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Remote Sensing and GIS Based Poverty Mapping Small- Area Estimation Approach In Rural Oromiya Regional State

 

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Remote Sensing and GIS Based Poverty Mapping Small- Area Estimation Approach in Rural Oromiya Regional State

THESIS SUBMITTED TO THE SCHOOL OF GRADUATE STUDIES, ADDIS ABABA UNIVERSITY, IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR
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Declaration

This thesis is my original work and has not been presented for a degree in any other university, and that all sources of material used for the thesis have been duly acknowledged.

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The thesis has been submitted for examination with my approval as a university advisor.

Dr.K.V Suryabhagavan

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(Atreshiwal Girma)

Contents

List of Tables

List of Figure

ACRONYMS

AAU – Addis Ababa University

CSA – Central Statistical Agency

DEM –Digital Elevation Model

EMA – Ethiopian Mapping Agency

FAO – food and Agricultural Organization

FGT0 –Foster Greer Thorbecke

GIS – Geographic Information system

GPS – Global Positioning System

HICES - House Hold Income, Consumption and expenditure Survey

HH – House Hold

MoFED – Ministry of Finance and Economic Development

NASA - National Aeronautics and Space Administration

NMS –National Metrological Agency

POVmap –Poverty Mapping

SAE – Small Area Estimation

UTM - Universal transverse Mercator

WMS – Welfare Monitoring Survey

ABSTRACT

GIS is increasingly used in poverty mapping. This research raises awareness about the need for a generic poverty data model for use in poverty mapping, and applies a recently developed small-area estimation technique. The Small Area Estimation (SAE) of Poverty in Rural Oromiya Region was prepared with an objective to provide a more disaggregated picture of poverty in Oromiya Region down to the EA(Enumeration Area) and woreda level, based on detailed information from the 2004/5 household survey with the 2007 population census. The focus of this research is on the spatial representation of poverty. It helps to improve the targeting of public expenditures by identifying where the poorest populations are located. By integrating spatial measures of poverty with other data, access to services, water facility, road and other possible contributing factors, leading to a more complete understanding of different dimensions of human well-being. The research measures the estimation process in detail and describes results of statistical tests for quality checks. According to these tests, the poverty estimates at the Ea (Enumeration Area) and Woreda level are reliable. The report also enhances the transparency of the process and intends to serve as a guide for future updates.

The results from the SAE are compared with other geo-referenced database. It is observed that, generally poor woreda tend to have limited access to road networks and similarly, access to water facility is relatively low in poor areas while densely populated. As such, overlaying a poverty map with other geo-referenced indicators is highly informative, and some of these findings can be used for designing, planning and monitoring poverty alleviation strategies at the regional or zonal or woreda or Kebele level. Therefore the high overall level of poverty in Oromiya Region, there are considerable spatial diversified in poverty levels across small administrative units (EA) within the region.

Keywords: Poverty mapping, GIS, Small-Area Estimation, Census and Welfare, Data Model

CHAPTER ONE

1.0 Introduction

Poverty Mapping is the methodology for providing a detailed description of the spatial distribution of poverty and inequality within a country/region. It combines individual and household (micro) survey data and population (macro) census data with the objective of estimating welfare indicators for specific geographic area as small as village or hamlet. (Fzavidis, Nikos 2010).

Spatial patterns of inequality between and within countries have become an important focus of the development community, and research on patterns of poverty and inequality across districts, municipalities, and communities and it has accelerated over the past decade. With spatial variables increasingly recognized as determinants of poverty. (Bedi et al. 2007, Hyman et al. 2005), The role of Geographic Information Systems (GIS) in poverty assessment has increased in importance, particularly as a means of generating explanatory variables and because of its data integration and spatial analysis capabilities.

This research, estimate consumption-based welfare (poverty) measures for Oromiya Regional States, at woreda and EA levels by combining the 2004/05 household survey and the 2007 population census. Although on this thesis describes a GIS data model that has been designed to aid schema creation and management of a spatial database. Data modeling is required to better capture the components, processes, and meanings of poverty assessment as with any other geographic phenomenon, and translating the knowledge into a GIS (Glennon, 2010). The data model consists of both spatial and non-spatial datasets that are used for assessing poverty levels in Oromiya region. This data model can be modified for use in analyzing other poverty related problems, such as food security, etc. This work is an attempt at putting together content for such a data model from looking at real life examples. Data modeling is an abstraction process where the essential elements are emphasized and the non-essential ones eliminated with regard to a specific goal (Bédard and Paquette 1989) and also data models are simplified views of a part of reality. The aim is to model real world entities and the relationships in a way that maximizes benefits while utilizing a minimum amount of data (Kufoniyi, 1997).

Poverty is endemic and heterogeneous phenomenon in our country, though slightly change over time. (MoFED, 2008) indicates that over 38.7 percent of the population is found below the poverty line. The problem of poverty is highly pronounced in rural areas, more than it does in towns or cities with the coverage of 39.3 and 35.1 percent of the respective population.

Poverty maps, spatial descriptions of the distribution of poverty in any given country, are most useful to policy-makers and researchers when they are finely disaggregated, i.e. when they represent small geographic units, such as cities, towns, or villages.

Poverty measured in different ways, varies between and within countries and regions. There is no agreed international definition of poverty. Poverty is hunger.

http://web.worldbank.org/wbsite/external/topics/extpoverty/extpa)

Poverty is also lack of shelter. Poverty is being sick and not being able to see a doctor. Poverty is not having access to school and not knowing how to read. Poverty is not having a job, is fear for the future, living one day at a time. Poverty is powerlessness, lack of representation and freedom. A person is considered poor if his or her consumption or income level falls below some minimum level necessary to meet basic needs. This minimum level is usually called the "poverty line". What is necessary to satisfy basic needs varies across time and societies. Therefore, poverty lines vary in time and place, and each country uses lines, which are appropriate to its level of development, societal norms and values.

(http://web.worldbank.org/wbsite/external/topics/extpoverty/extpa).

A map is a graphic representation of a portion of the earth's surface drawn to scale. It uses colors, symbols, and labels to represent features found on the ground. The ideal representation would be realized if every feature of the area being mapped could be shown in true shape. A map provides information on the existence, the location of, and the distance between ground features, such as populated places and routes of travel and communication. It also indicates variations in terrain, heights of natural features, and the extent of vegetation cover. It is necessary to show on maps to provide information to different elements and to resolve logistical operations and planning purposes. Much of this planning must be done by using maps. Therefore, any operation requires a supply of maps; however, the finest maps available are worthless unless the map user knows how to read them. (http://www.map-reading.com/ch2-1.php). Mapping is defined as representation usually on a flat surface, as of the features of an area of the earth, showing them in their respective forms, sizes, and relationships according to some convention of representation.

Relay the spatial determinants of poverty are important for understanding the distribution of assets that are fundamental for alleviating poverty. These include human capital such as health, education and technology, and social capital such as the ability to cooperate and participate in social networks. Spatial analysis has most promise in the area of natural resources, because natural capital-asset holdings such as natural resource stocks, land quality and environmental quality are difficult to characterize with conventional variables, and are spatially distributed by definition. Infrastructure variables such as road density and quality, and access to labor, product and input markets also have an important spatial dimension.

1.1 Background of the Study Area

Oromiya is one of the biggest Regions of Ethiopia; Covering 363,136 km^2 stretches in from the western border in an arc to the southwestern corner of the country, accounting for about 34.3 percent of the total area of the country. Geographically, figure 1 shows that the Region extends from 3^{o}24'20"–10^{o}23'26"N latitudes and 34^{o}07'37"-42^{o}58'51"E longitudes (Ahmed Hussein et al. 2011). According to the 2007 population and housing census, Oromiya region has a population of 27,158,471, with an annual growth rate 2.9 between 1994 and 2007. And have 20 administration zone and 276 woredas. The topography and climate of the region is characterized by high plateau and very limited lowland areas. The altitude of the region ranges from below 500masl at the rift to 4377masl at Mt. Tullu Dimtu. The region experiences annual temperature ranging from 10^{0}C to 30^{0}C, with mean annual temperature of 190C. (Ahmed Hussein 2011) (www.ethiopiar.net)

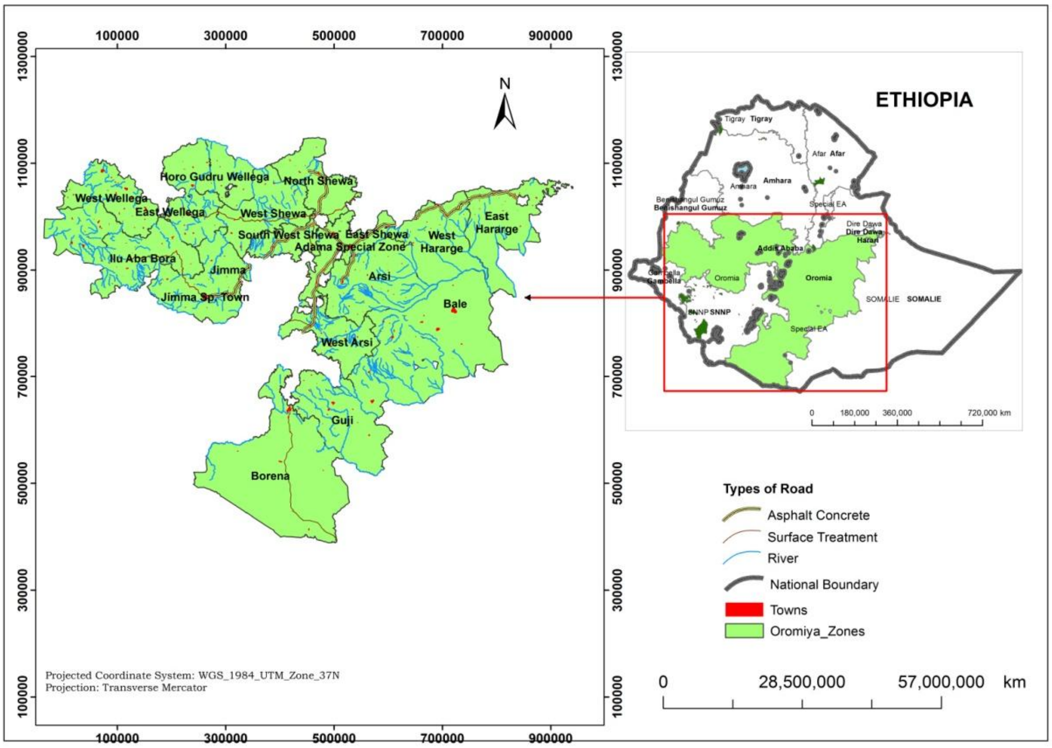

Figure 1.1 Location map of the Study Area

1.1.1 Rainfall

Rainfall is one of the most important climatic variables, which shows the nature and climatic conditions of Oromia region. The region has four seasons, named as summer, autumn, winter and spring. Summer and autumn are high rainfall seasons; whereas, winter and spring are dry. (Ahmed Hussein et al. 2011)

Oromia Region has bi-modal rainy seasons with the annual rainfall ranges from 329-2214mm. 85 percent of the population in the region is predominantly an agrarian economy, which is rain-fed and small scale farming for providing livelihoods. (Ahmed Hussein, et al. 2011). The Agriculture is devastatingly dependent on the timely start, amount, duration, and distribution of rainfall.

Figure 3.2 maps shows Annual rainfall of the region which derived from National metrological Agency data. This map displays the annual rainfall over the last 50 years. It is frequently used to represent the annual distribution of rainfall.

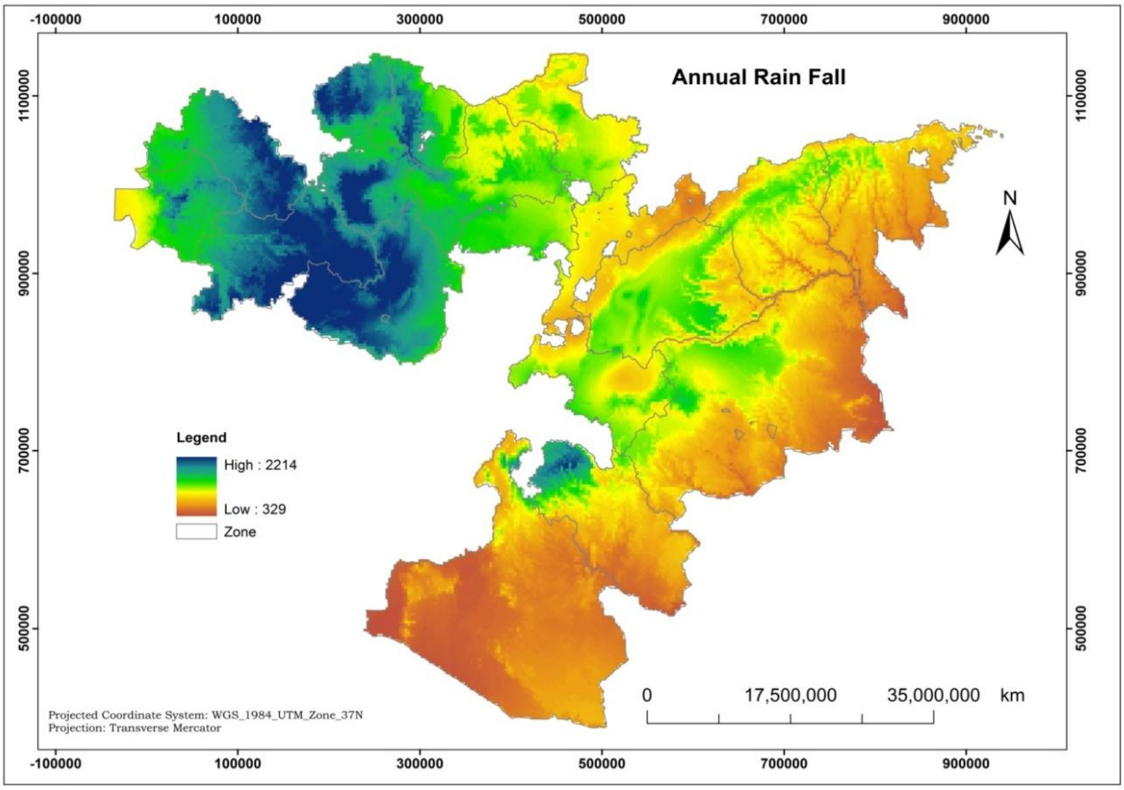

Figure 1.2 Rainfall Distributions

Low annual rainfall represents risk for farmers who depend upon rainfall for crop production. Low annual rainfall is experienced in eastern part of the region, this making productive agriculture difficult to realize. The western highlands in Oromiya region have particularly good rainfall, averaging over 1200mm annually in west part of the region. Rainfall decreases steeply with loss of elevation, especially towards the east.

Changes in rainfall pattern are likely to lead to severe water shortages and/or flooding. Rising temperature will cause shifts in crop growing seasons which affects food security and changes in the distribution of disease vectors putting more people at risk from diseases such as malaria and dengue fever. Temperature increases will potentially severely increase rates of extinction for many habitats and species. (Ahmed Hussein, et al. 2011).

