weights become non-representative once the weights have been adjusted to control for unrepresentativeness in other dimensions. On the other hand, if the adjustment corrects for a genuine sampling error, the comparability between the survey and the census should improve in all dimensions. To check the appropriateness of re-weighting, we compared the set of variables that were considered identical on the basis of wording, coding and enumerator instructions and assessed how many passed the survey-census means comparison test before and after re-weighting. Re-weighting considerably increased the number of variables that passed this test in all rural strata, whilst improving the fit for household size related variables.

4.3 First Stage

The first stage estimation was conducted using the household survey data, census and biomass data. Since we were analysing only rural data, the household survey was stratified into four sub-regions, and we estimated four different models. In this stage, we constructed more interaction terms from the selected census, survey and biomass variables. We then used a stepwise regression approach in SAS to select the variables, which provided the best explanatory power to the log per capita expenditure. As is the case with other similar studies, we used a significance level criterion with no ceiling on the number of variables to be selected. The significance level used for selecting variables was 5 percent.

To develop an accurate model of household consumption, we considered the model specified in equation (1). In this model, the error component is attributable to location and household specific effects. The presence of these errors makes welfare estimates less precise. Since unexplained location effects reduce the precision of poverty estimates, the first goal is to endeavour to explain the variation in consumption due to location with the choice and construction of explanatory variables. We attempted to reduce the magnitude of the location effect in four ways:

I. We included district dummies and their interaction terms with key household level variables (household size, level of education, age of head of household) in our specification. All districts in Uganda were represented in the survey;
II. We calculated means at the enumeration area in the census of household characteristics, such as household size and composition, and the gender, age and average level of education of household heads. We then merged these EA means into the house-

hold survey and considered their interactions with household characteristics obtained from the survey, for inclusion in the household regression specification;

III. For the information collected from the long form questionnaire (on housing characteristics, use of fuel, access to water sources etc.) we calculated district means and interact these with household characteristics. (Note: the long form questionnaire addressed 10% of the rural households and was representative at the district level);

IV. Finally, we included in our specification biomass variables and their interaction terms with key household level variables. The biomass variables included information on distance to roads, proportion of land under grassland, woodland, water, farmland and forests.

So far, in the household model, cluster level means and biomass data interacted with household characteristics were included. To further select location variables, we determined the common component in the household specific error terms and regressed this on enumeration area and district means. We then selected a limited number (5 at most) of variables that best explained the variation in the cluster fixed effects estimates. The number of explanatory variables was limited to avoid 'over-fitting'. The selected location variables were included in the household regression model, after which a combined model was estimated comprising household specific and location variables.

A Hausman test described in Deaton (1997) was used to determine whether to estimate our final regression models for each stratum with household weights. We re-estimated the regressions in equation 1, but only after adding weights to the selected explanatory variables. Then, using the Hausman test, we tested the joint significance of the weighted explanatory variables, at 5 percent significance. Finally, we decided whether or not weighting is necessary for the regressions.

We modelled the idiosyncratic part of the disturbance by choosing variables from the set of potential variables selected from the census and survey, their squares and interactions. To select a subset of these variables, we used ε^2_{ch} as the dependent variable in the stepwise regression and chose no more than 10 variables that best explain the variation in the household specific part of the residual.

Finally, we determined the distribution of η_c and ε_{ch} using the cluster residuals $\hat{\eta}_c$ and standardised household residuals: $e^*_{ch} = \frac{e_{ch}}{\hat{\sigma}_{\varepsilon,ch}} - \left[\frac{1}{H}\sum_{ch}\frac{e_{ch}}{\hat{\sigma}_{\varepsilon,ch}}\right]$, respectively, where h is the number of households in the survey. We used normal distributions for each of the error components. The consumption model was then re-estimated with the Generalised Least Squares (GLS) method, using the variance-covariance matrix resulting from the above equation.[4]

Table 4 below summarizes the results of the first-stage regression, and it shows that the adjusted R^2s of the models for 1991 vary from 0.35 to 0.46[5], (see also Tables B1 to B4 in Appendix B for examples of regressions results). According to Table 4, the inclusion of

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4 For a description of different approaches to simulation see Elbers *et al.* (2002 and 2003).

5 Note that the regressions are simply association models, and therefore the parameter estimates should not be interpreted as causal effects.

biomass information helped to raise the R^2s by an average of 2 percentage points compared to the models without them. The relatively low R^2s in the rural areas may be attributed to at least two factors. Firstly, the number of variables in the census short forms is limited to mostly household composition, education and ethnic origin[6]. Secondly, household composition and education only change slowly over time. The 'returns to agriculture' variables are, to a great extent, dependent on rainfall, illness of family labourers, incidence of pests and diseases, and prices. Again, some of this variation may be captured (for instance the age of the head of household and susceptibility to disease are correlated), but much of the cross sectional variation attributable to any of these sources will remain unexplained and gets subsumed in the error term.

Despite not being high, the explanatory levels are comparable to those attained elsewhere in Africa. For instance, in rural Madagascar the adjusted R^2 range from 0.239 to 0.460 (Mistiaen *et al.* 2002) and in Malawi it ranges from 0.248 to 0.448 (Machinjili and Benson, 2002). Considering that for Uganda, the long form of the questionnaire was available for only 10% of the rural households, the Ugandan R-squares seem to do relatively well.

Table 4 Summary Statistics of First Stage Regression Models (Rural Strata).

Number of observations	IHS			
	Central	East	North	West
Number of observations used in regressions	1660	1640	1368	1637
Number of clusters[1]	163	165	144	163
Hausman test for weights	1.29	1.04	1.71	1.84
Regression weighted?	Yes	Yes	Yes	Yes
Adjusted R^2 without location means	0.27	0.32	0.39	0.31
Adjusted R^2 with location means no biomass	0.31	0.34	0.44	0.32
Adjusted R^2 with location means including biomass data	0.35	0.36	0.46	0.34

Note: In the IHS, clusters are defined by the census enumeration areas. The models without location means and with location means and no biomass are derived from Okwi *et al.* (2003).

4.4 The link between poverty and the environment

There have been attempts to link poverty to other socio-economic factors that do not follow administrative boundaries (e.g. Thornton et al. 2002). This suggests that combining poverty with other information (in this case on livestock) is key for a convincing integrated framework to address poverty issues for pastoralist populations. For Uganda, where most households are involved in agriculture, this finding motivates our attempt to combine poverty and environmental information.

The logical next step was to make a connection between welfare and bio-physical information. However, as already noted, the regression analysis presents association and not causal models. There is need, therefore, for careful interpretation of the regression results. But it is important to note that obtaining information on biomass use for adminis-

6 Inclusion of all the variables from the short form and biomass data raised the R^2 but not to the urban strata levels, implying that we still needed to use more information (such as housing characteristics) to improve them.

trative units is not straightforward. This is due to confidentiality, different data formats, the intricacies of geo-analysis and because environmental conditions do not follow administrative boundaries. We consider a number of bio- physical factors as described in Section 3.1. These include: i) proximity from parish centre to nearest main, tarmac and track roads (separated into 1 to 5 kilometres), ii) proportion of land use cover such as parish land under woodlots, coniferous forests, tropical high forests, degraded forests, woodlands, grasslands, papyrus (wetland), subsistence and commercial farmland, water and impediments.

The regression results presented in Tables B1 and B4 in the appendix suggest a certain degree of spatial correlation between poverty and some of the bio-physical variables. The ability of these variables to improve the explanatory power of the models is interesting, but different variables were selected for the different strata. Once again, note that we are explaining spatial correlation and not causality. A few principal variables stand out as clear correlates of poverty. Access to roads has much explanatory association with poverty in all the four rural strata. Despite the fact that the types of roads differ between the strata, the regression results indicate a close spatial correlation to poverty. In the rural central stratum, access to main and track roads was an important variable, while in the north rural stratum, access to both main and tarmac roads was important. Likewise for the east rural stratum, access to track and tarmac roads was important, and in the west rural stratum, tarmac and track roads are important. The spatial correlation between poverty and access to roads is evident. Although our evidence is indirect, we conclude that access to various types of roads is potentially an important issue in Uganda. By implication, any policy focused on improving access to roads will yield disproportionate benefits for the poor.

Tables B1 and B4 in Appendix B and the Table E1 in Appendix E summarize the available evidence of the association between poverty and other bio-physical information. Besides access to roads, the proportion of land under woodland, subsistence and commercial farms turned out to be the most important biomass variables associated with rural poverty in the central rural stratum. Meanwhile, in the east rural stratum, the proportion of land under commercial farms, woodland and the proportion of degraded forests were important spatial variables correlated with poverty. In the north, the proportion of land under water, subsistence farmland and subsistence farmland in the wetlands were the important spatial variables. The selection of water bodies and wet farmland is probably suggestive of the fact that the northern region is generally dry, and access to water or wetlands could be important factors in explaining poverty (given that most of Uganda's rural population depends on agriculture). For the west rural stratum, the proportion of land under woodlots and subsistence farmland has spatial relations with poverty. In addition to the selected variables, how biomass variables interacted with household characteristics also proved to be important in explaining the correlation between poverty and biomass. The results from the regression analysis clearly display regional variation in the spatial correlation between bio-physical and poverty information. This evidence suggests that there is strong relationship between poverty and biomass variables. We conclude that access to subsistence and commercial farmland, wetlands/water, woodlands, roads and grasslands are important spatial factors correlated with poverty in Uganda.

5. Results

Once the census and bio-physical data sets are integrated, ELL welfare estimates can be improved (see for instance Mistiaen et al. (2002) for Madagascar). The preliminary poverty estimates for rural Uganda control for spatial autocorrelation solely by relying on PSU means calculated from the census. The second stage analyses sought to use the rural models to highlight the importance of bio-physical factors in poverty estimation. Firstly, the results of the second stage analysis are used to examine the extent to which the poverty estimates from the census and bio-physical data[7] match the sample estimates at the level at which the survey is representative (regional). Secondly, we ask how far we can disaggregate our census/bio-physical-based poverty estimates, when we take the survey based sampling errors to indicate acceptable levels of precision. Lastly, we focus on the ultimate goal of the analysis, namely to produce disaggregated spatial profiles of poverty and biomass. Using poverty/biomass maps, we show how projecting poverty estimates and biomass information produces a quick and appealing way in which to convey a considerable amount of information on the spatial relationship between poverty and the natural environment to users. We use poverty and biomass overlays to show the spatial heterogeneity of poverty and the natural environment.

The results of the welfare indicators measured by the conventional Foster-Greer-Thorbecke measures FGT(α) are reported with α-values of 0, 1 and 2 reflecting poverty incidence, poverty gap and the poverty gap squared, respectively. As a benchmark, the official monthly per capita poverty lines (in 1989 prices) are used, i.e. 15,947 Ugandan shillings for rural Central, 15,446 shillings for rural East, 15,610 shillings for rural North and 15,189 shillings for rural West. Table 5 below summarizes the poverty inequality estimates based on the predictions of the combined biomass and census at the regional level, and the survey based estimates. The detailed estimates for the district level are presented in the appendices. To reduce clutter, the poverty estimates for the county and sub-county are presented in the form of maps.

At the stratum level, the results are reasonably close to those from the survey. Interestingly, most standard errors were lower than when no biomass data was included, in some cases by up to 40 percent. As shown in Table 5, the results show a consistent story with regard to the survey and census-based estimates. Central rural emerges with the lowest level of poverty, even when census/biomass data is used for prediction, while north rural remains the poorest of the four strata. When other measures of welfare (such as the poverty gap (α=1) and the poverty gap squared (α=2)) are used, the comparison among the rural strata still remains consistent with the survey rankings. The inclusion of the bio-physical data improved the poverty estimates at the stratum level and lowered the census-bio-physical based standard errors consistently. This even occurred when some parishes in the North and West did not have corresponding bio-physical data.

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7 Some observations were missing in the census/biomass data, therefore the populations represented may not be exactly the same as if they were based on census data alone.

Table 5 Poverty measures for four rural areas from different data sources, 1992.