1.1.2 Agro ecological zones

An Agro-ecological zone refers to the division of an area of land into smaller units, which have similar characteristics related to land suitability, potential production and environmental impact.

According to the area coverage of the region, all four types of agro ecological divisions are found. Semi humid zone accommodates areas within the altitudinal range of 1500 to 2400m and an average annual rainfall is different according to the different zone. These Agro ecological zones are found in all parts of the Oromiya region. The cool humid zone consists of areas with altitudes ranging from 2300 to 3200m and an average annual rainfall of 1200 to 2200 mm.

Agro ecology is important base of sustainable agricultural development planning of a region. It assess basically the yield potentialities of various crop Combinations, develop future plan of action involving crop diversification. An Agro-ecological zone determines suitability of different crops for optimizing land use. Agro-ecological zones over all serve as a focus for the targeting recommendations designed to improve the existing land use situation, either through increasing production or by limiting land degradation. Because of Ethiopia's location near the equator, elevation has a very strong influence on temperature and, to a lesser extent, on rainfall.

Elevation is the basis for traditional agro-ecological divisions which have long been used to characterize different environments in Ethiopia. Ethiopia is traditionally classified into four broad agro-climatic zones. These are termed as: cold-moist, cool-humid, semi-humid and arid and semi-arid. Figure 1.3 map shows agro ecological zones within the region that is in west part of North Shewa zone, east part of west shewa, Eastern part of south-west shewa , Central part of Arsi and West Arsi zone and East part of western part of Bale zone in the region. Cold moist encompasses all areas 3200m above the mean sea level, with an average annual rainfall of over 1031mm, unsuitable cold mois refers to highland areas above 3700 meters it is found in Central part of Arsi, west Arsi and East part of Bale Zone.

Finally semi-arid and zone refers to areas lying below 1500m with the average annual rainfall of 800 mm. This Agro ecological zone found in Western part of Qelem wellega zone, Western and south part of Borena zone, South part of Guji Zone and Western part of Bale zone. Arid refers to hot lowlands of less than 500 meters above mean sea level, these zone are fond most part of the region more found in western part of the region. (Negash 1987)

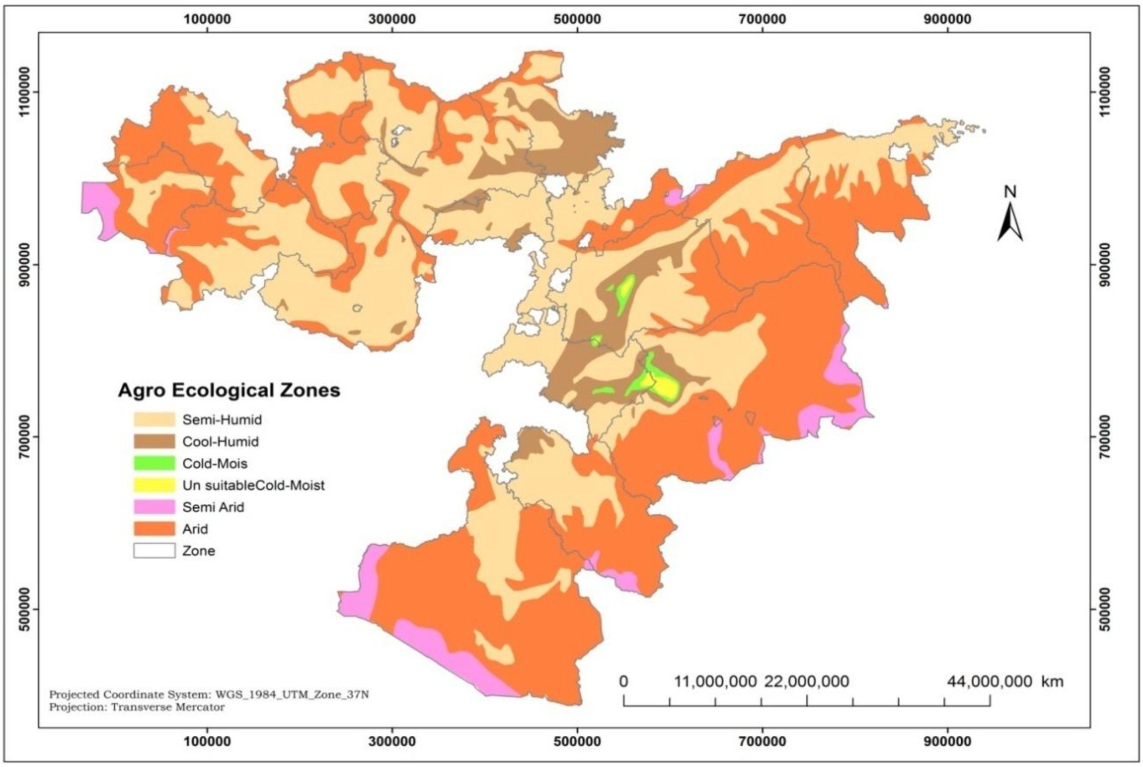

Figure 1.3 Agro –ecological zones map

1.1.3 Soil

The highlands of Oromia are relatively dominated by fertile soils of volcanic origin. However, some soils may be too acidic or basic, while others may be ferruginous, sodic or saline. In general, there are 14 major soil units/types in the Region, which are derived from (FAO 2006). Figure 3.4 of the map shows the soil type within the region. Soil is one of the most important natural resources on which our food supplies directly or indirectly depend.

The dominant soil types of the Region are Nitosols found on flat to sloppy terrain in high rainfall areas and fairly textured, well-drained, and easily workable soil types in the region. Such soils are resistant to erosion and belong in the most productive soil groups in the humid tropics (FAO 2006). Vertisols found on flat waterlogged areas, Cambisols found on slopes of

Bale, southwest of West Harerghe and Arsi, Luvisols and Acrisols mostly found on sloppy terrain of the Region. (Ahmed Hussein, et al. 2011)

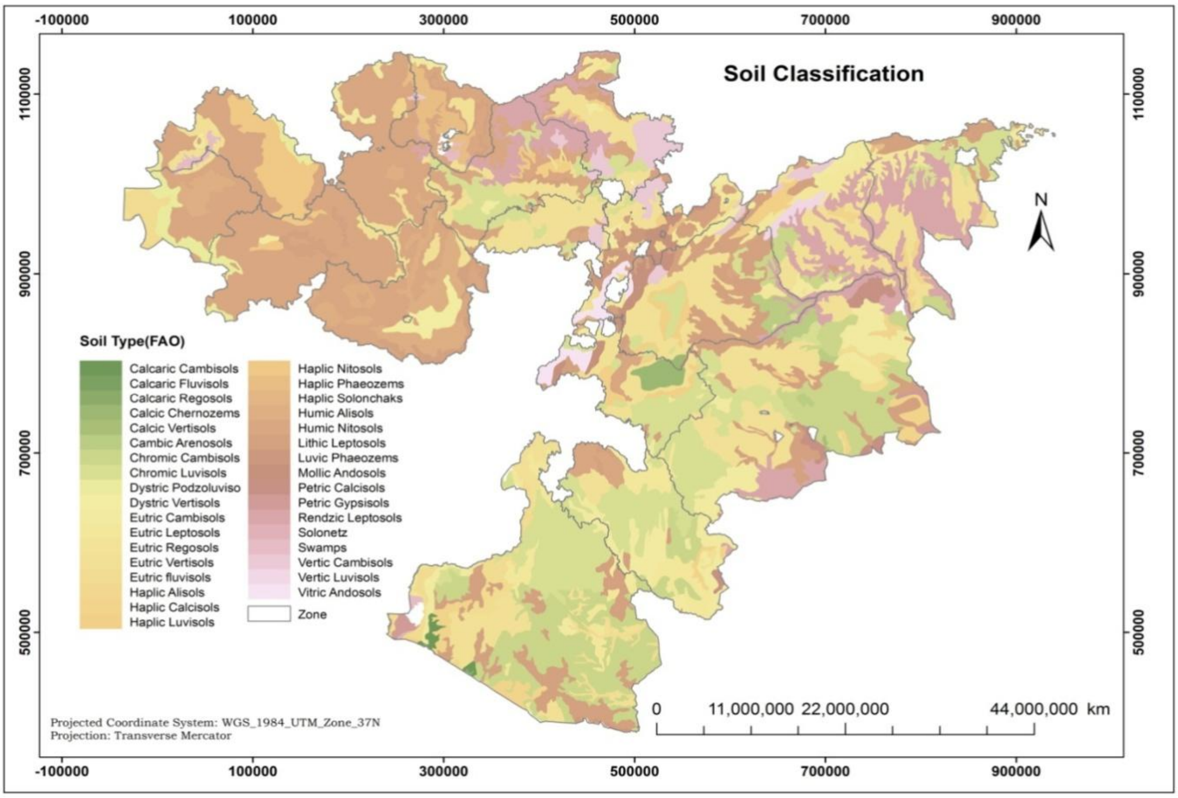

Figure 1.4 Soil Map

1.2 Statement of the Problem

It is difficult to measure poverty in developing country like Ethiopia, because of lack of reliable information. Typically, the poverty indicator is an expenditure-based indicator of welfare, such as the proportion of households that falls below poverty line. It is better to know about the nature, magnitude, distribution and trend of poverty in Oromiya Regional State. This show the way to ask different questions like:-

- Are general-purpose spatial datasets adequate, or are special datasets needed, and what specifications are desirable for poverty mapping applications?
- What spatial datasets should be considered essential for decision making and poverty problem solving?

- Really, are there poor people live only in some part of the region?
- Where are high concentrations of poor live, why?
- How can we link or join spatial data with tabular data to do poverty mapping?
- What are the types of spatial data in use for poverty mapping, and how are they used?
- What are the practical implications of selecting a particular spatial indicator for use in assessing poverty?

1.3. Argument

Poverty mapping information is a means to any persuasive framework for policy makers, related research and development priority setting. An agreement on appropriate criteria is needed and collection and maintenance of crucial baseline data.

This research seeks to enhance current understanding of the geographic distribution of poverty and conditions of where the poor live. Additionally, the research gives a hint for development agencies, and the poor themselves with regard to interventions to reduce poverty.

1.4 Objective

General objective of the research is focus on the use of GIS, remote sensing and statistical tools to analyze poverty distribution and the linkages between poverty and different geospatial data,

Specific objectives are:-

- To examine the factors associated with poverty in Oromiya Region
- Concurrently, to display different dimensions of poverty and/or its determinants
- Produce household level estimates of poverty measures by merging information from census and household surveys

Analyse and examine the using selected model and to validate model applicability on existing data.

1.5 Sources of Data

Population and housing censuses

Census is commonly defined as counting the population of a country. Central Statistical Agency in Ethiopia (CSA) describe population census as "the total process of collecting, compiling, analyzing or otherwise disseminating demographic, economic and social data pertaining, at a specific time, to all persons of a country or a well-defined part of a country". It is to be noted that the Population and Housing Census is a huge nationwide operation which could not be undertaken by a single organization and personal researcher. Thus, full cooperation and assistance of government and non-government organizations, donor agencies and the general public have been obtained for the 2007 (CSA: Population and Housing Census 2007).

Surveys

Surveys provide information for a randomly selected set of households or individuals. Welfare Monitoring System, the CSA has been conducting the two surveys that provide poverty related data: Household Income, Consumption and Expenditure Survey (HICES) and Welfare Monitoring Survey (WMS) 2004/5. The HICE and WMS surveys provide crucially useful information for the designing and monitoring and evaluation of the country's poverty reduction strategy: Sustainable Development and Poverty Reduction Program (SDPRP), the various socioeconomic policies and programs and hence monitor the progress towards meeting the Millennium Development Goals (MDGs). (CSA 2004)

Table 1.1 indicates the lists of data's that are used for the preparation of this research thesis. The data types, why used this data and the sources are described as well.

Table 1.1 List of data source and materials

Data Type	Purpose	Source	Remark
Census Data	Build consumption model database	CSA	2007
Survey Data	Build consumption model database	CSA	2004/05
Topo-Sheet/Topographic map	Digitizing boundaries	EMA	1984
Spot 5 satellite image 2006	Land use/land cover	CSA	2006
Soils	Soil map	FAO	1997
Rainfall	To find out Distribution of rainfall mapping	NMS	2004/05 & 2007
Agro-Ecology	Agro- ecology mapping	MOA	
DEM	To collect point data	CSA	30m resolution
GPS	Determining ground truthing	CSA	

1.6 Poverty determinants

A poverty map can be used to display simultaneously the outcome of interest (income poverty, indices of disease, school enrolment, etc.) and its determinants (school location, infrastructure, health center location, natural resources endowment, access to input and output markets, etc.). This allows deepening our understanding of the determinants of poverty. The spatial representation can therefore complement regression analysis to help us understand the influence of these determinants and their interaction.

1.7 Measures of poverty

There are various expenditure-based measures of the extent of poverty

- The head count index.
- The poverty gap index
- Squared poverty gap (Poverty severity) index.

- Indices of poverty (headcount index): This is the share of the population whose income or consumption is below the poverty line, that is, the share of the population that cannot afford to buy a basic basket of goods. If α =0, there is no concern about the depth of poverty and the corresponding poverty index is called the headcount index. Hence headcount index corresponds to the fraction of individuals falling below the poverty line. The head-count index is easily understood and communicated, but it is insensitive to differences in the depth of poverty. It fails to capture the extent to which Individual income (or expenditure) falls below poverty.

- Poverty severity (squared poverty gap): This takes into account not only the distance separating the poor from the poverty line (the poverty gap), but also the inequality among the poor, that is, a higher weight is placed on those households further away from the poverty line. (MOFED, April 2008)

Table 1.2 Poverty line used in the Ethiopian poverty analysis report of 1995/96, 1999/2000 and 2004/05 all measured at 1995/96 national average prices

	Food Poverty Line in birr per Adult Per year	Kcal Per	Total Poverty Line in birr Per
Poverty Line	647.81	2200	1,075.03
Moderate Poverty Line	809.76	2750	1,343.78
Extreme Poverty Line	485.86	1650	806.27

Source: (MOFED, April 2008)

- Absolute poverty line: is fixed with a change in the standard of living in society (Hagenaars: 1986). It refers to the position of an individual or a household in relation to a poverty line, whose real value is fixed over time (Ravallion: 1992).

- Relative poverty line: is related to the general standard of living in a society (explained by median income), i.e. Relative poverty line increases and decreases by the same percentage that the standard of living of the society moves. In other words, while a relative poverty line has elasticity of one with respect to changes in living standard of the society, absolute poverty line has zero elasticity (Hagenaars: 1986).

1.8 Categories of Major Poverty measures

- Economic. These include monetary indicators of household well-being, particularly food and non-food consumption or expenditure and income. These measures are primarily used by economists.
- Social. These include other non-monetary indicators of household well-being such as quality and access to education, health, other

basic services, nutrition and social capital. These measures are sometimes grouped into basic-needs or composite development indices by agencies such as UNDP.

- Demographic. These indicators focus on the gender and age structure of households, as well as household size.
- Vulnerability. These indicators focus on the level of household exposure to shocks that can affect poverty status, such as environmental endowment and hazard, physical insecurity, political change and the diversification and riskiness of alternative livelihood strategies. (Davis, 2003).

1.9 The role of geographical information systems

In order to present the disaggregated information on maps, one needs to have some kind of geographic location coordinate for each observation. Geographic information systems (GISs) 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. These systems are used to spatial location of poor people facilitates integration of data from sources such as satellites, censuses, household surveys, models and simulations for the analysis of the determinants and impacts of poverty into a single platform, where each observation is matched with the identifier of the area it covers. It also permits the analysis of spatial association between different dimensions. In particular, GIS permit the simultaneous analysis of variables which are observed at different levels. For instance, poverty status might be observed at the district level. Or some infrastructure might serve broad areas (hospitals, major roads) while others serve smaller zones (primary school or health post). The GISs allow the simultaneous analysis of information from heterogeneous sources, as long as it have geographic location coordinates. For instance, for each village, a GIS can generate the distance to the nearest market town, the average rainfall within a 20 kilometer radius, demographic indicators, and village-level estimates of income poverty. (Poverty mapping in Madagascar,www.worldbank.org/poverty)

Integration of multiple databases from different sources, Analysis of spatial association between variables, Inclusion of spatially generated descriptive variables into the multivariate analysis of the determinants of poverty, including natural capital and infrastructures, and access to public service and product and labor markets. Disaggregated poverty measures can show correlations with other outcomes.

GIS techniques can be used to incorporate spatial analysis into the determinants of rural and urban poverty, or into issues that are important allocation tools for planners or policy makers to alleviating poverty. This could include the determinants of migration participation in off-farm labor activities, product market participation, and crop choice or technology adoption. One of the most common applications is to the analysis of the causal relationship between poverty and the environment, where few links have been found, often because of technical, estimation or data limitations (Davis, 2003).

GIS based poverty analysis makes it easier to integrate poverty data from var ious sources. GIS techniques provide functions in poverty mapping (Bigman and Deichmann. 2000a):

1.10 The Role of Satellites image and Digital Image processing

Remote Sensing and GIS used to accomplish the analysis based on the aim of the objectives. Remote sensing imagery from satellite sensors and aerial photography can play an important role in environmental impact studies. Satellite imagery is frequently used to support and organize emergency assistance in case of natural disasters because it produces rapidly information on large territorial surfaces. However, in the different situations, earth observation from satellites offers other distinctive advantages such as objectivity, monitoring of locations not accessible to staff due to security problems, and updated information on road networks and their current state. Remote sensing and Geographic Information Systems (GIS) have greatly expanded opportunities for data integration and analysis, modeling, and map production. As populations grow, as countries improve their economies, as landscapes change, the concerned researcher, organization or person have increasingly relied on up-to-date satellite imagery and other geospatial data for applications such as environmental planning, land registration, disaster response, public health, agricultural biodiversity conservation and forestry. The role of DEM (Digital Elevation Model) is a digital model or 3-D representation of a terrain's surface commonly for a planet (including Earth), moon, or asteroid created from terrain elevation data. Determining attributes of terrain, such as elevation at any point, slope and aspect finding features on the terrain, such as drainage basins and watersheds, drainage networks and channels, peaks and pits and other landforms modeling of hydrologic functions, energy flux and forest fires Statement of the Problem

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CHAPTER TWO

2.0 Literature Review

Recent studies have stressed the importance of geography and spatial variables as determinants of poverty. Most of the recent research on poverty has been surprisingly limited to rudimentary and one–dimensional characterizations of the roles of regions and access to different types of infrastructure, public services and product and labor markets. Many poverty-mapping exercises involve simply ranking of areas by some poverty, food security or marginality indicator and have no need for maps except as communication tools. (Davis 2003).

2.1 Small Area Estimation for Analyzing Rural Poverty

Small area estimation method developed by Elbers et al., 2003,.Some studies illustrate the use of the SAE (Small Area Estimation) procedure to calculate a welfare indicator relevant to rural areas and food security concerns. Of these studies, the Mexico, Ecuador, Bangladesh and Sri Lanka studies use a food poverty line—the expenditures for buying food to meet minimum nutritional requirements. The Vietnam, Malawi and Kenya studies employ a poverty line that includes minimum food needs plus a minimum number of additional non-food expenditures. Beside different countries did poverty mapping and some authors write literatures on poverty mapping, their methodologies and other related topics are stated as follows:-

Global:- The Global Poverty Mapping Project indicate that, Advances in data collection and technology make it possible to depict poverty with greater spatial detail than ever before, helping to better target poverty alleviation policies and programs. Working in collaboration with the World Bank, the Global Poverty Mapping Project collected poverty data from around the world, integrating it spatially and making it available to the public in the form of easy-to-download tabular and spatial data sets and maps. These data facilitate better understanding of both the underlying causes of poverty and how poverty may be related to geographical and biophysical factors.
They support efforts to monitor progress towards meeting the UN Millennium Development Goals and to target needed interventions. The project

Highlights, Sub national, small area estimate data of poverty and inequality at high resolution, searchable online map gallery containing more than 300 maps, downloadable in pdf format, Where the Poor Are: An Atlas of Poverty, a full- color atlas with 21 pages of featured maps along with practical examples of how geo-referenced poverty data sets have been used, and may be used, in decision making and poverty interventions. (National Aeronautics and Space Administration (NASA, February 2009: http://www.nasa.gov)

Horn of Africa:- According to IGAD LPI working paper no, 08-08 on Poverty and Welfare Measures in the Horn of Africa Saied that, in East Africa, as with most developing countries, the majority of the poor population live in rural areas and are largely dependent on agriculture for their welfare. Factors such as climatic variability, soil characteristics, water availability and animal health affect the productivity of land and livestock and have, therefore, a massive impact on the welfare of the population. Fluctuations in these factors contribute to year-to-year changes in levels of poverty and food security. This paper reviews the available poverty measures in the IGAD region and the role of poverty maps in the context of livestock interventions for poverty reduction. In this reported that more than half of the population in the IGAD region live below the poverty line of 1 US dollar a day (IGAD, 2003), while at least 70 million (out of some 160 million living in the region) face chronic hunger and poverty (IGAD, 2005). The majorities of the poor population in the IGAD region live in rural areas and are largely dependent on agriculture for their welfare. Factors such as climatic variability, soil characteristics, water availability and animal health affect the productivity of land and livestock and therefore have a massive impact on the welfare of the population. Fluctuations in these factors contribute to year-to-year changes in levels of poverty and food security. In terms of poverty maps and poverty mapping approaches this paper describes under-nutrition and infant mortality maps; the small area estimate methodology; the environmental approach to poverty mapping; and the livelihood zones estimates. (Francesca Pozzi and Tim Robinson 2007)

Sri Lanka: - The Sri Lanka study demonstrates the potential effectiveness of targeting by quantifying numbers of poor households that did not receive benefits versus number of non-poor households that did receive financial assistance in a national poverty reduction program. Poverty assessments and maps reveal the importance of prioritizing interventions based on poverty prevalence, absolute numbers of poor and measures of inequality. The Vietnam case study shows that more poor people live in areas with lower prevalence of poverty. Interventions targeted to individual households would fare well in these areas. Interventions that broadly affect the population of an area, such as infrastructure and public works, may work better in areas where a large proportion of the population is poor. Similarly, the Bangladesh study shows that some areas with lower prevalence of poverty are also areas of high inequality. Neglect of these regions would miss a great number of poor people in a country. Poverty mapping assessments can help plan interventions according to sector. Several of the studies have implications for agricultural policy. Field testing of new technologies can be targeted to locations with high numbers of food poor, as indicated by the Mexico study. The Sri Lanka poverty map illustrates the importance of irrigation and land access to welfare outcomes, indicating that land reform policy and agricultural infrastructure could impact on rural poverty. The Malawi, Bangladesh, Sri Lanka and Ecuador studies show the importance of non-farm income and non-agricultural employment, implying that employment and small enterprise policies could be effective in selected regions of these countries. These policies might promote agribusiness, artisan production, tourism and ecotourism. (G.W.J. Chandrasiri and Lal Samarakoon, Geoinformatics Centre, Asian Institute of Technology 9 May 2002)

Bhutan:- The Bhutan Poverty Mapping applied a Small Area Estimation (SAE) method developed by (Elbers et al. 2003); this methodology has been widely tested and applied around the world. Small Area Estimation (SAE) of Poverty in Rural Bhutan was prepared with an objective to provide a more disaggregated picture of poverty in Bhutan down to the Gewog level, based on the Bhutan Living Standard Survey (BLSS 2007) (National Statistics Bureau Royal Government of Bhutan June 21, 2010) and Population & Housing Census of Bhutan (PHCB 2005) (National Statistics Bureau Royal Government of Bhutan June 21, 2010). The report records the estimation process in detail and describes results of statistical tests for quality checks. According to these tests, the poverty estimates at the Gewog level are reliable. The results from the SAE are compared with other geo-referenced database. It is observed that, generally poor Gewogs tend to have limited access to markets and road networks. Similarly, access to rural electrification is relatively low in poor areas. As such, overlaying a poverty map with other geo-referenced indicators is highly informative, and some of these findings can be used for designing, planning and monitoring poverty alleviation strategies at the Gewog level. (National Statistics Bureau Royal Government of Bhutan June 21, 2010).

Mozambique: - Another research in Mozambique combines data from the 1996–97, Mozambique National Household Survey of Living Conditions with the 1997 National Population and Housing Census to generate small-area (sub district) estimates of welfare, poverty, and inequality, with the associated standard errors. These small-area estimates are then used to explore several dimensions of poverty and inequality in Mozambique, particularly with regard to geographical targeting of antipoverty efforts. Reliably identifying and targeting the poor can be administratively costly, especially in rural Africa, where low population density and weak administrative capacity are common. Geographical targeting, or targeting poor areas, is sometimes proposed as a feasible alternative to targeting poor people, and poverty maps may serve as a valuable tool in this regard. Unfortunately, the notion of poor areas might not always be especially useful, as appears to be the case in Mozambique. The poverty maps do not reveal a particularly strong spatial concentration of poverty; the differences in poverty levels between areas tend to be delicate. This pattern is also observed in the decomposition of small-area inequality estimates, which shows that only about 20 percent of consumption inequality is accounted for by inequality between districts or between administrative posts. http://www.worldbank.org/poverty October 2004

South-Africa: - South Africa poverty map has been to help contain the spread of cholera in Kwazulu-Natal province in early 2001. In formulating a disease control strategy, the Department of Health (DOH) worked with Statistics and other government departments in the so-called Social (sector) Cluster to acquire the necessary information for targeted intervention. Another known use of the poverty map results is in an ongoing study of the socioeconomic factors correlated with crime. This information will be used to help develop crime prevention strategies in South Africa. The poverty map has also been used as a major input in the formulation of nodal areas for priority work under the Integrated Sustainable Rural Development Program

(ISRDP) and for the Urban Renewal Program (involving integrated and fast-track provision of services such as education, health, and infrastructure). Furthermore, communities and their political representatives are making use of poverty profiles and maps to assess and evaluate their development status. Beside The poverty map results have had a significant impact on decision-making in South Africa. (Statistics SA. 2000. Measuring Poverty in South Africa. Pretoria: Statistics South Africa)

Cambodia: - Poverty maps were produced in Cambodia in 2002 as a result of a collaborative effort of the Ministry of Planning of Cambodia, the World Food Program (WFP), and the World Bank. The standard method used to construct poverty maps combines a census data set and a survey data set to produce poverty estimates for small geographical areas. The primary objective of the poverty mapping exercise in Cambodia was, from the outset, to develop a tool for policy making and, especially, for the allocation of resources. While the results reported in Ministry of Planning and (WFP, 2002. (Dujii, Tomoki, To Use or Not to Use? Poverty Mapping in Cambodia)

Thailand: - The government is aspiring to eradicate poverty nationwide. As part of its ambitious Millennium Development Goal–Plus agenda, it is aiming at reducing the poverty head- count to below 4 percent by 2009 (NESDB 2004). Meeting this goal will be a significant challenge because maintaining progress is a different task from launching progress. As Thailand's provincial, regional, and national poverty rates have fallen, the focus has shifted to the remaining pockets of poverty. Poverty maps are therefore an aid in reaching the poverty reduction objective. They help to make visible those poor who are otherwise hidden behind the averages of large regional aggregations. Small area estimation techniques allow the construction of poverty measures at the district and village levels that are comparable to the poverty measures at the provincial, regional, and national levels. The main motivation behind the use of such methods is to combine the advantages of population censuses (extensive coverage of the population) with the advantages of household surveys (reliable expenditure and income data). In response to a 2002 request by the National Economic and Social Development Board (Thailand's national planning agency, the NESDB) and the National Statistical Office (NSO), the Thailand Development Research Institute drew on technical expertise from the World Bank to derive Thailand's first small area poverty map, which was based on the 2000 population and housing census and the 2000 household socioeconomic survey. Since then, the institute and the NSO have completed the 2002 small area poverty map and have launched the 2004 map. (Somchaijitsuchon and Kasparrichter Thailand's poverty maps from construction to application 2007).

CHAPTER THREE

3.0 MATERIALS AND METHODS

3.1 Methods

3.1.1 Data collection

The study will use both primary and secondary data. The primary data for this paper will obtain from CSA raw data. Regarding secondary data I use different data from different organization such as EMA, Metrology, FAO and CSA. Beside I used, Topo-sheets, GPS readings, Satellite Images, Government and city administration documents, different books, different reports, publications, published and unpublished papers and journals.

The major methods around the globe are small- area estimation and community-level data method, but this paper uses standard household-level small-area estimation that is used by the World Bank. Small – area estimation is a statistical technique that combines survey and census data to estimate welfare or other indicators for disaggregated geographical unit such as municipalities or communities or in our country context the disaggregated geographical unit is regional, zonal, woreda, kebele, EA (enumeration area) and Households level.

According to Davis, there are five elements or constraints taken together guide and justify the choice of poverty-mapping methodology:-

1. The purpose or objective of the exercise,
2. the poverty philosophy of a practitioner or institution,
3. data availability,
4. analytical capacity
5. Cost.

For this study used data availability for choosing the methodology. Data availability is different types of data constitute the basic inputs into poverty mapping. Data availability is thus a fundamental constraint in choosing a poverty-mapping method. This constraint has two levels: the existence of data, and access to existing data. Many methodologies depend on the existence of data derived from extremely expensive collection efforts such as a population census and national household surveys. Few poverty-mapping exercises can justify such a level of expense for this single use, so in marketing its small-area estimation technique, probably the most data-intensive methodology, the World Bank wisely argues that their method serves to utilize data that already exist. (Davis 2003)

The common spatial datasets for poverty mapping are Census and Survey (Household Income and welfare Monitoring). Beside, land cover, rainfall data, Agro-ecology, soil fertility and quality are the most important common datasets. Utilizing measures of distance and physical accessibility such as travel times to cities whose population are more than 50 000 and distances to major towns and facilities, etc. are also increasingly important in poverty mapping.