Stratum		Central			East			North			West		
Poverty Measure		Estimate	Standard Error	CV#	Estimate	Standard Error	CV#	Estimate	Standard Error	CV#	Estimate	Standard Error	CV#
Poverty incidence FGT(0)	Survey	54.30	2.20	0.041	60.60	2.30	0.038	74.30	2.60	0.035	54.30	2.50	0.046
	Census*	54.10	1.69	0.031	63.80	1.57	0.025	74.50	1.84	0.025	55.50	1.69	0.030
	Census/ Biomass	53.42	1.25	0.023	63.40	1.48	0.023	74.80	1.07	0.014	55.40	1.37	0.025
Poverty gap FGT(1)	Survey	18.70	1.20	0.065	23.00	1.30	0.057	29.00	1.90	0.067	19.20	1.40	0.071
	Census*	17.90	0.84	0.047	23.90	0.93	0.039	30.30	1.10	0.036	20.30	1.02	0.050
	Census/ Biomass	17.85	0.71	0.040	23.90	0.93	0.039	32.00	0.70	0.022	20.10	0.77	0.038
Poverty gap squared FGT(2)	Survey	8.80	0.70	0.080	11.40	0.80	0.070	14.80	1.30	0.090	9.30	0.90	0.094
	Census*	8.10	0.73	0.090	11.70	0.60	0.051	15.60	0.72	0.046	10.00	0.91	0.091
	Census/ Biomass	8.02	0.44	0.055	11.70	0.60	0.051	17.05	0.59	0.035	10.04	0.48	0.048
Mean Per Capita Expenditure, in thousand	Survey	18.131	0.629	0.035	15.460	0.486	0.031	13.899	0.636	0.046	16.256	0.537	0.033
	Census*	17.951	0.564	0.031	15.049	0.382	0.025	12.884	0.370	0.029	16.954	0.509	0.030
	Census/ Biomass	18.202	0.345	0.019	19.629	4.073	0.207	13.755	0.365	0.027	16.210	0.314	0.019

* The ‘Census’ poverty measures are derived from Okwi *et al*. (2003). The ‘Census’ and ‘Census/Biomass’ estimates are predictions based on the ELL method, while the ‘survey’ estimates are directly calculated from the IHS survey.

\# CV means ‘coefficient of variation’, which is defined as the ratio of the standard error over the point estimate.

The inclusion of bio-physical information in the small-area estimation procedures can have two effects. Firstly, the level of the poverty measures can change, and secondly, the standard errors of the estimates of poverty measures can change. Table 5 presents estimates of four poverty measures at the regional level in 1992. Poverty measures from three different sources are compared. The survey-based estimates are directly calculated from the IHS database. The 'Census predicted' estimates are based on the ELL method, without the use of bio-physical information (see Okwi et al., 2003). Finally, the 'Census/Biomass predicted' estimates are from the present study. In this study we focus attention on the comparison of 'Census' and 'Census/Biomass' estimates.

The level of the poverty measure estimates changed due to the inclusion of bio-physical information. In the Central stratum, all the poverty measures slightly declined, while for the East, all poverty measures hardly changed. Except for the poverty incidence, the level of the other poverty measures increased in the northern region. At the same time, the standard errors declined. The poverty estimates for West Uganda hardly changed, while the accompanying standard errors declined. The graphs in Appendix F show the new poverty estimates of the present study at different aggregation levels, compared to the 'old' results of Okwi et al. (2003).

In addition, we analyse the extent to which the inclusion of spatial features allows our poverty estimates to be robust. There are two major ways of determining the level of disaggregation at which the error becomes too big. They both yield similar conclusions in most cases. One way to approach this is to consider the absolute level of the standard error. The other method, which is used in this study, is to calculate the coefficient of variation (CV) (which is the ratio of the standard error over the point estimate for each administrative unit) and compare this with the survey-based ratios.

The inclusion of biomass variables has improved the standard errors (in some cases by up to 40 percent) of our estimators at the stratum level. Finally, this section offered insights into the inclusion of bio-physical and other spatial features in poverty estimation. It demonstrated that, with the inclusion of more explanatory spatial characteristics, relative improvements could be made in the estimation of welfare. That is, by controlling for bio-physical characteristics at the estimation procedure, the efficiency of the derived poverty estimates may be improved. This then leads to more precise estimates and enhances the level of spatial disaggregation that is attainable. Awareness of this association, combined with well-designed policies, are key factors that may support poverty reduction in these areas.

Table C1 to C2 in Appendix C present the poverty estimates at a district level. These poverty estimates show some level of heterogeneity. All the standard errors fall below the stratum level survey based ones, with the exception of the Kalangala district in the central region. The case of the Kalangala district is interesting and expected. Firstly, this is a small district with a total population of 14, 218 people, which is significantly less than the population of most sub-counties and even parishes in the region. For example, in the Central region, the poverty estimates range from 25 percent to 63 percent at the district level and 19.6 to 74 percent at the county level. In the Eastern region, the poverty levels range from 39.5 to 82 percent at the district level. At the county level, the observed distribution is more interesting than at the district level. In the North region, Arua is the least poor district (64 percent) while Kotido is the poorest, with 91 percent poor.

Similarly, the Western region shows significant variation in poverty levels. Whereas Masindi has about 76 percent headcount ratio, Mbarara is the least poor, with only 43 percent. Generally, there is wide variation in the poverty estimates in all the strata and we cannot categorically identify one region as being the poorest as there may be pockets of wealthy areas within the poorest region. The level distributions of poverty at various levels are shown in the graphs in Appendix F.

Furthermore, to explain the link between certain bio-physical characteristics and poverty, we use overlays presented in Appendix D.[8] The overlays are simply meant to provide a visual explanation of the relationship between poverty and land-sue. For example, from the overlays, we can identify the poverty hotspots and correlate them with the type of land use in the area. A clear example is that poverty is more pronounced in the Northern parts (which are typically wooded and grassland areas) and less pronounced in the degraded lands of all the regions. The implication of the latter result is that the poor are actually using the ecological resources to improve their welfare, but in the process they degrade the natural environment. However, a contrasting picture emerges from the grassland areas in the Western and Northern regions, which portray less and more poverty respectively (see also according correlation coefficients with opposite signs in the Table E1 in Appendix E). A question that emerges is 'Why the difference?' One possible explanation for the difference could be that the pastoral lands in Western Uganda have been modified to produce high yielding varieties of crops (thus directly improving their welfare), while the pastoralists in the North maintain traditional norms of cattle rearing. The overlays generally have helped us to answer the following questions: Where are the poor? Which poor (rich) areas have similar types of land-use features? Which areas provide which type/amount of ecosystem services? How do the land-use types overlap with poverty? How does the location of poverty compare to the distribution of ecosystem services? Which areas have access to better resources and what are the benefits and costs? This information may help policy-makers to design effective policies to improve the situation. For detailed maps, see the poverty and biomass maps for all strata in Appendices E.

6. Conclusions and implications for policy

This study combines census, survey and bio-physical data to generate spatially disaggregated poverty/biomass information for rural Uganda. It makes a methodological contribution to small area welfare estimation by exploring the inclusion of bio-physical information. By combining the generated poverty estimates with national bio-physical data, this study explores the contemporaneous correlation between poverty (welfare) and natural resource degradation, at a level of geographic detail that has not been feasible previously. In this welfare estimation method, association relationships are used to explain welfare rather than causal relationships are explored. However, the resulting estimates of poverty measures were improved by the inclusion of bio-physical information. In some cases, the levels of poverty measures have changed. For North Uganda, the poverty gap

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8 The county level estimates of the household expenditures and the head count are presented in Chapter 4 of Okwi *et al*. (2005).

and poverty gap squared increased compared to the estimates without bio-physical information.

By providing comparable welfare and bio-physical information for many data points, this study solves numerous problems faced by previous studies. For instance, previous studies (see Atkinson and Brandolini, 1999) on poverty and the environment were based on case studies that were unrepresentative. This study presents results of a representative sample and population. Secondly, previous studies have also been cross-sectional, thus raising data incomparability problems. By using data from one country (collected by the same institution), with comparable questions in the questionnaires, and within a period of less than 2 years, data incomparability problems are solved. Thirdly, this study has provided a practical analysis of the link between welfare and the environment. Other studies have only looked at the theoretical link between poverty and environmental degradation (Ambler 1999; Barbier, 2000; Roe, 1997; Chomitz, 1999; Ekbom and Bojo, 1999). This study has shown that accounting for spatial differences in welfare is key to producing high precision maps and explaining poverty environment relationships.

The poverty estimates appear to be more robust, as the standard errors show a decline in some cases by up to 40 percent. Moreover, the coefficient of variation (that is, the ratio of the standard error and the point estimate) decline in general as well. Overall, we conclude that the estimates of the poverty measures are more robust when bio-physical information is taken into account. One of the outputs of this study is a series of maps showing poverty and biomass overlays for Uganda. These maps can be used as a planning tool and for targeting purposes.

In terms of policy, by implication, any policy focused on improving access to roads is directly related to the welfare of the poor. Similarly, the conservation of wetlands and forests, improvement of grasslands (mainly pasture land), and access to water could be important policy issues to consider in understanding the relationship between poverty and the environment. Given that most of Uganda's rural population depends on agriculture and the environment, and considering the spatial relationship between subsistence farming, degraded lands and poverty, the results suggest that focusing on improving production in the subsistence sector may prove important in reducing poverty and improving the biomass conditions. The results from the regression analysis clearly display regional to county level variation in the spatial correlation between bio-physical and poverty information, and therefore imply region-specific policy designs. Finally, in future research, with more information, the causal relationship could be analysed in more detail.

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Appendix A Bio-physical information for Uganda

This appendix summarizes the bio-physical information for Uganda in 1991/1992. We have two types of biomass indicators. Firstly, a land use indicator, i.e. total area per land use type divided by the total area. Secondly, distance to road indicators, i.e. the total area within a certain distance of a particular road type divided by the total area.

In Figure A1, we use classes based on natural groupings inherent in the data. The break points are identified by picking the class breaks that best group similar value and maximize the differences between classes. The features are divided into classes whose boundaries are set where there are relatively big jumps in the data values.

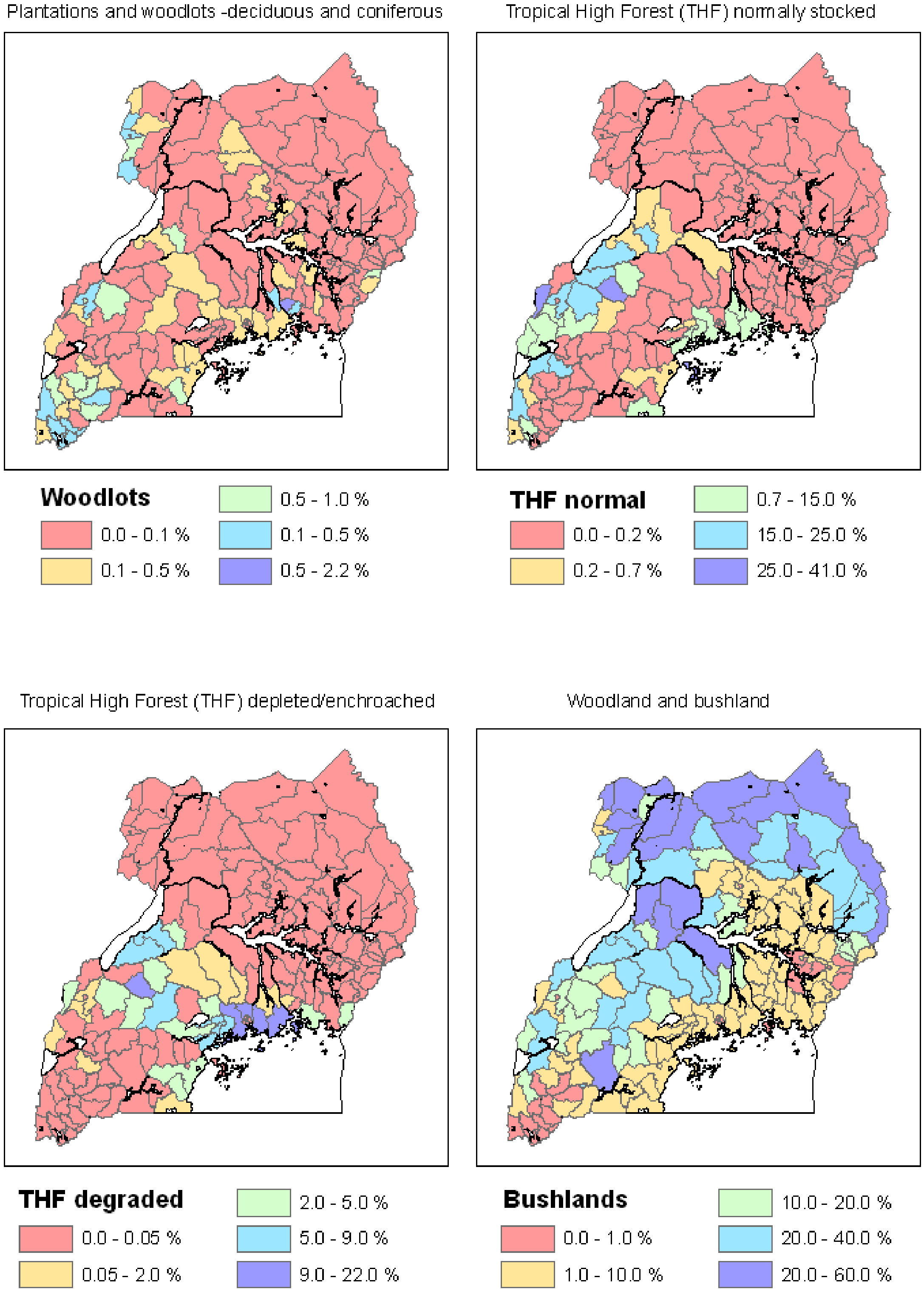


Figure A1 Land use classifications: Proportion of county area under different land use types.