In the first stage of the analysis the two data sources are subjected to very close study towards identifying a set of common variables. In the second stage the survey is used to develop a series of statistical and consumption models, which relate per capita consumption to the set of common variables identified in the preceding step. In the final stage of the analysis the parameter estimates from the previous stage are applied to the population census and used to predict consumption for each household in the population census. Once such a predicted consumption measure is available for each household in the census, summary measures of poverty can be estimated for a set of households in the census.

3.1.2 Implementation Procedure

1. Matching variables in survey and census
2. Estimating the model
3. Simulations on census data
4. Calculation of poverty indicators

1. Matching variables in survey and census

This part is the process of selecting variables that are found on both Census and Survey that means the process of selecting dummy variables that are represent categories. Use dummy variables to find out certain category makes a difference and compared with not being in that category. The values are all either 0 or 1. “Dummy” is an adjective, not a noun (Baker, Samuel L., 2006). On this research “1” is for the dummy variable if each observation that has high quality whereas “0” for each observation that has low quality. In a spreadsheet, a dummy variable looks like a column of 0's and 1's. They are state on the table 1.3.

The purpose of this selection of variables is to assess the relative importance of these factors as determinants of poverty. It does so through regression analysis. The regressions are the relationship between the qualities of the variables for example Wall, I take wall high quality construction material and low quality construction material. These results are generated by combining information based on data sets from the census and survey (HICES and WMS). All results use the sample weights provided by CSA and thus can be considered to be regionally. Standard errors based on clustering at enumeration area level and all regressions control for regional fixed effects.

Table 3.1 Dummy Variables/ explanatory variable

hh_adult	Number of Adults in the Household head
hh_kids	Number of Kids in the Household
hh_women	Number of women
hh_men	Number of men
head_fem	Number of head females
Household Size	Number of persons living in the household
Wall High	High quality wall construction
Wall Low	Low quality wall construction
Roof High	High quality roof construction
Roof Low	Low quality roof construction
Drinking water High	High quality types of drinking water
Drinking Water Low	Low quality types of drinking water
Toilet High	High quality Toilet facility
Toilet Low	Low quality Toilet facility
Light High	High quality Source of light
Light Low	Low quality Source of light
Cooking Low	Low quality Source cooking materials
ed_prim	Primary education
ed_sec	Secondary education
ed_psec	Post secondary education
rain high	Rainfall above annual mean
rain low	Rainfall below annual mean
Agro high	Agro ecology highly favorable climate zones
Agro low	Agro ecology less favorable climate zones

2. Model Selection

The Oromiya Region Poverty mapping exercise prepared consumption models at rural areas. As mentioned earlier, failure to capture regional differences in consumption patterns could bias poverty estimates produced with the Elbers et al. method. Regional differences in consumption pattern can often be substantial. For example, the educational attainment of household heads might be a good predictor of household wealth in urban areas, whereas it might not be as important in rural areas, where the agricultural sector dominates.

➢ Consumption Models

The accuracy of poverty estimates depends on the predictive power of consumption models. This predictive power is gauged by R-squared statistics. Both R-squared and Adjusted R-squared statistics provide information on how well a consumption model can predict the actual consumption expenditure of each census household. Specifically, the R-squared is a statistic that indicates how well the predicted expenditure from a consumption model fits the actual household expenditure. The higher the R-squared, the better the predicted expenditure fits the actual household expenditure. Adjusted R-squared is a modification of R-squared that adjusts for the number of repressors in a model. R-squared always increases when a new variable is added to a model, but adjusted R-squared increases only if the new variable improves the model more than would be expected by chance. The final result shows on Annex 1, table 1.

Beside from the table 1.3 selected variables , the research used House Hold income, Total Expenditure at household Level and kilo- calories at household level. Because according to CSA the main objectives of the WMS are to provide data that enable understand the non-income aspects of poverty. Consumption and poverty are associated with household demographic characteristics, human capital, and assets. Concerning, estimating the model, Simulations on census data, Calculation of poverty indicators, these three implemented on the software that is called Povmap2. Figure 3.5 shows the general flow of work in the study

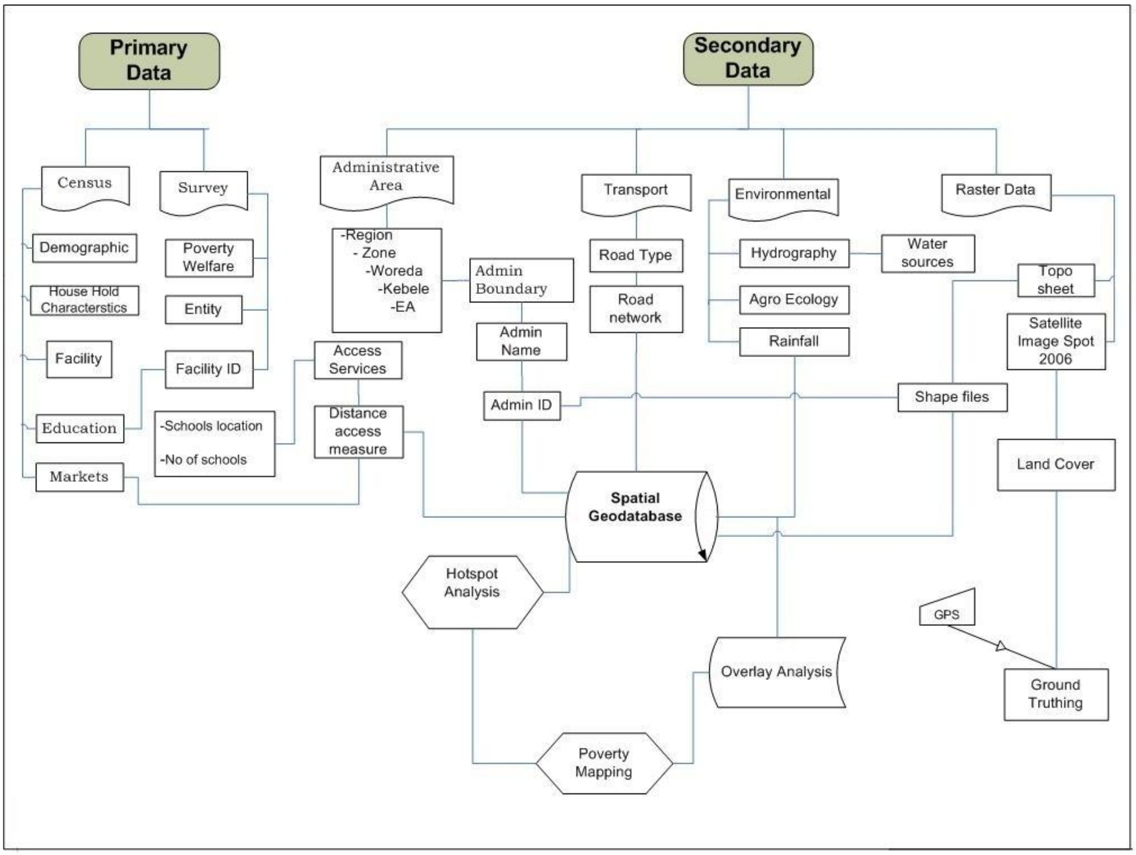

Figure 1.5: Flow Chart

Finally, to analyze the attribute data I used:-

- Categorizing – grouping the similar things. Which allow organize and make sense of data
- Ranking – put features in order from high to low
- Getting as ratio – show the relationship between quantities
- Counting & getting amounts – gives actual values of features
- Use Hotspot analysis (Getis-Ord-Gi*) tools to GIS analysis

3.2 Methodology

-The first step consists of a regression model of log per capita expenditure is estimated using the survey data, employing a set of explanatory variables which are common to the survey and the census. Next, parameter estimates from that regression are used to predict log per capita expenditure for every household in the census. Finally, "welfare indicators" are constructed for geographically defined subgroups of the population using these predictions. (Johan A. Mistiaen, Berk Özler, Tiaray Razafimanantena, 2002).

-The second step consists in using the estimated coefficients from these regressions (including the estimated error terms associated with those coefficients) to predict expenditure or consumption for every household in the census. Basically, the coefficients are used to “predict” the expenditure or consumption level of each household on the basis of the explanatory variables that are common to the census and the survey. These household level data are then used to compute poverty estimates for small areas. (Demombynes' A Manual for the Poverty and Inequality Mapper Module and Zhao's User Manual for PovMap).

All of these – or other – indicators can be the basis for the construction of high-resolution spatial maps. The factors like Adults, Female Headed, Access to safe drinking water, Energy Access to electricity /fuel wood, Education Primary school enrollment rate, income, Agro-climatic variables, Rainfall, Access to markets. This all can distinguish between status and outcome indicators. For example, low income can be both a cause and an effect of low education and poor health (Ravallion 1996). Socioeconomic assessments typically include both status and outcome variables.

In this thesis I used consumption model. These methodologies are likely to lead to different outcomes with regard to locations - that is, maps. I interested in the technical details of the methodology done by Johan A. Mistiaen, Berk Özler and Tiaray Razafimanantena, on the book “Putting Welfare on the Map in Madagascar”, Africa Region Working Paper Series No. 34, August 2002. So that I used the methodology as it is because it is important and better to explain for my thesis.

Even though, the approach is conceptually simple, properly accounting for spatial auto-correlation in the first stage model and estimating standard errors for the welfare estimates requires additional elaboration. The method can be divided into Three Basic Stages

- Zero stage: establish comparability of data sources; identify/merge common variables; understand sampling strategy.
- First stage: estimate model of consumption.
- Second stage: take parameter estimates to census; predict consumption, and estimate poverty and inequality.

The first stage analysis with the survey data and the second stage analysis with the census data, and a “zero stage” associated with defining and selecting the set of comparable variables common to the survey and the census.

First Stage

The first stage estimation involves modeling per capita household expenditure at the rural levels for which the survey is representative. In Oromiya regional state, this is at the woreda level, broken down into kebele, EA (enumeration Area) and household level. The first stage begins with an association model of per capita household expenditure for a household *h* in location *c*, where the explanatory variables are a set of observable characteristics. The consumption (Beta) model is as follows: (Johan A. Mistiaen, Berk Özler, Tiaray Razafimanantena, 2002)

$$(1)\quad \ln y_{ch} = [\ \ln y_{ch} \backslash\ \mathbf{x}_{ch}]\ \mathrm{u}_{ch}$$

Where: - c is the subscript for the cluster; h is the subscript for the household within cluster c, y_{ch} is the per capita expenditure of household h in cluster c, x_{ch} is the household characteristics for household h in cluster c.

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

Using a linear approximation for survey data to the conditional expectation, the household's logarithmic per capita expenditure is modeled as:

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

where: - c is the subscript for the cluster and h for household, ln y_{ch} is the log per capita household consumption, x_{ch} is the set of explanatory variables in the household, $\boldsymbol{\beta}$ is the estimated regression coefficients giving the effects of X variables on Y, u_{ch} is the disorder term which is the sum of common(cluster) component, and a household component.

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

Where $\boldsymbol{\eta_c}$ is a location component and $\boldsymbol{\varepsilon_{ch}}$ is a household component.

This error structure allows for both spatial autocorrelation, i.e. a "location effect" for households in the same area, in the household component of the disturbance. The two components are independent of one another and uncorrelated with observable characteristics. (Johan A. Mistiaen, Berk Özler, Tiaray Razafimanantena, 2002):

Second Stage

In the second stage analysis is combining the estimated first stage parameters with the observable characteristics of each household in the census to generate predicted log expenditures and simulated disturbances. There is a series of simulations, where for each simulation *r* draw a set of first stage parameters from their corresponding distributions estimated in the first stage. Thus draw a set of beta and alpha coefficients, $ß^r$ and a^r, from the multivariate normal distributions described by the first stage point estimates and their associated variance-covariance matrices. Additionally, draw $(\sigma_{\eta}^{2})^{r}$, a simulated value of the variance of the location error component. Combining the alpha coefficients with census data, for each census household we estimate $(\sigma_{\varepsilon,ch}^{2})^{r}$, the household-specific variance of the household error component. Then, for each household draw simulated disturbance terms, η_c^r and ε_{ch}^r, from their corresponding distributions. Simulate a value of expenditure for each household, y^r_{ch}, based on both predicted log expenditure, $x_{ch}\, ß^r$, and the disturbance terms:

$$(4)\quad y^r_{ch} = \exp(x_{ch}\, ß^r + \eta_c^r + \varepsilon_{ch}^r).$$

For each simulation R, y^r_{ch} is the simulated value of consumption, x_{ch} is the census household characteristics, $ß^r$ is the coefficients from the multivariate normal distribution described by the first stage parameter estimates, η_c^r is the cluster level residual drawn from the empirical distribution of $\hat{\eta}_c$, ε_{ch}^r is the household level residuals drawn from the empirical distribution of $\hat{\varepsilon}_{ch}$. Finally, the, the full set of simulated per capita expenditures, y^r_{ch}, are used to calculate estimates of the welfare measures for each spatial subgroup.

This procedure repeat n- times (n is identified of Common Variables) drawing a new a^r, $ß^r$, $(\sigma_\eta^2)^r$ and disturbance terms for each simulation. For each subgroup, take the mean and standard deviation of each welfare measure over all selected (identified) variables simulations. For any given location, these means constitute the point estimates of the welfare measure, while the standard deviations are the standard errors of these estimates. There are two principal sources of error in the welfare measure estimates produced by this method. The first component, referred to as model error in (Elbers, et al 2002), is due to the fact that the parameters from the first-stage model in equation (2) are estimated. The second component, termed idiosyncratic (individual) error, is associated with the disturbance term in the same model, which implies that households' actual expenditures deviate from their expected values. While population size in a location does not affect the model error, the individual error increases as the number of households in a target subgroup decreases. (Johan A. Mistiaen, Berk Özler, Tiaray Razafimanantena, 2002)

Once the data are collected, tables and percentages have been used to make description, analysis and expansion. Tools used for this problem are: GIS software, Arcview, Erdas9.1, PovMap 2.0, SPSS17and STATA 11.

Although Cloud-free SPOT images, it obtained November 2006 having the resolutions of 5meter were used prepare the primary input thematic map like land cover for the selected woredas with the help of field investigations. Secondary input themes such as shape file of the woredas and facilities prepared from topo-sheets of scale 1:250000. All the input datasets were georeferenced to Adindan_UTM_Zone _37N coordinate system. In the case of Index CSA produce its own index for SPOT image it prepare 25km by 25km as one index, therefore Oromiya region has 4216 indexes. Land cover is done by Madcate software by supervised method (visual interpretation). After the classification was made the polygons changes to shape file and taken to the field for cross checking using Garmin GPS 72. Using ArcGIS software, the selected points (GCPS) were adding and link with the woreda shape. Spatial geodatabase is designed to include the input datasets, their derived datasets and secondary tabular data sets. The shape files are exported to the corresponding feature data sets and the raster files are exported as individual raster datasets in the geodatabase.

3.3 Groundtruthing

The purpose of the ground truth was to verify the accuracy of the Land use interpretation estimates shown through the map and to determine the areas where well interpreted. The next figures are samples that I go to the exact place and take pictures.

3.3.1 Steps followed during land use verification & display in ArcGIS

1. Different points were selected by the researcher based on the reflectance on the Spot 5 image. In most cases the selected points are representative of many areas with the same reflectance & actually appearance in the Spot. Here to safe time points are selected near to road so that it will be accessible for car.
2. After selecting the points addressed, preparation of lay out by having the spot image under & the interpretation superimposed & labeled to show the interpretation label. The selected points also have both X & Y value so that after loading these points on the GPS navigation of points is facilitated easily. Besides overview map of the area is prepared so that tentative schedule is prepared for the field visit. In this step logistics needed for the field is identified like GPS, battery & camera.
3. During the field visit every point are addressed by navigating using GPS & camera shoots are taken in four direction from North, East, South & West. Notes are also taken to describe the point & the area surrounding the point.
4. The office work is started by downloading the points reading from the GPS & by adding some fields like description field to describe the point & surrounding area & link field for linking the points with respective picture taken in four directions. During filling the link field caution has to be take in order to locate the exact location of the picture in the drive so it is better to copy the source & paste in the respective row & also by renaming the name of the picture copy to the row & lastly putting dot & writing Jpeg. To use the link tool right click on the layer & then property then display then putting the field LINK lastly choose do

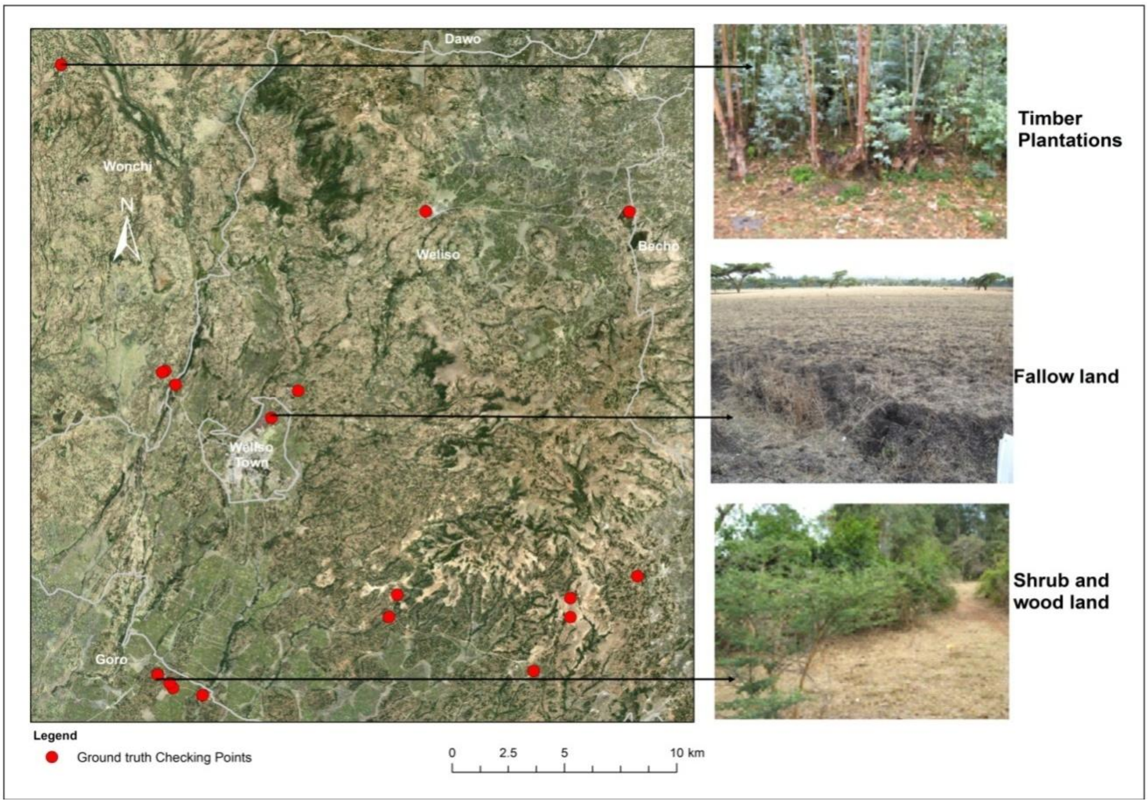

Figure 3.2: West and South-West Shewa Zone Verification

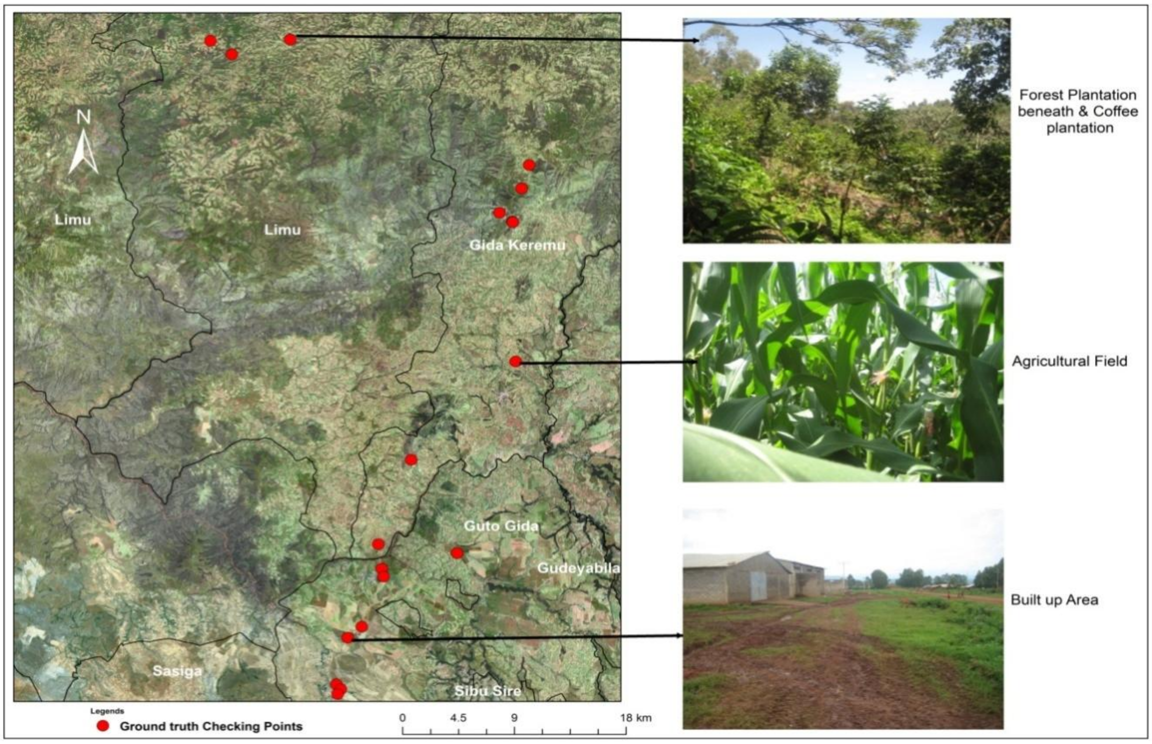

Figure 3.3: East Wellega Zone Verification

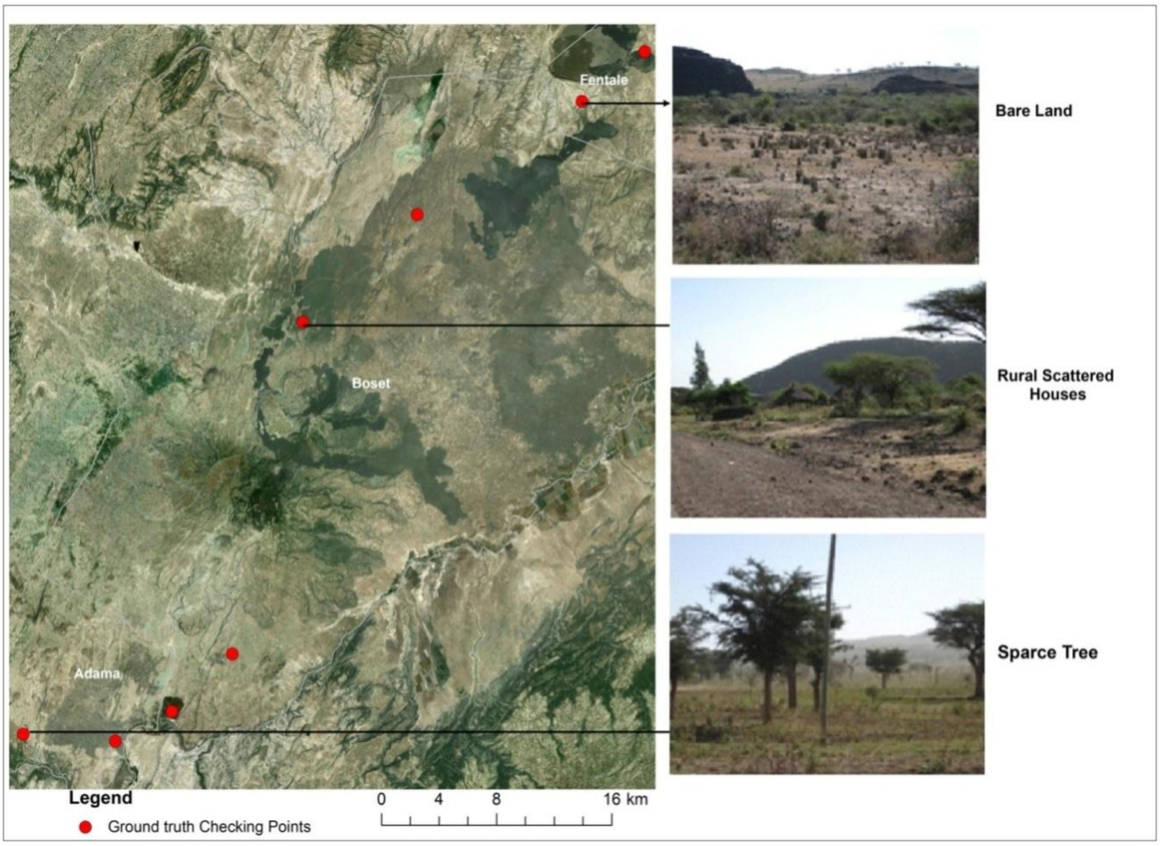

Figure 3.4: East Shewa Zone Verification

CHAPTER FOUR

4.0 RESULTS AND DISCUSSION

4.1 Poverty mapping

The poverty maps at the small area level will be an effective tool in allocating resources to the target population, enabling not only efficient use of the scarce resources but also functioning direct interventions to the poor. A class of poverty measures are defined by (Foster, Greer & Thornbacks (FGT)1984).The Poverty Mapping was implemented to largely help fill the data gap. It combines existing census and survey data, and produces reliable poverty estimates at lower levels of disaggregation than existing survey data would allow. Performance monitoring could also be improved with the availability of poverty maps that permit the tracking of poverty at the local level over multiple time periods. Overlaying a poverty map with other geo-referenced information such as transport infrastructure, public service centers, and information on natural resources, like soil quality, may also help identify the investments necessary to lift such areas out of poverty. Access to water facility and road network maps are examples of this geographical database.

4.2 GIS Analysis

GIS analysis is a process for looking at geographic patterns in existing data and relationships between features. Data can come from heterogeneous sources: satellite images, census data etc. And it provides more accurate up-to-date information. When to start to analyze the data I have to ask some question and answer it. The next questions are some examples.

1. What are the data needed?
2. Which method to use?
3. How to present the results?

The Result of the analysis id displaying as a map and values are on the table. Figure 4.1 map shows the most important result from the poverty mapping in Ormiya Region by the method of categorizing (grouping the similar things which allow organize and make sense of data). It is the production of a disaggregated poverty headcount index at the Woreda level. Geographic patterns of poverty in Oromiya region are varying by area. Some EA or woreda records among the highest poverty indices in the region, while some record among the lowest.

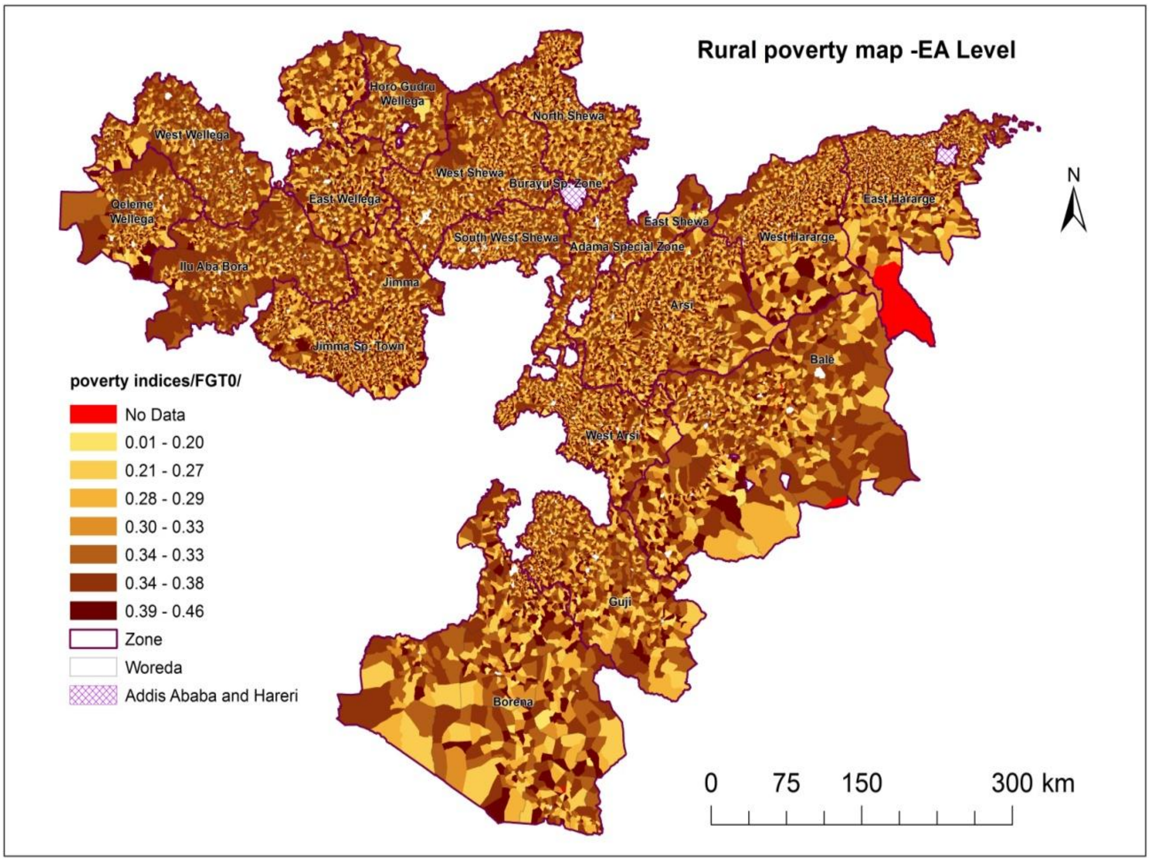

Figure 4.1: Rural poverty map EA level

Overall the result, Figure 4.1 shows there is clear spatial pattern between Ea's (Enumeration Areas) rural poverty. On this figures try to show differentiations of the House Holds that are found within Ea's.