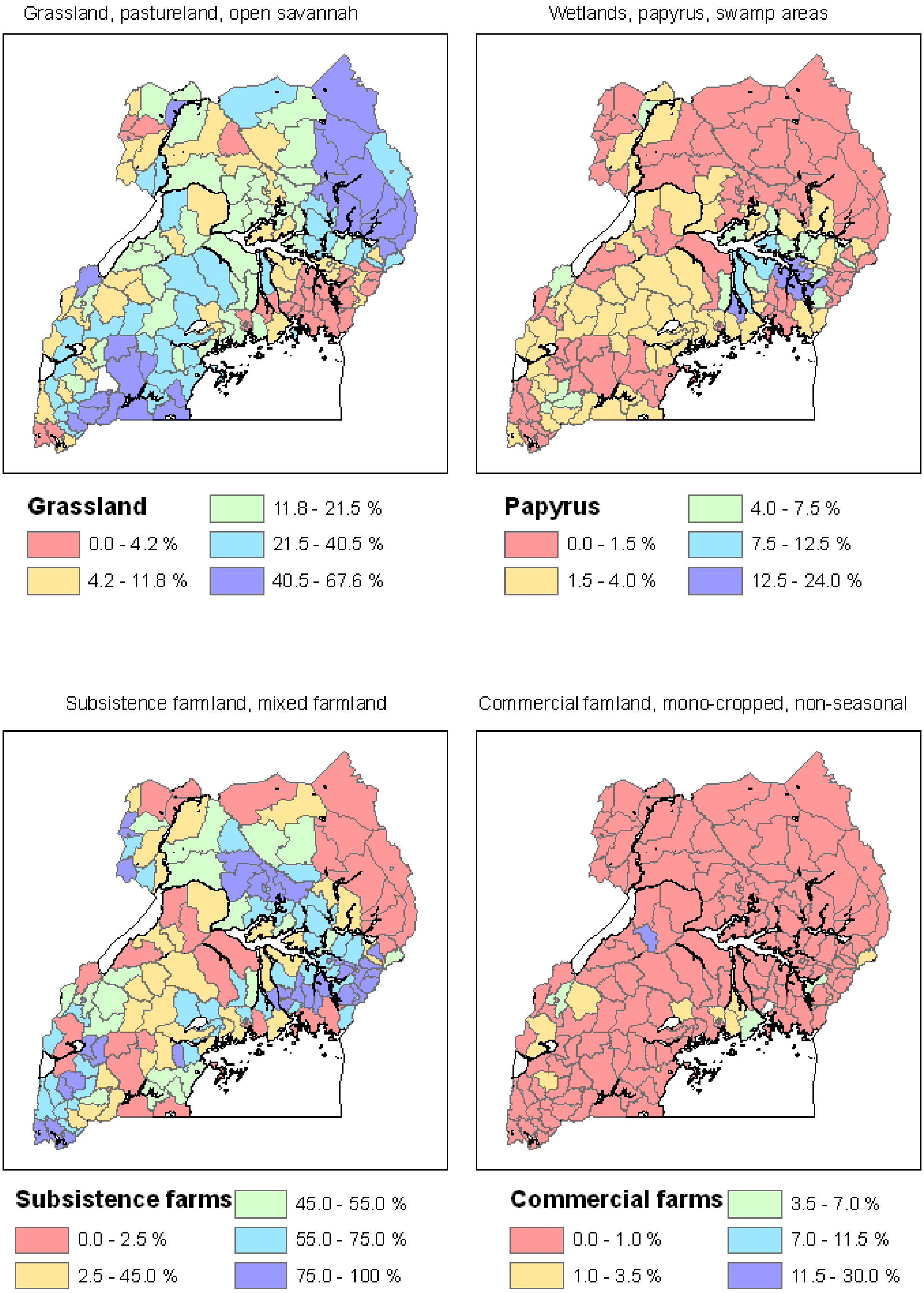


Figure A1 Land use classifications: Proportion of county area under different land use types (continued).

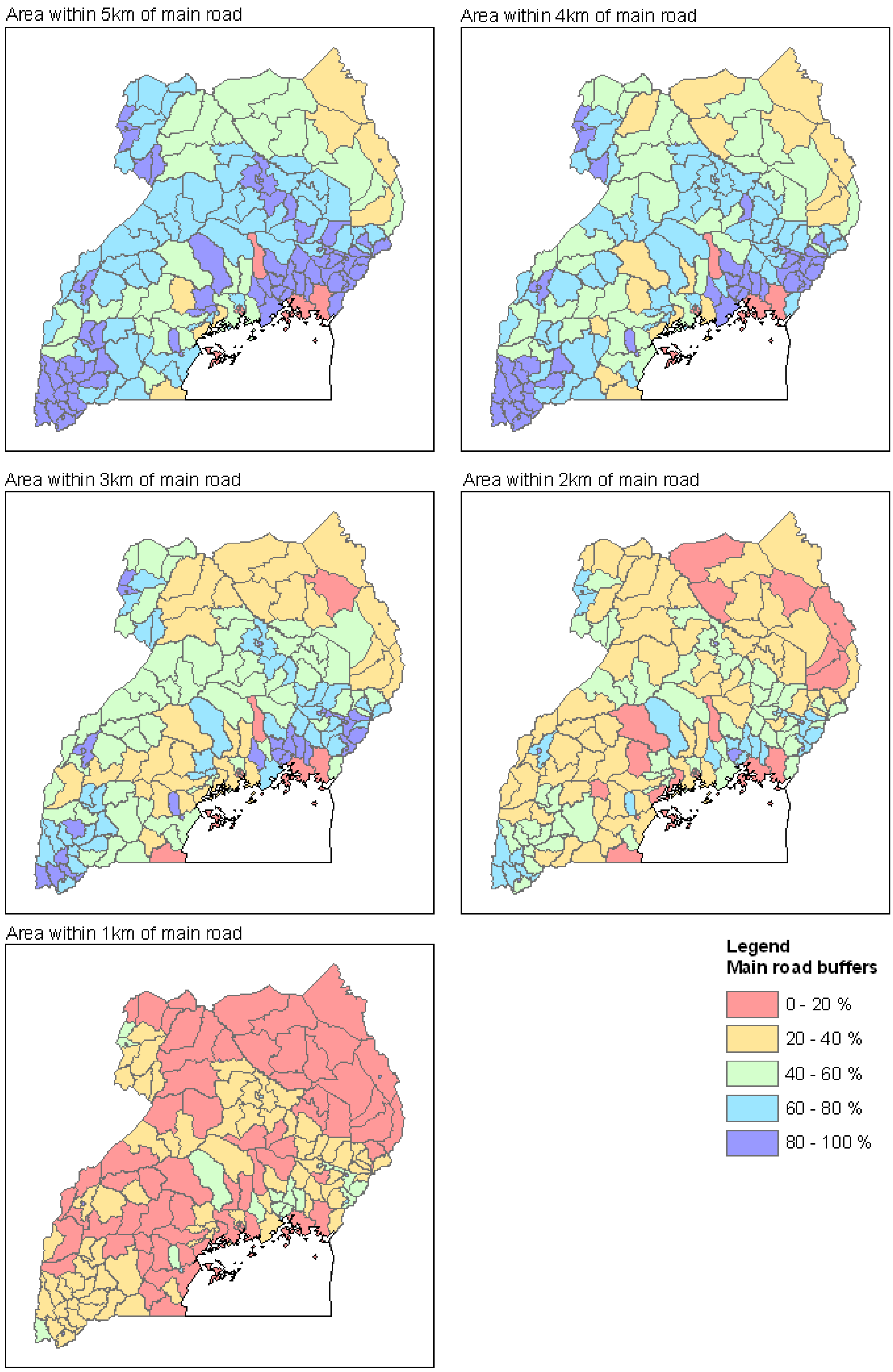


Figure A2 Main road buffers: Proportion of county area within a distance of 5 down to 1 kilometre to main roads.

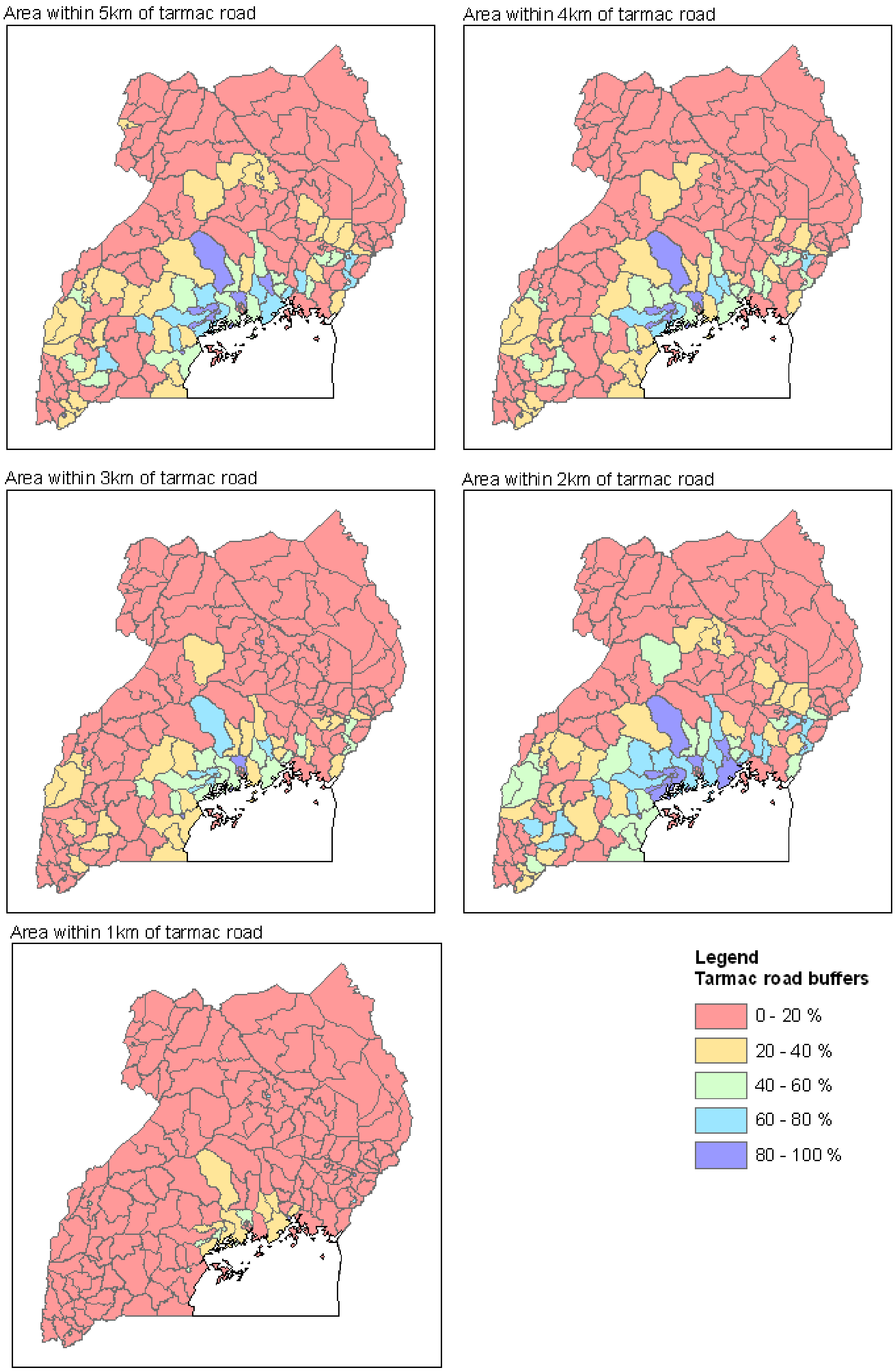


Figure A3 Tarmac road buffers: Proportion of county area within a distance of 5 down to 1 kilometre to tarmac roads.

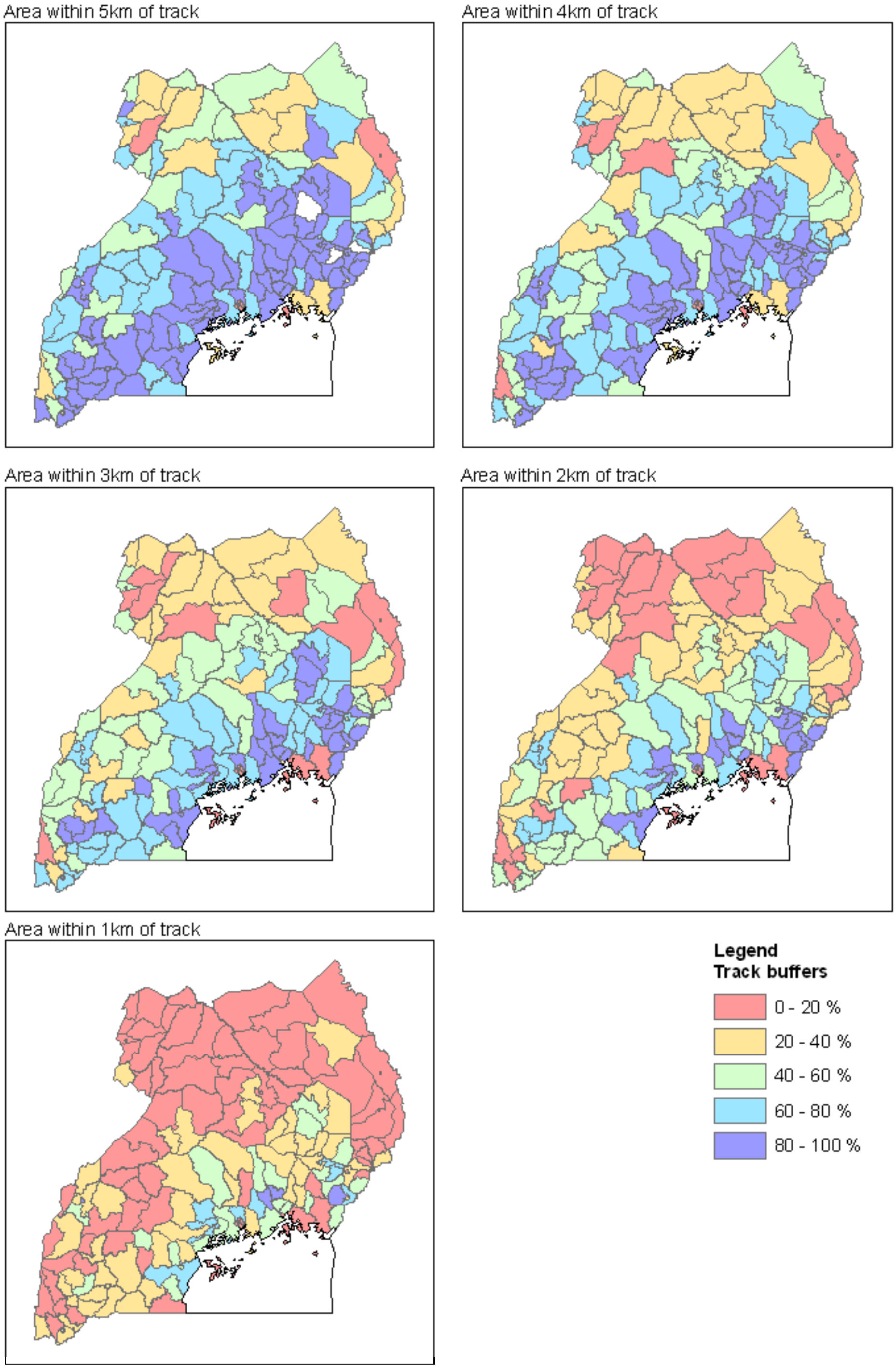


Figure A4 Track road buffers: Proportion of county area within a distance of 5 down to 1 kilometre to tracks.

Appendix B First stage regressions

Table B1 First stage regression results for Central region.

Dependent Variable: log of per capita consumption expenditure		
Number of observations:	1660	
Number of Clusters:	163	
Adjusted R^2:	0.35	
Variable	Parameter estimate	Standard error
Intercept	10.326	0.138
Number of females aged 6-14	0.037	0.017
Household size squared	0.001	0.000
Logarithm of household size	-0.382	0.029
Proportion of males with secondary school	0.872	0.150
Proportion of males without education	-0.153	0.046
Proportion of males with education at A 'level	0.426	0.136
Age of household head squared	0.000	0.000
Mean years of education head squared	-0.005	0.001
Number of females aged 45 or older	-0.056	0.025
Buffer zone within 1km of main road	0.341	0.078
Buffer zone within 2km of track road	-0.402	0.116
Buffer zone within 4km of track road	-0.304	0.052
Proportion of woodland (parish)	0.380	0.144
Logarithm of age of household head*Alur tribe	0.929	0.267
Logarithm of age of household head *Toro tribe	2.670	0.423
Logarithm of age of household head *Lugbara tribe	0.422	0.183
Logarithm of age of household head * Males aged 30 or older	-0.213	0.036
Logarithm of age of household head * Males aged 30 or younger	0.081	0.012
Logarithm of age of household head *Kitchen shared	0.703	0.198
Max. numbers of years of education*Ganda tribe	0.022	0.006
Log. of age of household head *Prop. of females aged 0-5 squared	-2.399	0.626
Logarithm of age of household head * Mubende district	-0.062	0.013
Log of age of household head * Prop. of subsistent farming (parish)	0.083	0.020
Log of age of household head * Prop. of commercial farming (parish)	0.183	0.058
Log of age of household head * Prop. of water (parish)	0.057	0.026
Mean number of years of education of adults * Buffer within 5km of tarmac road	-0.026	0.009
Mean number of years of education of adults * Prop. of commercial farming	-0.346	0.103
Proportion of males with A'level education*Kiboga district	-0.300	0.126
Number of males with education at level P5-P7*Prop. of grassland	0.188	0.047
Male hh. head separated or divorced * Number of males aged 30 or younger	-3.089	1.353
Hh. head with education at P5-P7 level * Prop. of town (parish)	2.999	0.766
Hh. head with education at P5-P7 level * Prop. of degraded THF	1.004	0.249
Number of males aged 30 or younger * Mpigi district	-0.050	0.014
Japadhola tribe	-2.278	0.556
Mugwere tribe	5.369	1.371

Table B2 First stage regression results for the Eastern region.

Dependent Variable: log of per capita consumption expenditure		
Number of observations:	1640	
Number of Clusters:	165	
Adjusted R^2	0.36	
Variable	Parameter estimate	Standard error
Intercept	9.379	0.142
Household size = 10	-0.152	0.073
Logarithm of adult equivalent size	-0.444	0.024
Prop. of males with no secondary education squared	0.437	0.139
Number of males aged 15-29 years	-0.061	0.018
Age of household head squared	0.000	0.000
Prop. of persons with education under A' level	0.457	0.115
Proportion of males with education years 1 to 4 Squared	0.241	0.061
Buffer zone within 1km tarmac road	-0.255	0.105
Prop. of degraded tropical high forest (parish)	6.927	1.197
Prop. of commercial farm land (parish)	4.100	0.706
Prop. of males with secondary education * Teso tribe	0.229	0.042
Number of males with education between P5-P7* Ganda tribe	2.535	0.521
Maximum years of education * Rwanda tribe	-1.886	0.650
Heads education between P5-P7*Ganda tribe	-2.824	1.261
Log of age of household head *Kamuli district	-0.069	0.016
Log of age of household head * Kapchorwa district	0.093	0.021
Log of age of household head * Kumi district	-0.070	0.015
Log of age of household head *Soroti district	-0.070	0.014
Maximum years of education*pit latrine	-0.070	0.005
Maximum years of education *Kamuli district	-0.070	0.008
Number of males education between P5-P7*Iganga district	0.062	0.021
Number of males education between P5-P7*buffer within 1km track	0.049	0.021
Male hh. head separated, divorced*Kamuli district	-0.348	0.131
Number of males aged 30 or younger* Prop. Of woodlot	1.220	0.303
Number of males aged 30-49 (EA mean)	0.584	0.184
Household size = 1	1.722	0.281
Household size = 8	1.587	0.546
Number of females aged younger than 10 (EA mean)	-0.692	0.266
Number of females aged 6-14 (EA mean)	-1.449	0.235
Number of females aged younger than 15 (EA mean)	1.112	0.288
Number of males with education P1-P4 years (EA mean)	0.444	0.105
Number of males with education P1-P4 years squared (EA mean)	-1.904	0.738

Table B3 First stage regression results for the Northern region.

Dependent Variable: log of per capita consumption expenditure		
Number of observations:	1368	
Number of Clusters:	144	
Adjusted R^2:	0.46	
Variable	Parameter estimate	Standard error
Intercept	10.225	0.093
Number of males with at least secondary school	0.061	0.029
Household size =5	0.090	0.036
Household size =13	0.366	0.121
Maximum years of education 13 squared	-0.001	0.000
Log of adult equivalent size	-0.681	0.052
Proportion of females aged 30-49 squared	0.350	0.141
Number of males with education years 1 to 4	-0.083	0.019
Number of males with primary education	0.101	0.016
Proportion of males with education O'level and above	0.512	0.179
Number of females aged 30 or older	0.092	0.026
Buffer zone within 1km from main road (parish)	0.682	0.233
Buffer zone within 1km from tarmac road (parish)	6.153	1.623
Buffer zone within 3 km from tarmac road (parish)	-8.865	1.692
Buffer zone within 4 km from tarmac road (parish)	5.732	0.969
Proportion of subsistence farmland (parish)	-0.130	0.054
Proportion of wet subsistence farmland (parish)	-3.714	1.160
Proportion of water (parish)	0.856	0.140
Age of household head age* tribe Lugbar	0.007	0.002
Age of household head age* district Arua	0.008	0.002
Meal hh. head separated or divorced squared	2.866	1.169
Maximum years of education* tribe Madi	0.057	0.008
Number of males aged 30 and above* district Arua	-0.143	0.051
Number of males aged 50 and above * Head male separated divorced	-0.406	0.106
Number of males aged 50 and above*tribe Lugbar	-0.569	0.114
Number of females aged 15 and below* district Apac	0.066	0.012
Age of Household head* Proportion of parish within 1km from main road	-0.020	0.004
Log of adult equivalent size * Distric Gulu	-0.346	0.087
Log of adult equivalent size * Prop. of parish within 1km from main road	0.253	0.115
Log of adult equivalent size * Prop. of parish within 1km from track road	0.105	0.047
Head males separated divorced * district Gulu	0.564	0.233
Head males separated divorced * district Kitgum	-0.445	0.176
Head males separated divorced * district Nebbi	-3.059	1.076
Maximum years of education * district Gulu	0.059	0.011
Maximum years of education* district Lira	0.015	0.005
Maximum years of education* district Moroto	0.106	0.041
Maximum years of education is 13 years* district Gulu	0.025	0.012
Number of males aged 30 and above* district Moyo	-0.177	0.063
Number of males aged 50 or older *Main road buffer zone of 1km	0.609	0.133
Proportion of females aged 0-5 squared (EA mean)	-4.514	1.140
Proportion of females aged 45 plus (EA mean)	-0.599	0.134

Table B4 First stage regression results for the Western region.