On the next findings the maps are produced at woreda level because to correlate with other georeferenced data like school attendance, market accessibility and other it needs woreda level poverty indices data, so figure 4.2 and other shows poverty indices at woreda level. Therefore figure 4.2 show Eastern part of the region shows high rate of poverty and, the western part of the region shows low and medium rate of poverty. However, wordas are varying considerably in terms of poverty headcount rates. The use of regional level poverty estimates cannot reflect the large variation in poverty indices with in a region so this research conducted at EA and woreda level while the poverty numbers are shown in Annex I, Table -2.

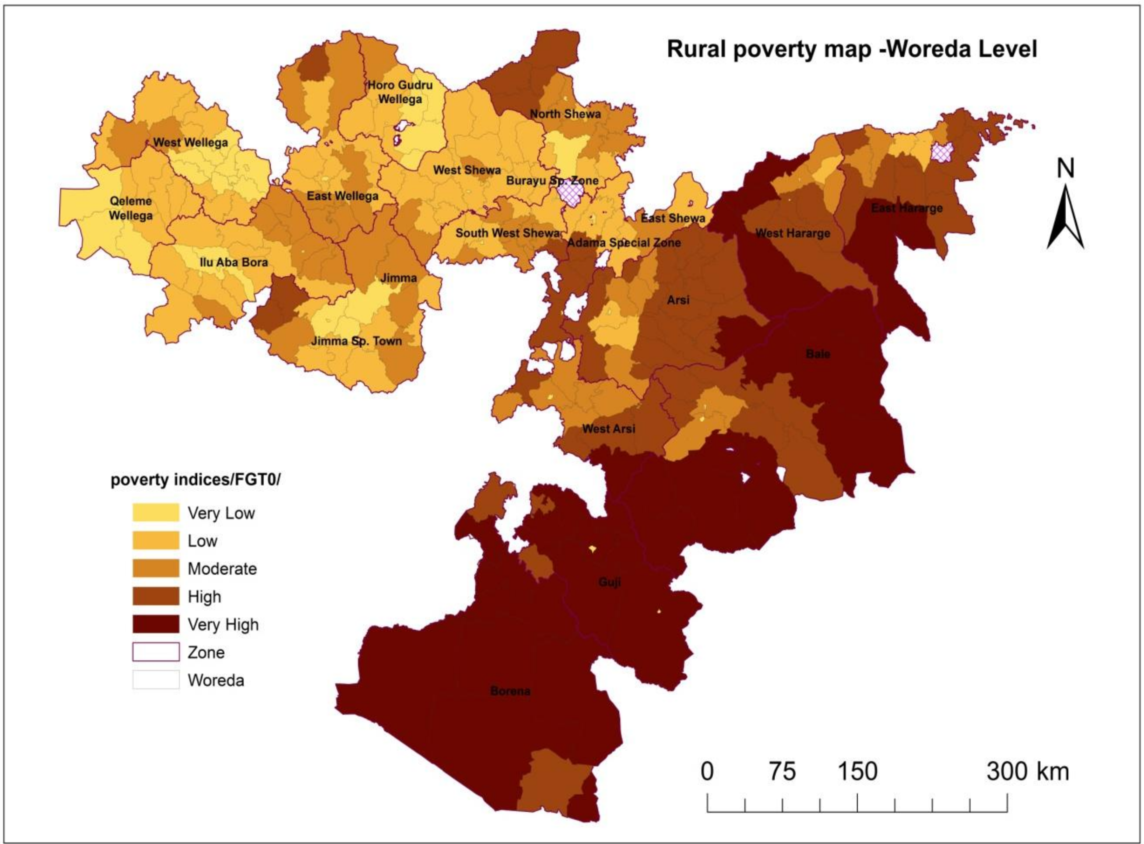

Figure 4.2: Rural poverty map Woreda level

4.2.1 Hotspot analysis for Poverty Indices

The Hot Spot Analysis tool calculates the Getis-Ord Gi* statistic for each feature in a weighted set of features. The G-statistic tells us whether features with high values or features with low values tend to cluster in a study area. This tool works by looking at each feature within the context of neighboring features. If a feature's value is high, and the values for all of its neighboring features are also high, it is a part of a hot spot. The local sum for a feature and its neighbors is compared proportionally to the sum of all features; when the local sum is much different than the expected local sum, and that difference is too large to be the result of random chance, a statistically significant Z score is the result.

Hotspot analysis requires data to be aggregated to some form of geographic unit (e.g. Census block, grid cell). Adjacency/contiguity (i.e. which neighbors' to consider) and it is a units within a specified radius.

Gi* statistic

In this statistical method we can ask "Does local spatial association exist?" To answer this question we must analyze the Gi* results or Z scores indicate the place of a particular value in a dataset relative to the mean, standardized with respect to the standard deviation.(Chainey, Spencer)

Advantages of using Gi*

- Adds statistical significance to hotspot analysis
  - Which are the hotspots that are significant?
  - Where is there something really unusual going on?
- Better at predicting where Poverty will occur

Potential Applications

Applications can be found in crime analysis, epidemiology, voting patterns, economic geography and demographics. (ESRI developer Network, edndoc.esri.com, Chainey, Spencer, 2000)

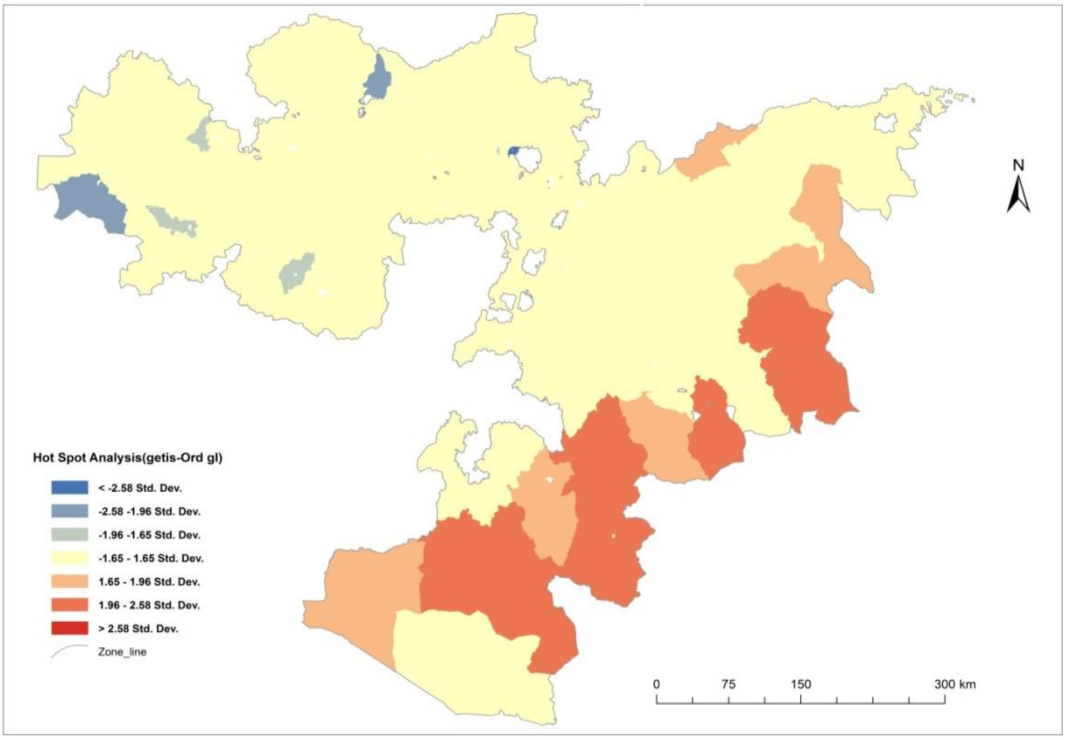

Figure 4.3: Hotspot Analysis for Poverty Indices

Interpretation

Statistical significance measure: Test statistic (Z-score) and P value to indicate if result is statistically significant. Software that I used is ArcGIS Spatial Statistics Tools.

- $Z = 0$ is equivalent to the sample/data mean
- $Z < 0$ is a value less than the mean
- $Z > 0$ is a value greater than the mean

Therefore, the above map portrays hotspot analysis calculated from poverty headcount index (poverty head count index) with in the region. The larger the Z score is, the more intense the clustering of high values. For statistically significant negative Z scores, the smaller the Z score is, the more intense the clustering of low values. (Chainey, Spencer)

Figure 4.3 map Gi* values, shows positive for each cell this means lots of high counts of Poverty head count close together, and Gi* values will be negative for each cell and close together it shows lots of low counts of poverty head counts within the region. So in Eastern and some parts of southern in the region have positive value this means there is high poverty head count index, on the other hand, on the some parts of western and northern area the value shows less poverty head counts and most part of the central part of the area shows moderate poverty head counts index.

4.3 Poverty maps with other Geo-referenced Data

Geo-referenced poverty data is helpful to locate severe scarcity, which cannot be identified from poverty estimates at the regional level. Though, locating poor areas is not enough. It is important for policy makers to identify what are the constraints limiting economic opportunities in these areas. For this purpose, it is instructive to overlay the poverty map with other geo-referenced data.

Even though it has clear advantages, it is important to note such comparisons can only show illustration correlations rather fundamental relationships. For example, even if poverty and water accessibility are highly correlated, this does not necessarily mean improving water access reduces poverty. There is always a possibility that non-poor areas attract road and other infrastructure investment. To understand a fundamental relationship, a further careful experiential analysis is necessary.

4.3.1 Poverty Headcount vs. Number of Population

Poverty maps provide geographical distribution of where the poor are populated and the geographic patterns and variation of poverty in the region. The poverty headcount/indices index refers to the proportion of people who live below the poverty line. In addition, on figure 4.4 we can also look at the absolute number poor population and the ratio of human occupation by calculating the population of a woreda per area unit.

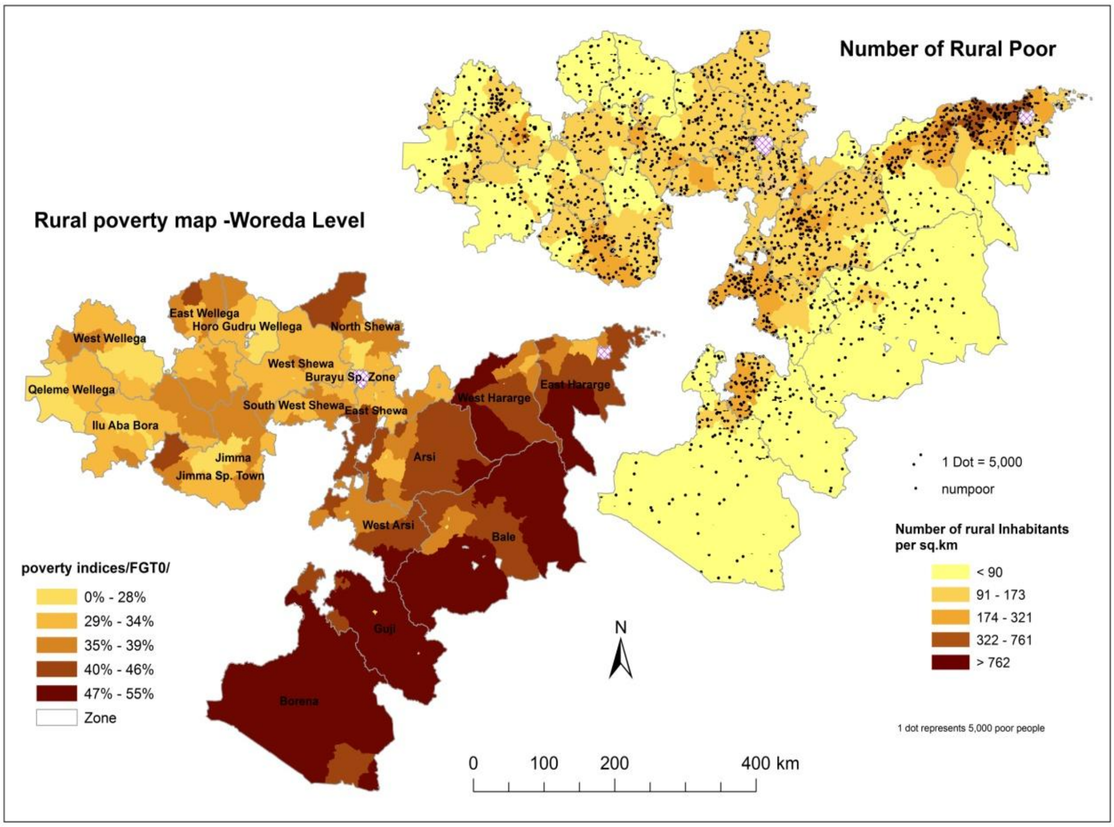

Figure 4.4: poverty indices and Number of Poor Population map

Figure 4.4 shows that few woredas in the west and North West, South and Eastern parts of the region are sparsely occupied with value ranging <90 persons per sq km. Whereas some Woredas in the North Eastern, Central, parts of the region have population density greater than762 persons per sq km. The eastern part of the area in the region has high poverty rates with small number of people. On the other hand, some part of western and central part have medium poverty rates but high number of people found in the region.

4.3.2 Poverty & Education

Education is universally agreed to be a factor that can help people out of poverty, by giving them better jobs and higher income. Access to education, regardless of children's circumstances and their parent's income, improves economic opportunities for the next generation of the region as well as the country, and facilitates growth and poverty reduction for the country as a whole. Oromiya region has made tremendous progress in access to education in rural areas; however, several challenges remain. Access to education is shown in the map by the percentage of population aged 5 -18 years old who are attending school (Figure 4.5). The map shows that there are many areas where few peoples attend school, and many of these woredas tend to also have high poverty rates and less population distribution.