Dependent Variable: log of per capita consumption expenditure		
Number of observations:	1637	
Number of Clusters:	163	
Adjusted R^2	0.34	
Variable	Parameter estimate	Standard error
Intercept	10.391	0.111
Number of females aged 6-14	0.047	0.017
Number of males with education above O'level	0.079	0.037
Household size squared	0.004	0.001
Household size = 11	-0.343	0.101
Log of household size	-0.246	0.041
Proportion of females aged 0-5 squared	0.934	0.235
Proportion of females aged 30-49 squared	0.451	0.129
Number of males with no education	-0.077	0.013
Number of males with education 1 to 4 years	-0.076	0.016
Age of Household head squared	0.000	0.000
Proportion of parish within 1 km from track road	0.975	0.165
Proportion of parish within 2 km from track road	-0.684	0.145
Proportion of parish within 3 km from tarmac road	0.169	0.049
Proportion of parish within 4 km from track road	0.226	0.066
Proportion of parish under woodlot	-6.715	2.067
Proportion of parish under subsistence farmland	-0.240	0.053
Proportion of parish under wet subsistence farmland	1.096	0.300
Log of household heads age* tribe Kiga	0.034	0.013
Log of household heads age* tribe Konjo	0.206	0.028
Log of household heads age * tribe Nkole	0.107	0.013
Mean education years = 18 * tribe Alur	0.216	0.082
Mean education years =18* tribe Nkole	-0.023	0.011
Mean education years =18* tribe Nyoro	-0.083	0.018
Head no education* tribe Alur	-1.828	0.560
Head male separated divorced* tribe Konjo;	0.574	0.250
Maximum years of education * tribe Alur;	-0.230	0.062
Maximum years of education*tribe Ganda;	0.231	0.077
Log of household heads age*district Hoima;	0.071	0.018
Log of household heads age* district Kasese;	-0.134	0.029
Mean education years 18* Proportion of parish under towns	-1.815	0.881
Head no education * district Kabarole;	-0.157	0.052
Proportion of males with no education*prop.of parish under towns	-11.510	4.072
Head males separated divorced* district Hoima;	0.478	0.198
Household size =6* district Kabarole;	0.348	0.098
Household size =6* district Kabale;	0.367	0.127
Number of males with education above O'level (EA mean)	0.840	0.172
Number of females aged 35 or older (EA mean)	-0.419	0.096

Appendix C Poverty estimates at district level

Table C1 Rural Strata: District Mean Per capita Expenditure, Poverty and Inequality Estimates.

Code	District	Population	Mean Y	FGT0	FGT1	FGT2
Central						
11	Kalangala	14,079	26452.51	25.09	6.21	2.25
			(2198.34)	(0.05)	(0.02)	(0.01)
17	Kiboga	131,445	15858.74	62.11	22.20	10.43
			(756.16)	(0.03)	(0.02)	(0.01)
23	Luwero	403,948	17501.48	55.45	18.41	8.21
			(527.67)	(0.02)	(0.01)	(0.01)
24	Masaka	723,415	18651.63	50.34	15.77	6.74
			(558.90)	(0.02)	(0.01)	(0.00)
30	Mpigi	761,066	19671.96	48.82	15.91	7.05
			(722.53)	(0.03)	(0.01)	(0.01)
31	Mubende	445,077	16176.08	63.00	23.20	11.10
			(888.90)	(0.03)	(0.02)	(0.01)
32	Mukono	705,227	19077.89	49.45	15.94	7.01
			(674.38)	(0.02)	(0.01)	(0.01)
35	Rakai	361,501	16312.77	60.87	21.49	9.99
			(563.14)	(0.02)	(0.01)	(0.01)
East						
7	Iganga	885,398	23364.78	58.38	20.59	9.58
			(8399.97)	(2.24)	(1.24)	(0.75)
8	Jinja	203,021	65272.74	39.53	12.38	5.35
			(54955.40)	(3.37)	(1.36)	(0.69)
13	Kamuli	460,682	12789.89	73.89	30.62	15.93
			(835.61)	(3.68)	(2.96)	(2.07)
14	Kapchorwa	102,019	19059.53	45.81	13.73	5.71
			(1677.03)	(6.31)	(2.70)	(1.37)
21	Kumi	216,150	10945.13	82.40	37.00	20.20
			(776.46)	(3.37)	(3.16)	(2.34)
26	Mbale	640,929	16205.49	58.85	20.51	9.49
			(545.66)	(2.26)	(1.29)	(0.78)
34	Pallisa	347,936	14909.63	63.66	23.01	10.90
			(485.59)	(2.15)	(1.29)	(0.81)
37	Soroti	358,452	11741.12	78.66	34.09	18.22
			(742.83)	(3.33)	(2.76)	(1.96)
38	Tororo	483,104	17926.81	62.84	22.84	10.83
			(1933.28)	(2.00)	(1.28)	(0.82)

Table C2 Rural Strata: District Mean Per capita Expenditure, Poverty and Inequality Estimates.

Code	District	Population	Mean Y	FGT0	FGT1	FGT2
North						
1	Apac	440,829	15661.78	64.34	23.61	11.33
			(790.82)	(2.91)	(1.64)	(1.01)
2	Arua	600,141	16778.39	64.01	23.21	11.00
			(862.38)	(2.93)	(1.80)	(1.10)
5	Gulu	277,223	12081.47	79.77	38.53	22.21
			(652.15)	(1.96)	(2.02)	(1.65)
19	Kitgum	327,085	13140.80	88.21	41.92	23.45
			(30480.45)	(1.29)	(1.54)	(1.24)
20	Kotido	111,552	8817.79	90.90	47.29	28.30
			(424.99)	(1.39)	(2.13)	(1.89)
22	Lira	454,193	13526.99	73.46	29.95	15.34
			(577.26)	(2.35)	(1.77)	(1.22)
28	Moroto	123,002	11349.58	83.74	42.62	25.44
			(1609.66)	(2.67)	(2.20)	(1.74)
29	Moyo	132,801	13994.23	70.20	28.16	14.36
			(664.04)	(2.75)	(1.84)	(1.23)
33	Nebbi	286,352	10019.24	87.93	40.72	22.27
			(327.17)	(1.32)	(1.58)	(1.27)
West						
3	Bundibugyo	103,236	16035.53	57.82	23.14	12.22
			(1100.32)	(3.88)	(2.51)	(1.72)
4	Bushenyi	711,713	18688.97	44.60	14.71	6.89
			(753.93)	(2.97)	(1.31)	(0.71)
6	Hoima	188,347	17334.30	52.34	19.01	9.48
			(1452.48)	(5.87)	(2.97)	(1.74)
9	Kabale	382,099	15746.15	55.93	19.74	9.60
			(858.46)	(4.05)	(2.01)	(1.15)
10	Kabarole	693,706	16887.08	51.31	17.82	8.60
			(704.22)	(3.00)	(1.43)	(0.81)
15	Kasese	294,155	15962.43	55.47	19.69	9.62
			(1314.83)	(6.27)	(3.25)	(1.88)
16	Kibaale	212,124	13310.58	68.60	26.68	13.71
			(614.08)	(3.11)	(2.12)	(1.38)
18	Kisoro	176,360	12929.51	70.26	27.33	14.03
			(749.21)	(4.07)	(2.68)	(1.71)
25	Masindi	225,504	11852.71	76.20	33.58	18.74
			(879.23)	(3.91)	(3.37)	(2.51)
27	Mbarara	865,415	19429.69	42.49	13.87	6.45
			(749.62)	(2.53)	(1.06)	(0.56)
36	Rukungiri	371,360	13854.28	65.35	24.11	11.99
			(594.17)	(3.17)	(1.78)	(1.07)

Appendix D Overlays of poverty and biomass

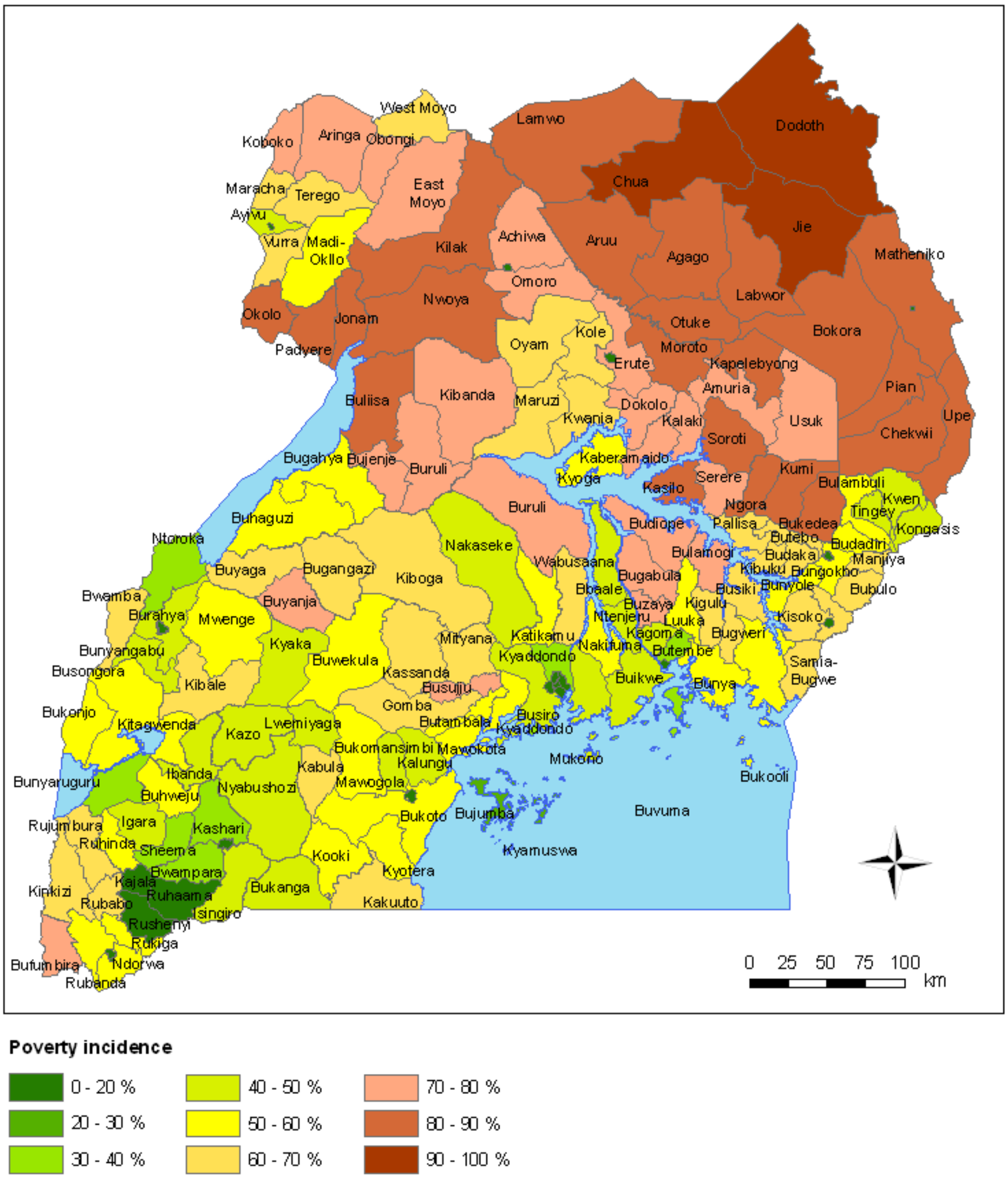


Figure D1 Map of poverty incidence in Uganda based on the poverty estimates with biomass.

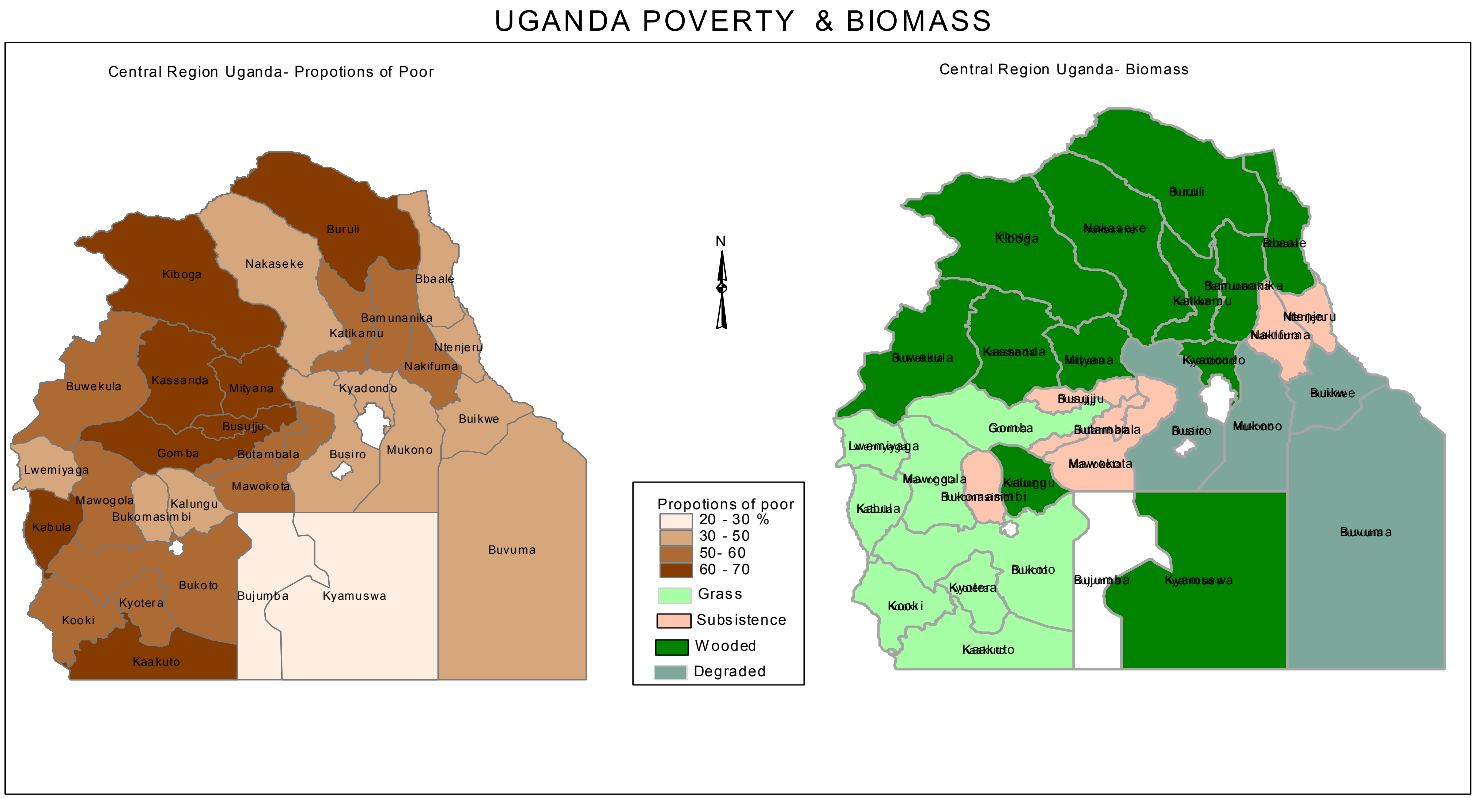


Figure D2 Poverty and biomass in Central region, Uganda, 1992.

UGANDA POVERTY & BIOMASS

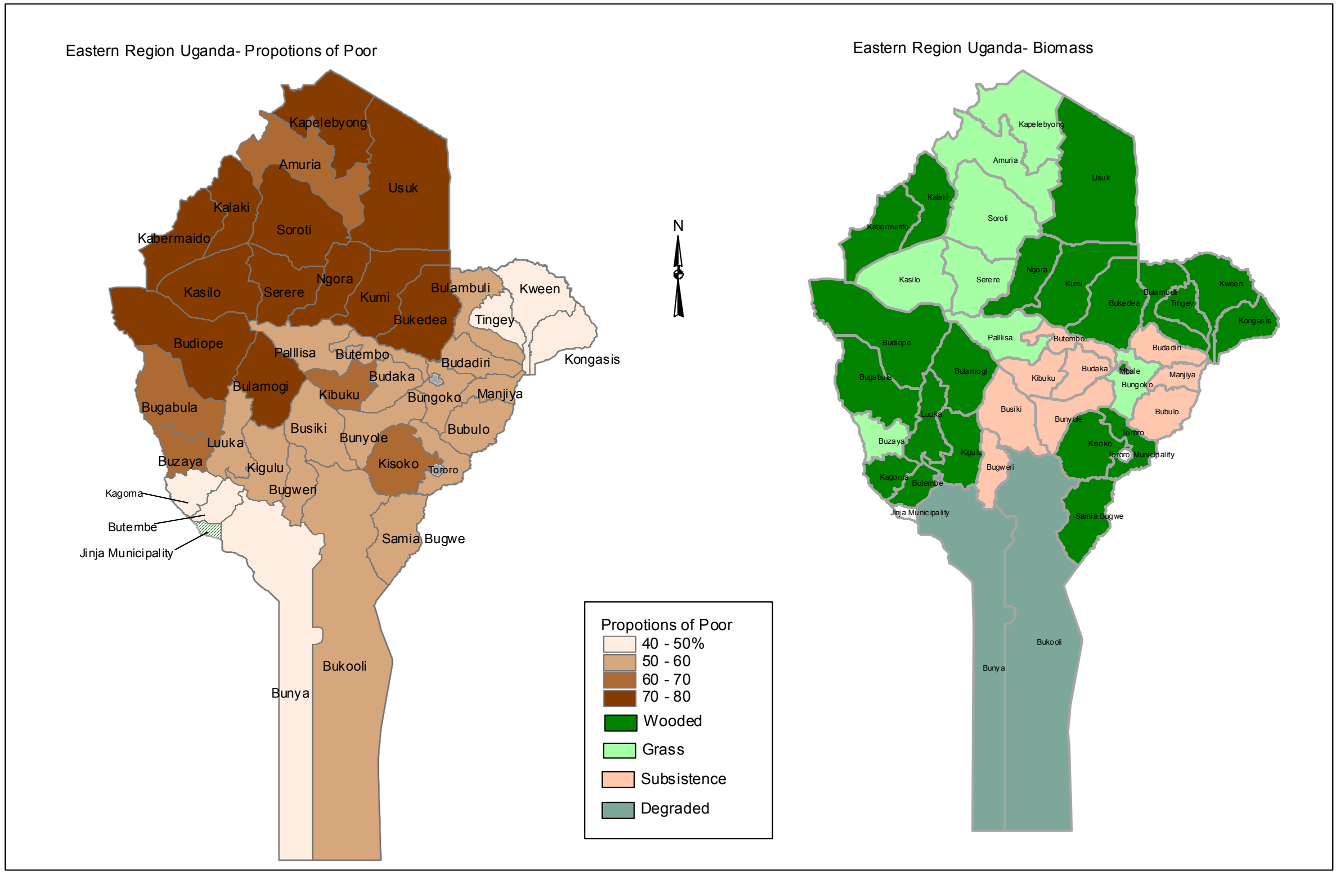


Figure D3 Poverty and biomass in Eastern region, Uganda, 1992.

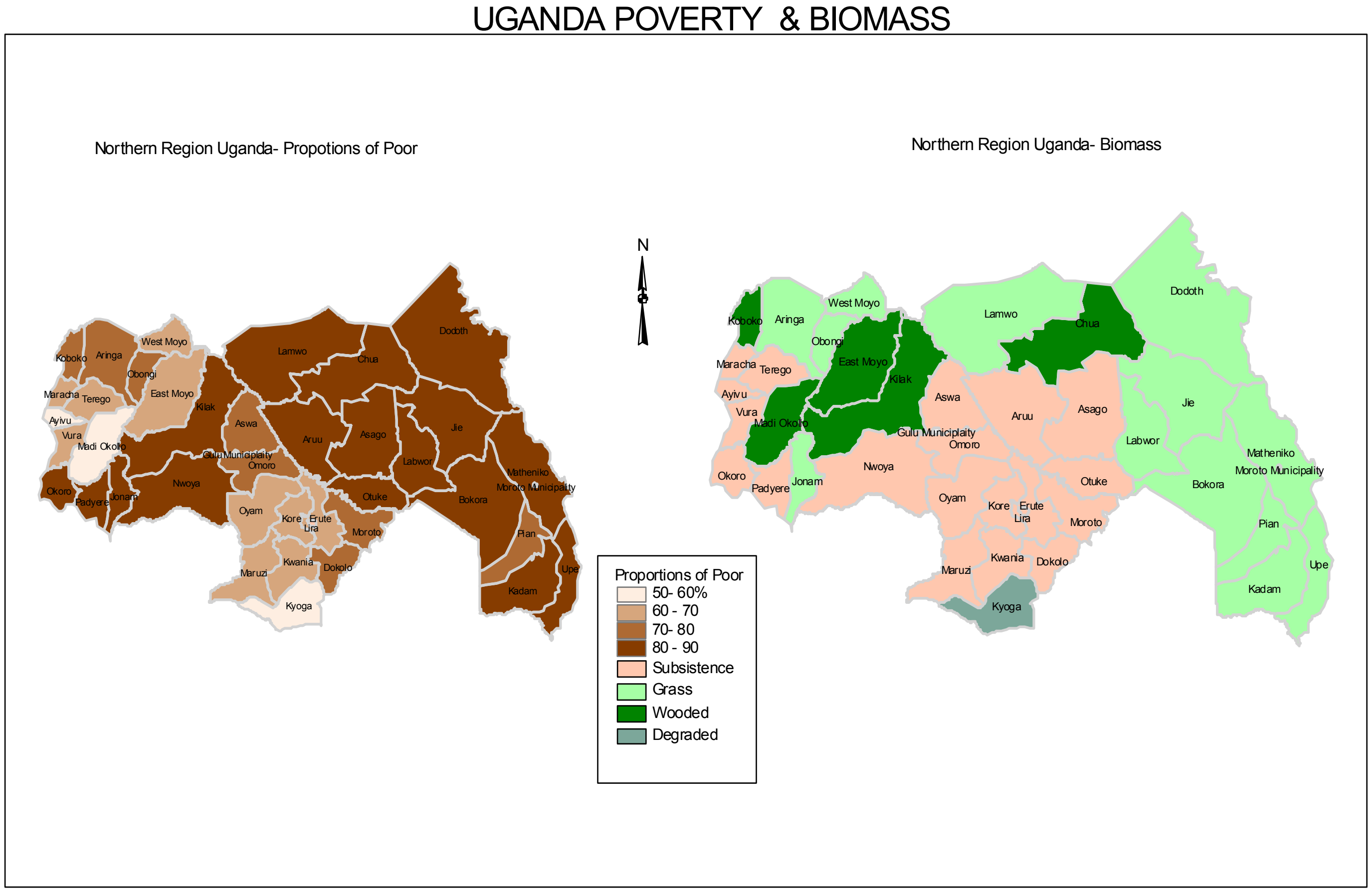


Figure D4 Poverty and biomass in Northern region, Uganda, 1992.