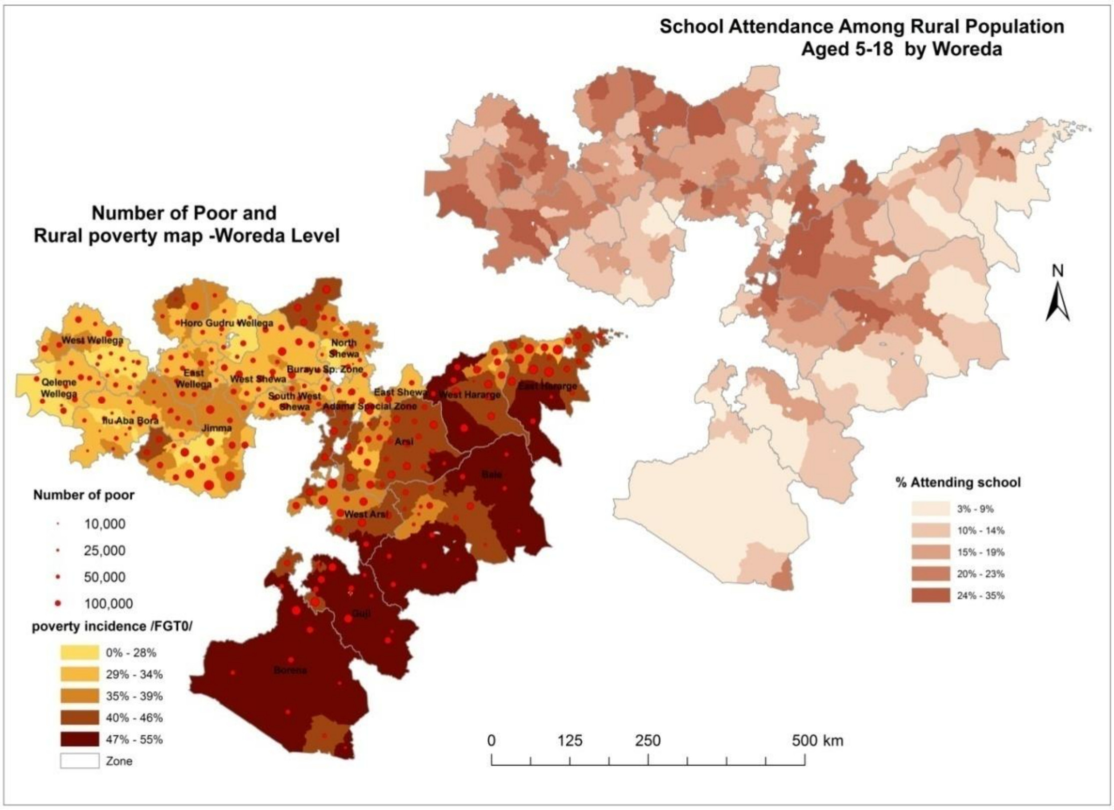

Figure 4.5: Poverty Indices and school attendance map

Gross enrollment is the ratio of all primary school students to all primary school aged children (5-18 year olds) in the population, expressed as a percentage, is the gross enrollment rate. Low gross enrollment rates reflect low net enrollment rates from lack of school attendance either because children have poor access to schools or are kept away by their parents. It indicates that its schools are of a relatively poor quality, and it seeks to improve the educational attainment of the people.

4.3.3 Poverty & Water

The greatest causes of poverty in Africa are also the most evident the lack of access to clean drinking water. In sub-Saharan Africa alone, 40 billion hours of labor are wasted each year carrying water over long distances. (Charles, van der Vyver and Dawid B., Jordaan. 2009).

Access to clean, safe water is essential if we are to reduce poverty and it encourages agriculture and ensures good health for all. The clear need for basic water for the poor assumes even greater significance when the linkages with other dimensions of poverty are considered. Water is related sicknesses put severe burden on health services and keep children out of school. Water related illnesses exploit from diarrhea-caused malnutrition and reduced life expectancy. in addition to water affects education by reduced school attendance by children (especially girls) due to ill health, lack of available sanitation, or water collection duties gender and social inclusion, load borne excessively by women, limiting their entry into the cash economy income/consumption, high proportion of budget used on water, reduced income earning potentials due to poor health, time spent on collecting water or lack of opportunity for businesses requiring water inputs, and high consumption risk due to seasonal or other factors. . (Charles, van der Vyver and Dawid B., Jordaan. 2010).

The Objective of this subject matter is checking the relationship between the water availability and Poverty Indices and to point up the distribution of it within the region. poverty and water mapping is used to identify areas of high levels of water poverty.

A figure 4.6 map indicates a two-way relationship between poverty and lack of access to safe water. More people live on less than a poverty line, including the vast majority of those without access to safe water. And shows save water density map with poverty head count index. On this map the eastern part of the region has less amount of water facility and also this area has high poverty rate. The central and some part of the area has less poverty rate and less safe water facility/Tap water/.

This finding used to assist in the targeting of water accessibility within the region. This ensures the most efficient use of resources to meet the development objectives of the region.

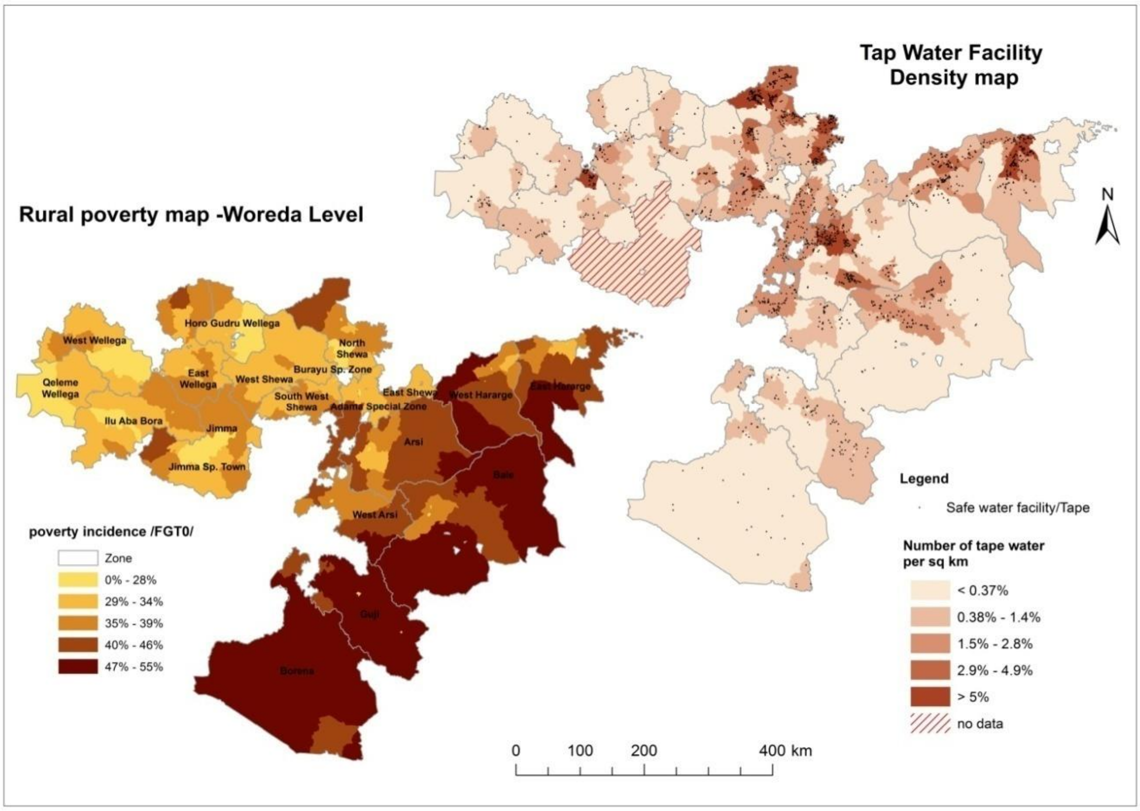

Figure 4.6: Tap Water Facility Density map

4.3.4 Poverty & Roads

Availability of the roads and the condition of the roads talk about the accessibility to the foods, health, jobs, education.etc. Briefly it impacts to the quality of life and the freedom of movement. Thus, lacking of it might be a one of symptom of the poverty.

It is very important to understand that infrastructure such as better roads carry a reflective role towards reducing poverty. In fact, most developed nations embrace the ideal of better road networks towards improving the quality of life.

Most part of the Region’s roads reflects the very limited investment. Roads are only used as a link for farm produce industrial products to reach the consumers. Beside, lack of communicative road network leads to inefficiency as to how goods are moved within a region. They serve as collectors for travel from the villages to the market towns, and are normally linked by all-weather roads to major population centers. They are thus vital to agricultural marketing structures and ensure most of the income of the rural population. If they are in bad condition, then the entire rural network is affected. http:// www. Rural roads.org /en/select.shtml).

The basic access method is simple to apply maps. Maps can be used to identify those who are geographically isolated from the center network.

In Ethiopia, perfect data on the location, type, and quality of road is difficult to generate because road works and conditions are constantly changing over time and within seasons. This map represents the most comprehensive and up-to-date information available on the national road network from Ethiopian Road Authority in 2006

Figure 4.7 shows road density as the ratio of meters of all-weather road per square kilometer of land area, calculated for each woreda and the road networks. (CSA, Population Atlas, 2007). Road density highlights the relatively developed transportation infrastructure in the highlands and between towns, whereas areas in the lowlands with lower population density have less transportation networks.

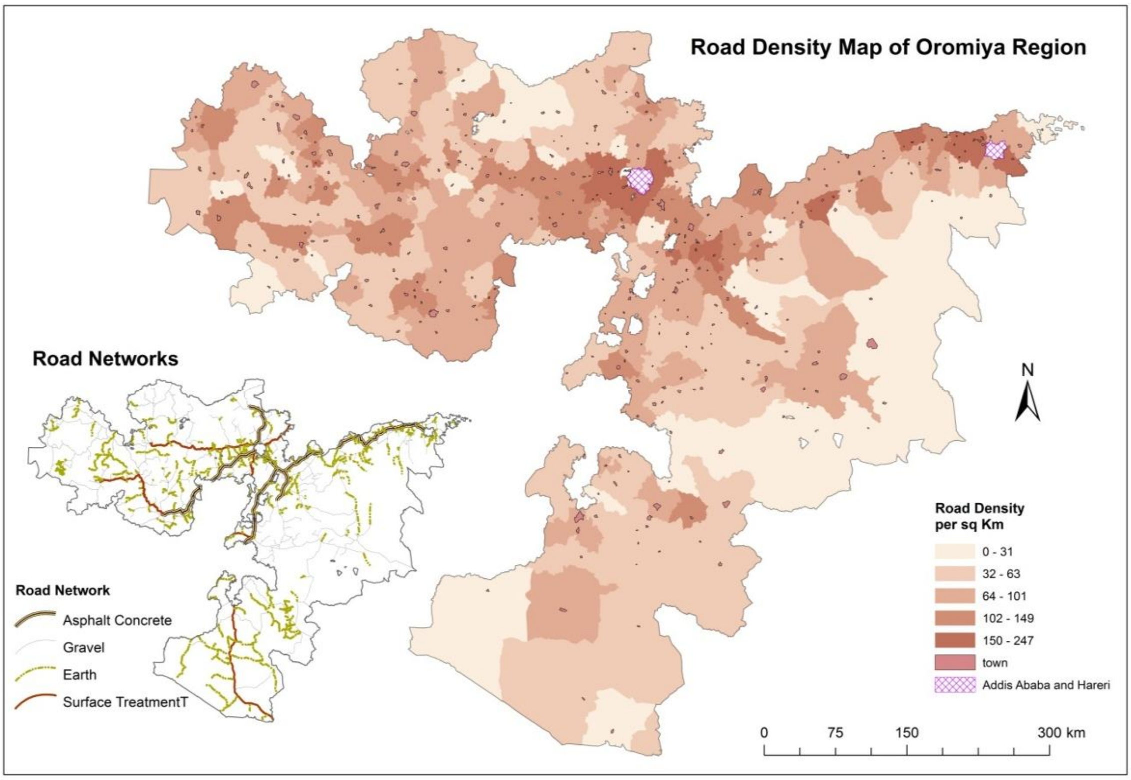

Figure 4.7: Road Density map

Beside this higher road density are concentrated more in the central part of the region and around the towns. Figure 4.8 shows that there are many areas there has less road density , and many of these woredas tend to also have high poverty rates.

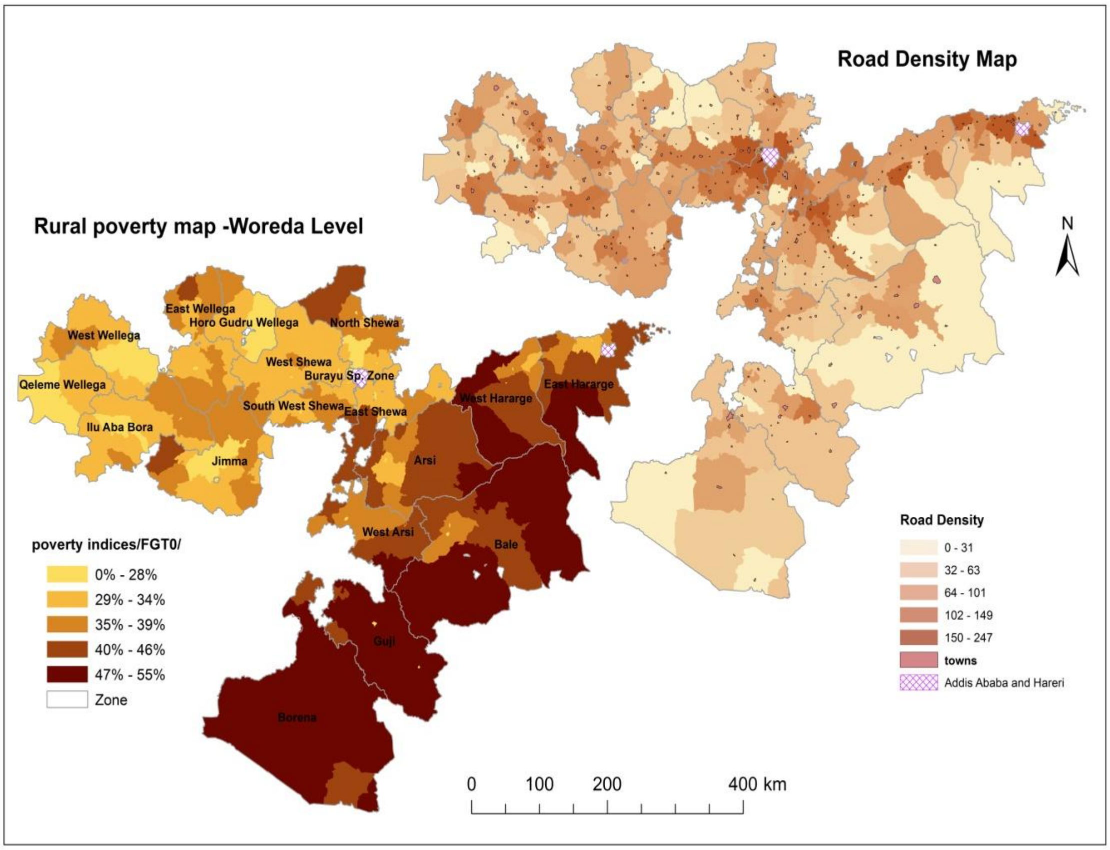

Figure 4.8: Road Density map with poverty indices

Obtained Result

- The majority of woredas which have low poverty indices value do not have high road density and the expected result for the wordas which have high poverty indices value, have low road density

4.3.5 Climate-Poverty linkages

There is a strong relationship between climate and poverty levels. Figure 4.9 and 4.10 maps shows the relation ship between poverty indicis with annual rainfall and agro-ecological zone of the region. The key findings on the map showed that wordas that fall within eastern and southern part of the region has Low rainfall (figure 4.9) with Arid/Berha/ecological zones(figure 4.10) tend to have higher poverty head count indexs than those with higher rainfall. Besid central part of the region has medium poverty indicesvalue with avrage annual rain fall. This indicated that climate change degrading the capacity of environmental resources.