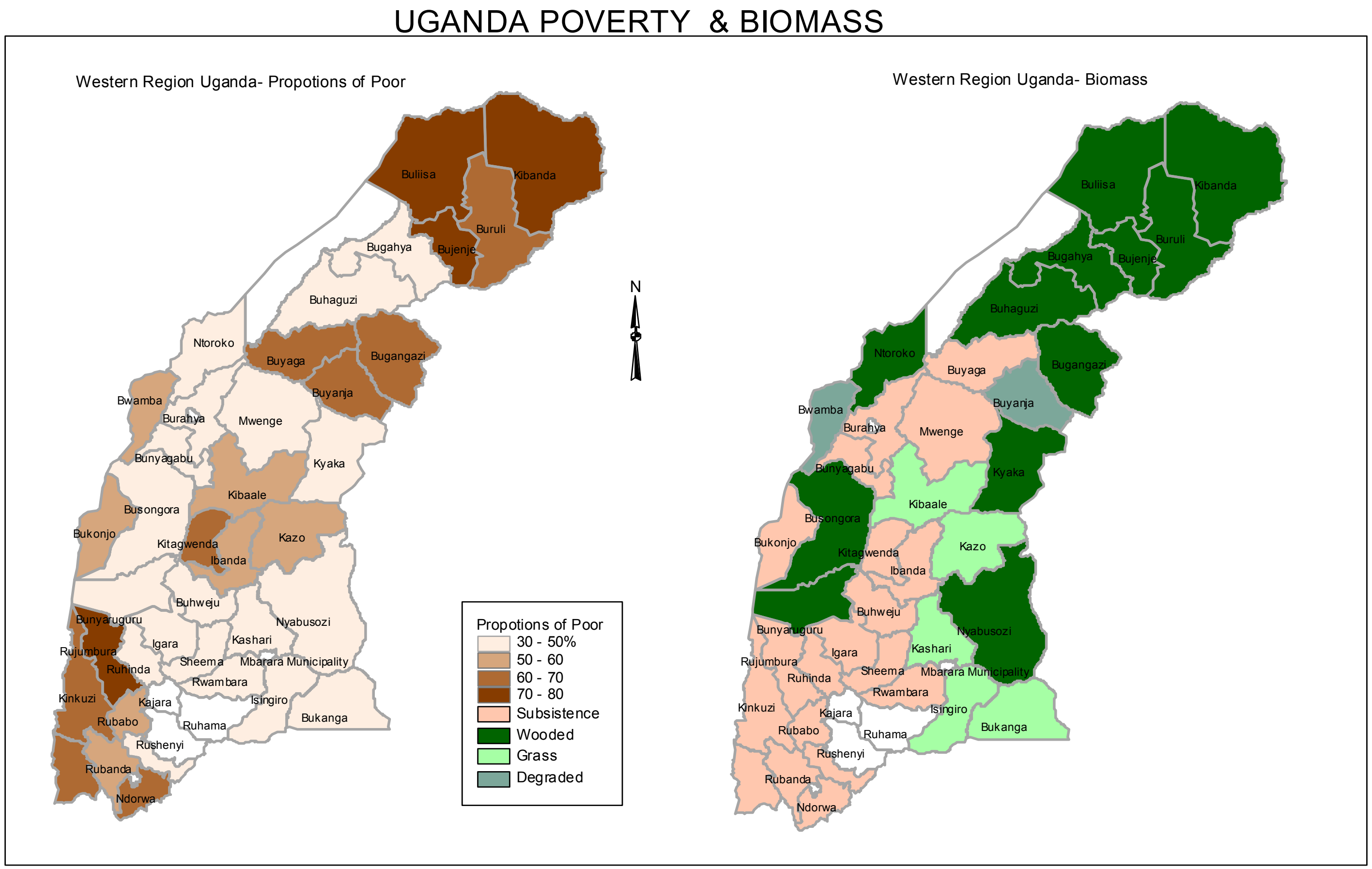


Figure D5 Poverty and biomass in Western region, Uganda, 1992.

Appendix E Correlations between biomass and poverty

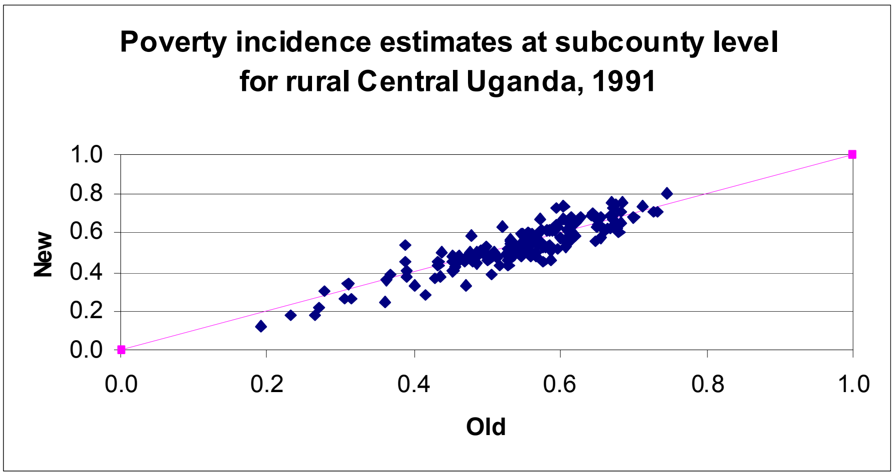
Table E1 Correlation coefficients between land use (biomass) and poverty incidence at county level.*

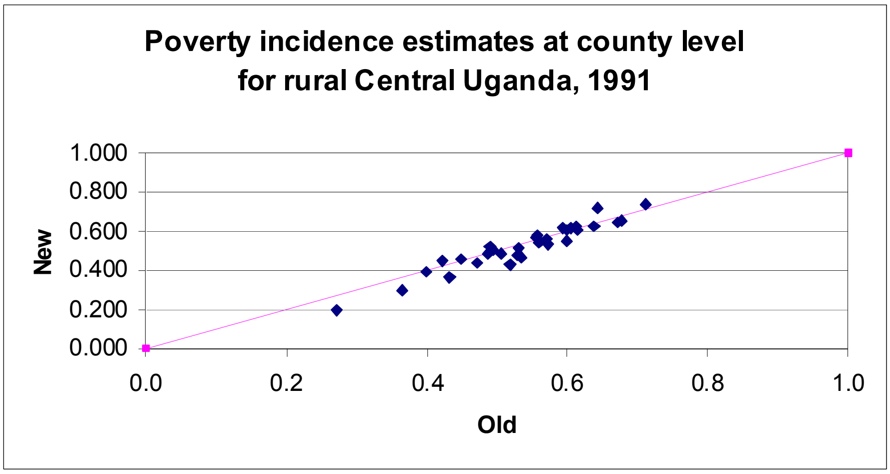
Bio-physical variable	Uganda	Central	East	North	West
Buffer zones of main road					
1 km	-0.031	0.136	-0.646	0.033	-0.653
2 km	-0.011	0.172	-0.662	0.027	-0.650
3 km	0.012	0.206	-0.664	-0.001	-0.648
4 km	0.046	0.227	-0.643	-0.019	-0.641
5 km	0.085	0.232	-0.604	-0.030	-0.627
Buffer zones of tarmac road					
1 km	-0.347	0.000	-0.511	-0.502	-0.173
2 km	-0.337	0.045	-0.507	-0.506	-0.220
3 km	-0.329	0.081	-0.501	-0.506	-0.267
4 km	-0.321	0.109	-0.494	-0.502	-0.300
5 km	-0.315	0.133	-0.491	-0.498	-0.324
Buffer zones of tracks					
1 km	-0.052	0.125	-0.365	-0.408	-0.337
2 km	-0.045	0.171	-0.401	-0.451	-0.356
3 km	-0.019	0.200	-0.409	-0.474	-0.363
4 km	0.015	0.214	-0.390	-0.462	-0.368
5 km	0.054	0.221	-0.365	-0.434	-0.369
Land use covers					
Hardwoods	-0.238	-0.068	-0.357	-0.109	-0.527
Softwoods	-0.072	-0.006	-0.361	-0.085	0.116
Tropical high forest -normal	-0.294	-0.564	-0.113	0.277	-0.020
Tropical high forest –depleted	-0.208	-0.160	-0.161	0.307	-0.113
Woodlands and bush lands	0.409	0.046	0.587	0.245	0.345
Grasslands	0.095	0.172	0.619	-0.417	0.444
Wetlands	-0.026	0.172	-0.071	-0.154	-0.080
Subsistent farmland	-0.135	0.315	-0.614	0.008	-0.409
Commercial farmland	-0.224	-0.103	-0.428	0.124	-0.424
Subsistent farmland/wetlands[#]	-0.069	-0.025	-0.429	0.305	-0.064
Built up areas	-0.322	-0.302	-0.673	-0.065	-0.460
Water	-0.239	-0.661	0.000	0.077	-0.146

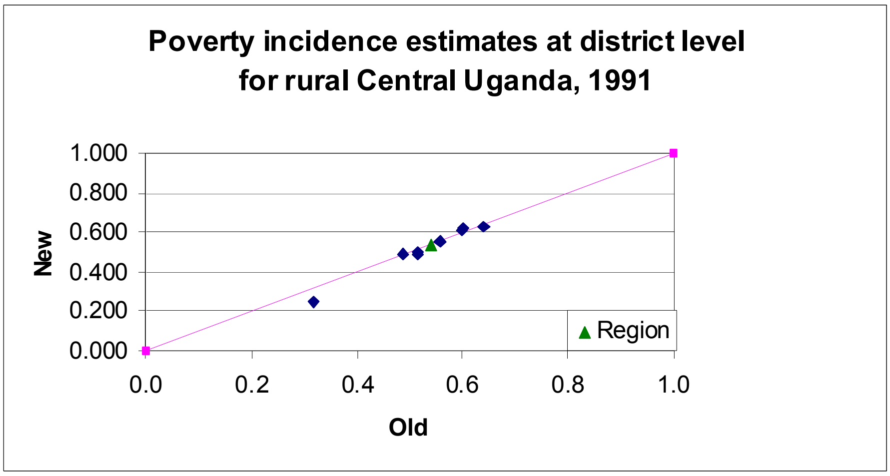
* The poverty incidences are derived from Okwi *et al*. (2003), and therefore are the poverty estimates without bio-physical information.

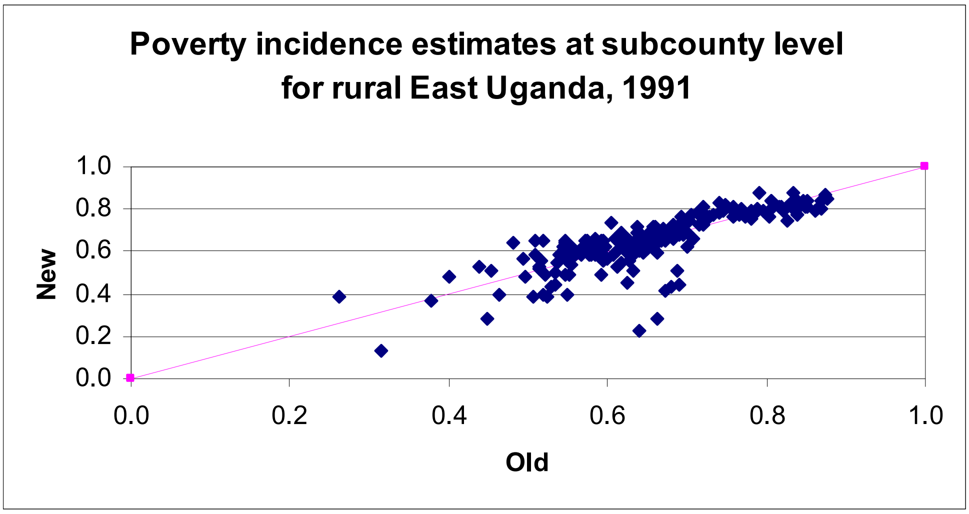
[#] Subsistent farmland/wetland is part of the Subsistent farmland.

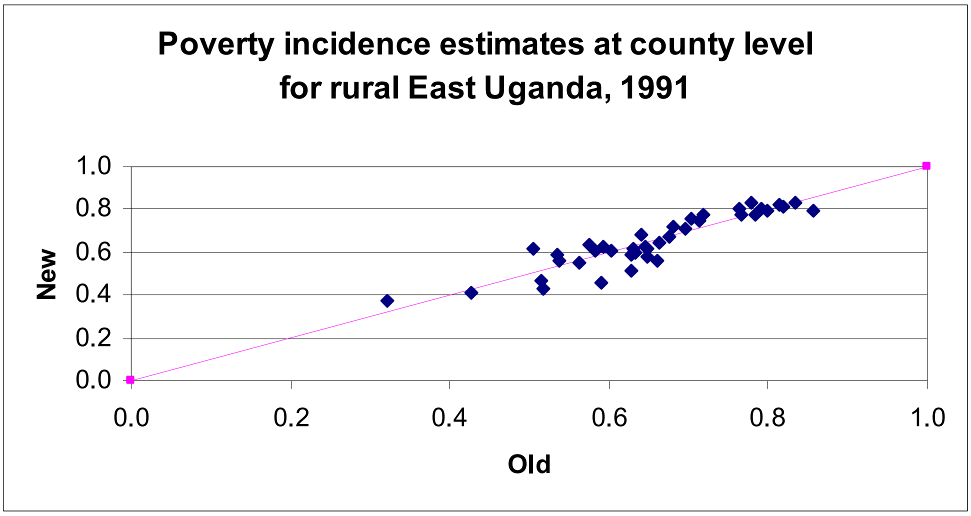
Appendix F Comparison of old and new poverty estimates








Poverty incidence estimates at subcounty level
for rural East Uganda, 1991
New
Old
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0


Poverty incidence estimates at county level
for rural East Uganda, 1991
New
Old
1.0
0.8
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0.2
0.0
0.0
0.2
0.4
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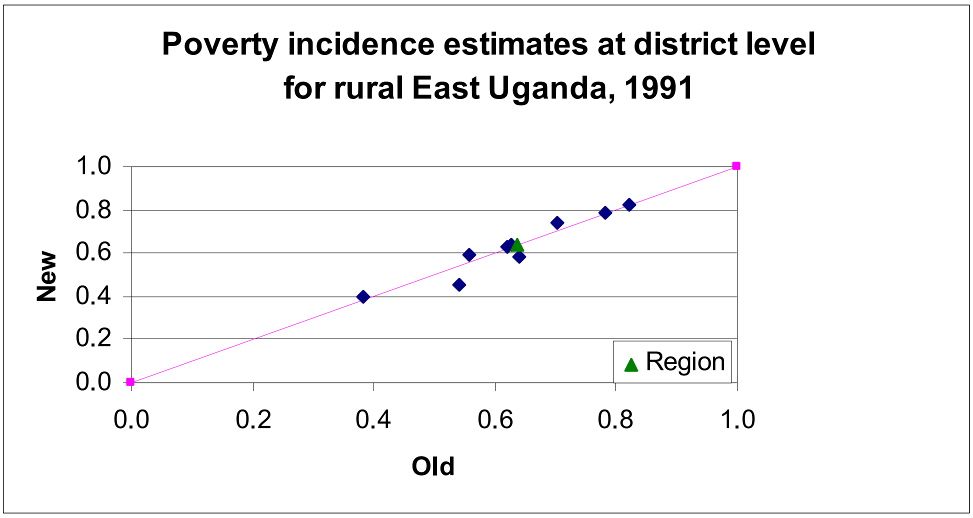
0.8
1.0


Poverty incidence estimates at district level
for rural East Uganda, 1991
New
Old
Region
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0.8
0.6
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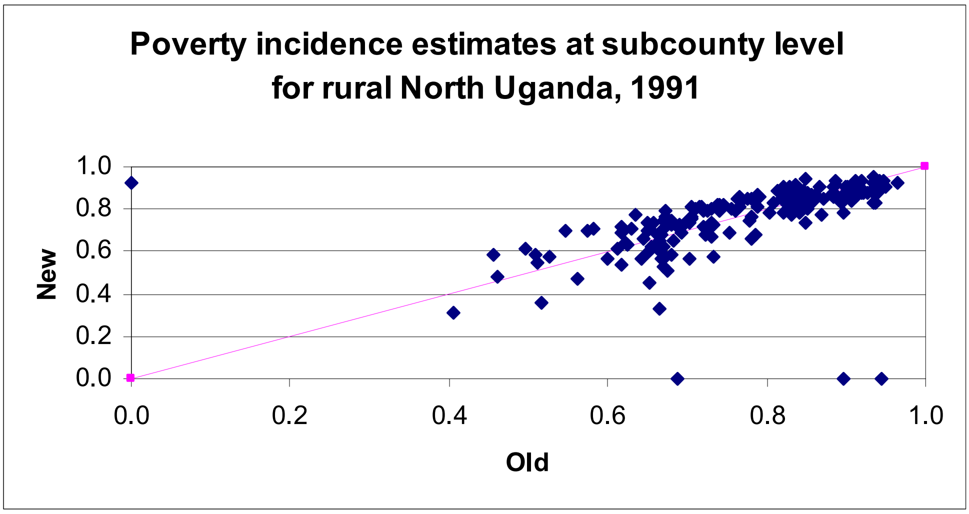
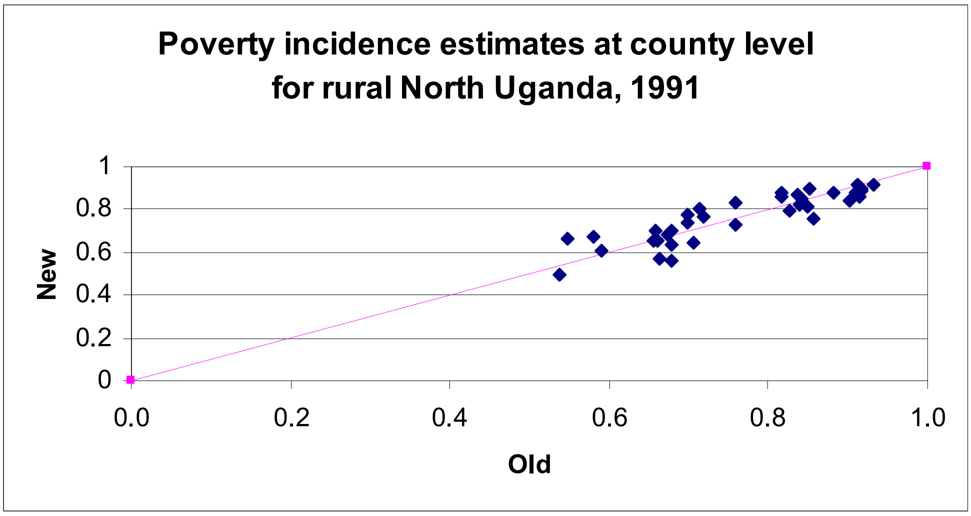
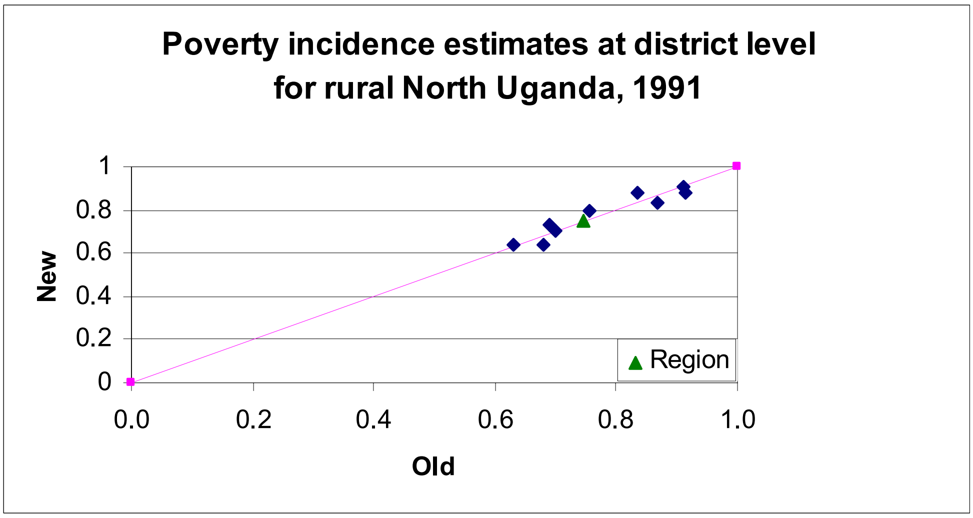
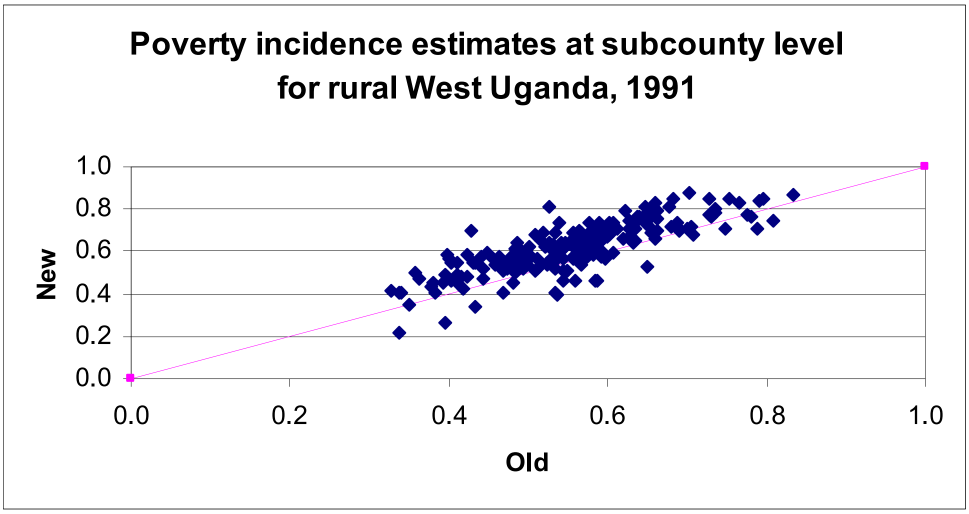
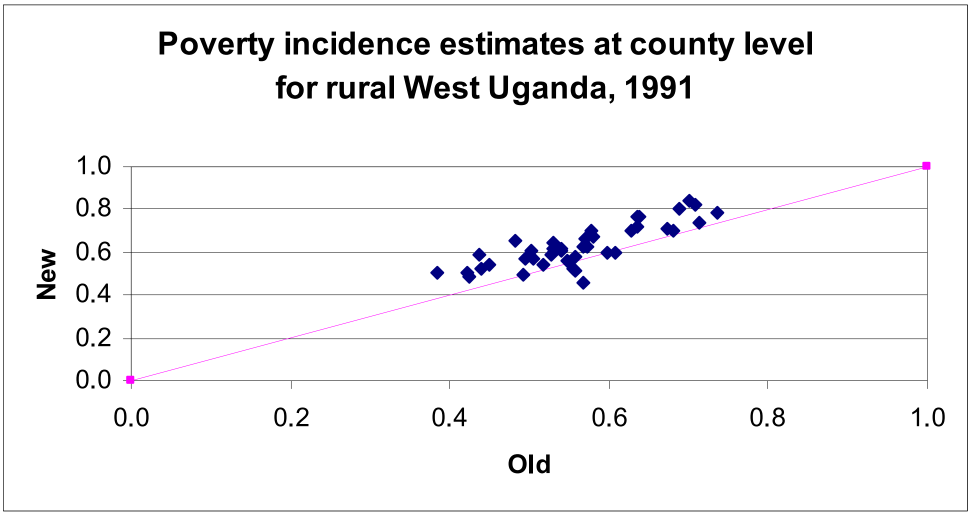
0.4
0.6
0.8
1.0

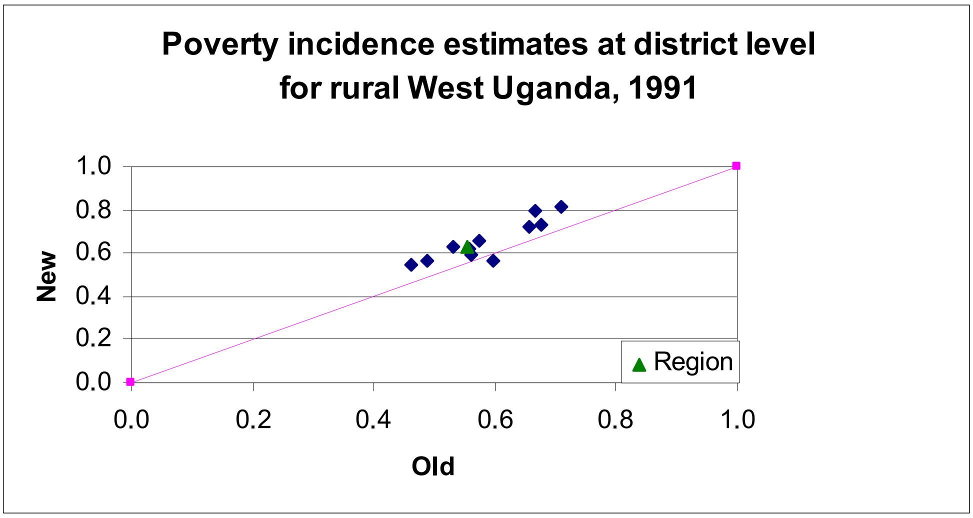

Poverty incidence estimates at subcounty level
for rural North Uganda, 1991
New
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
Old


Poverty incidence estimates at county level
for rural North Uganda, 1991
New
1
0.8
0.6
0.4
0.2
0
0.0
0.2
0.4
0.6
0.8
1.0
Old


Poverty incidence estimates at district level
for rural North Uganda, 1991
New
1
0.8
0.6
0.4
0.2
0
Region
0.0
0.2
0.4
0.6
0.8
1.0
Old


Poverty incidence estimates at subcounty level
for rural West Uganda, 1991
1.0
0.8
0.6
0.4
0.2
0.0
New
0.0
0.2
0.4
0.6
0.8
1.0
Old


Poverty incidence estimates at county level
for rural West Uganda, 1991
1.0
0.8
0.6
0.4
0.2
0.0
New
0.0
0.2
0.4
0.6
0.8
1.0
Old


Poverty incidence estimates at district level
for rural West Uganda, 1991
1.0
0.8
0.6
0.4
0.2
0.0
New
Region
0.0
0.2
0.4
0.6
0.8
1.0
Old