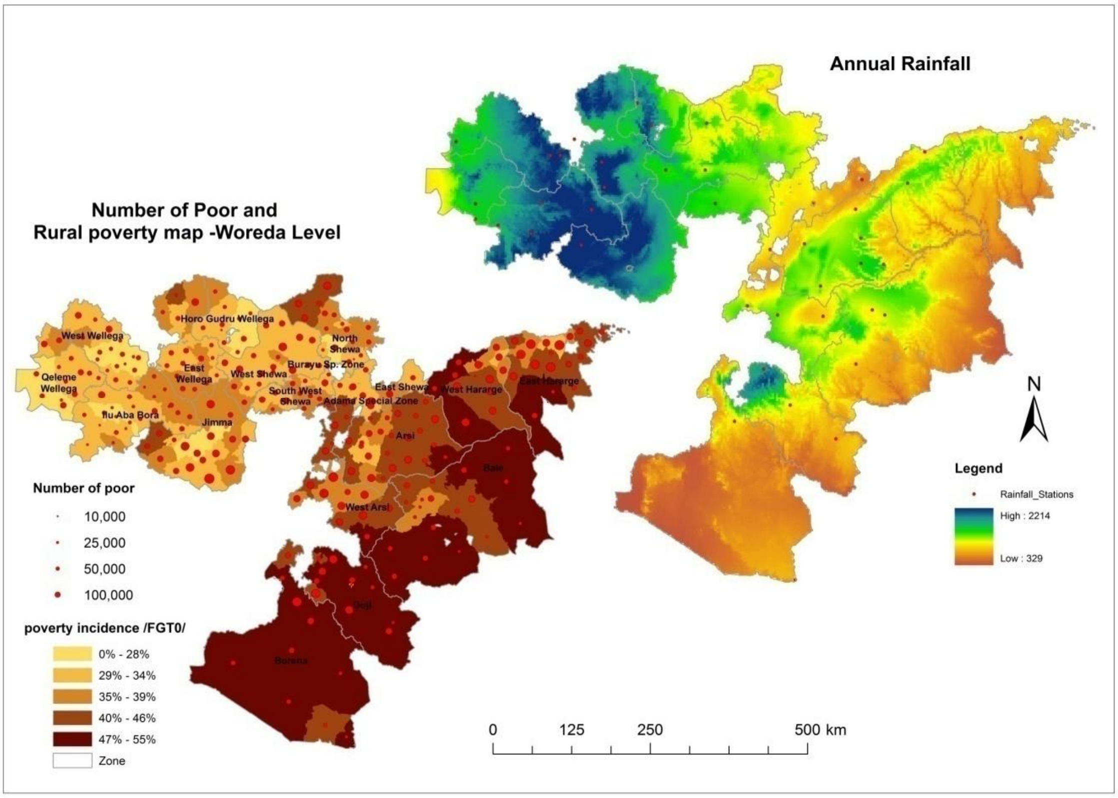

Figure 4.9: Annual rainfall map with poverty indices

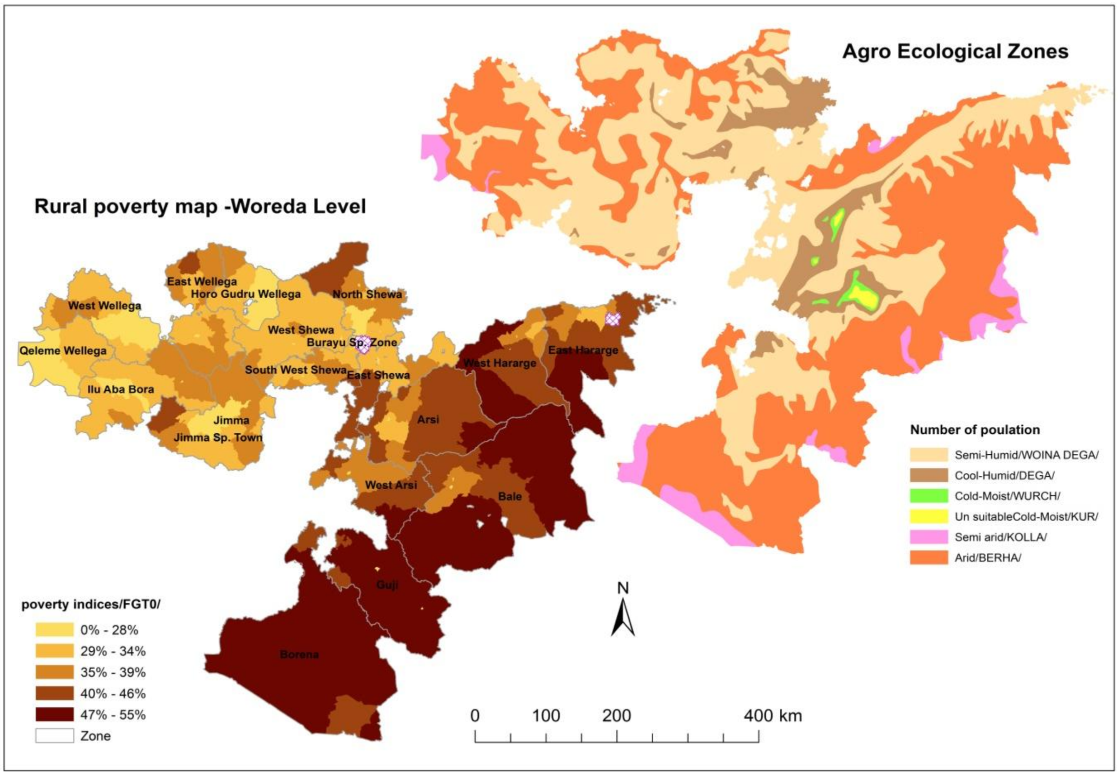

Figure 4.10: poverty indices of map with Agro Ecological Zones

4.3.6 Measures of Distance and Physical Accessibility

Analysts can assess the importance to welfare outcomes of travel time to facilities, services and markets using relatively new algorithms and tools (Geertman and van Eck, 1995, Bateman et al., 1996, Farrow and Nelson, 2001, Kwan et al., 2003). In Ethiopia 89% of the population live in rural area. Most of the times the people live in rural area are farmers. Income generation for farmers often depends on distance to markets and associated transport costs (Van De Walle, 2002, Jacoby, 2000). Many other general areas of welfare and development are related to accessibility (Leinbach, 1995). In Rural Ethiopia poor households and communities often suffer from difficult access to health clinics, schools, markets and other facilities.

The studies in this special issue demonstrate the calculation of GIS-based measures of travel time to markets and facilities. As long as evidence that, for small areas in the region, accessibility and distance to markets and services are important explanatory factors in poverty .

Travel time done for the towns whose population is 50,000. It is an indicator of market access. For the region, a city of 50,000 people or more can be regarded as a key market area that would stimulate agglomeration economies.

One of the indicators or findings on figure 4.11 map are the further away a rural location is from the nearest city of 50,000, has less potential interaction with the cities. In order to benefit from backward and forward linkages related to the market center, the farmer must be reasonably near, in terms of travel time, to city of 50,000.

Another finding on Figure 4.11 map is the areas that have high poverty indices value or high rate poverty are far from the city that is they spent more than 15 hour to reach in the city. This means when we are near to the towns, there is less poverty indices value. This indicate near to towns is less poverty and far from towns indicate high poverty.

Because of time and other factors doing land cover/ land use the whole Oromiya region is difficult. According to Central Statistical organization or experience to do the land use land cover for Oromiya region it takes one year and more than 6 month by 18 and more expertise.

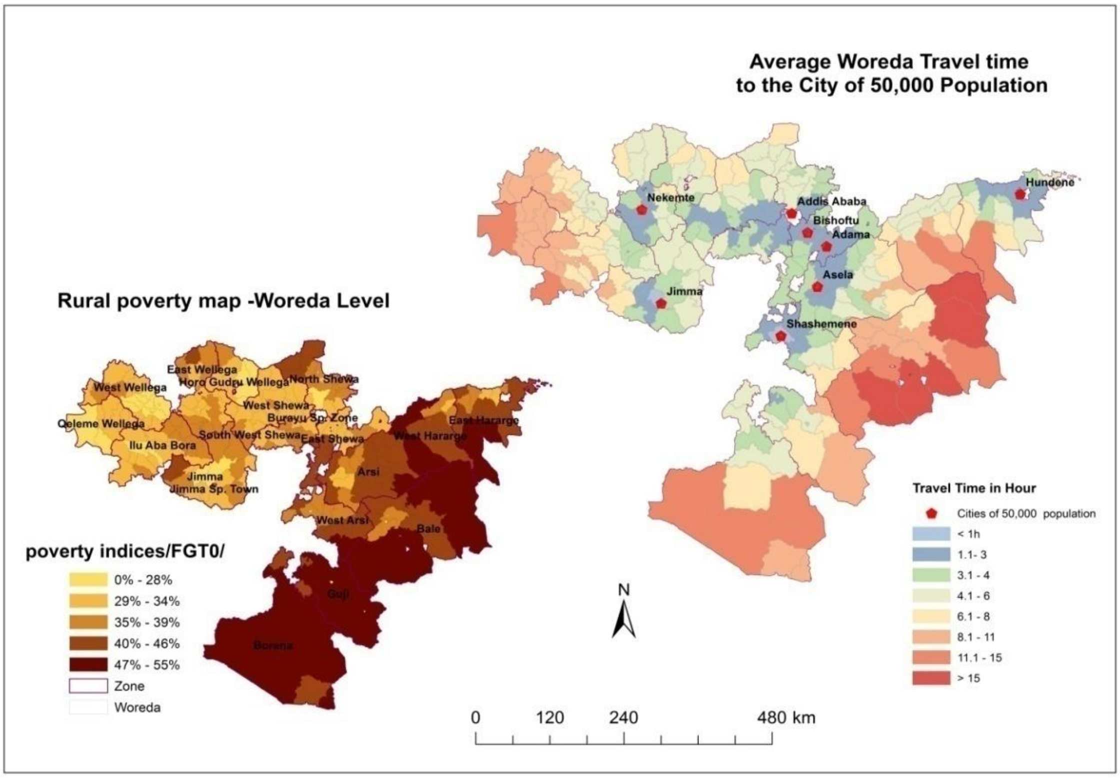

Figure 4.11: Travel Time map with poverty indices

4.4 Land Use/Land Cover: - Selected Woredas

Ethiopia is a country characterized by rapid environmental conversions and modifications attributed to various difficult human actions, like expansion of farm plots at the expense of vegetated lands, massive fuel wood and charcoal production, overgrazing and advance of farmsteads into vegetated lands. Oromiya Region covers for about 34.3 percent of the total area of the country. For this reason, a systematic analysis of land-use is so essential to exactly understand the extent of the land and take necessary measures to scale down the area of uses and protect the land cover resources sustainably. Oromiya region also famous for its massive mountain ranges, high flat plateaus, deep gorges, river valleys, lowland plains, extensive wetlands, and deserts. As indicated by (Aklilu 2006), the geographical setting of the region is generally distinguished by the highlands in the central part, circumscribed by the flat lowlands in eastern part of the region. (Ahmed Hussein, 2011)

This land use has made use of satellite images (spot 2006) and GIS technologies in combination with ground verification.

CSA did Land use land cover for area framing for agriculture purposes by Madcate, GEOVIS and DVININ soft ware's. This is done by the collaboration with FAO by the standard of GLCN (Global land Cover Network). GLCN is network it established to mitigate or address the issue of definition for land cover terminologies, for example forests have more than 200 definitions in the world. Therefore I use Tree cover to compensate forest on my classification. Therefore I did land use land cover for the selected woredas on the base of this classification. The selection is based on the areas that have high, medium and less value on the poverty indices (poverty headcounts). The Selected woredas are:-

From poverty indices value is high it means the area is highly poor, where as the poverty indices /FGTo/ value is less it means that the area characterized by less poor. Therefore From East Shewa – Liben woreda, Eastern Harerge zone, Meyu – Muluke woreda, Gugi zone- Liben and Bore woredas, Ilu Aba Bora zone – Diga woreda, from Jimma zone I select three woredas that are Limukosa, Gomma and Mana woredas, North shewa zone- Sululta woreda, South west shewa zone- Becho woreda and from west Harerge zone – Chiro woreda. To do this I used Central Statistical agency methodology.

The major land uses include agricultural areas, settlement areas, water bodies, Tree cover, Shrub lands, bare soil, Grass. There are different classes according to the selected woredas. On most parts of the selected woredas, large proportion of land is under 'Agricultural land use type.

Tree cover is more similar to forest but I did not use the word forest because according to Land Use Land cover analysis forest has more than two hundred definitions with different country, therefore I used the term tree cover. Beside the above types of class there are no data and cloud cover during capturing the satellite images. The next maps are clearly shows the selected woreda land cover.

- Selected woredas:- High poverty rate

Figure 4.12, 4.14, 4.16, 4.18, 4.20 and 4.22 shows the selected woreda who has high poverty rates. These woredas are Guji zone_ Liben and Bore woredas, Ilu Aba Bora zone Diga woreda, Eastern Harege Meyu Muleke woreda, South West shewa_ Becho woreda, and East shewa Zone _ Liben woreda. And also a figure 4.13, 4.15, 4.17, 4.19, 4.21 shows the area extent of the land use/land cover of the woreda. A table 4.1, 4.2, 4.3, 4.5, 4.6 and 4.7 shows the area coverage of land use/land cover by hectare and percentage of the coverage. Therefore, Guji zone Liben and Bore woredas, Illu Aba Bora zone Digga woreda, and East Harerege zone Muyu Muluke woreda are dominated by more than 55% shrub and tree cover and their categorized very high poverty indices. Whereas South west shewa Becho woreda and East shewa zone Liben woredas dominated by Agriculture, but in these research they categorized as high poverty indices. There for these two woredas need further research because these woredas are very productive area.

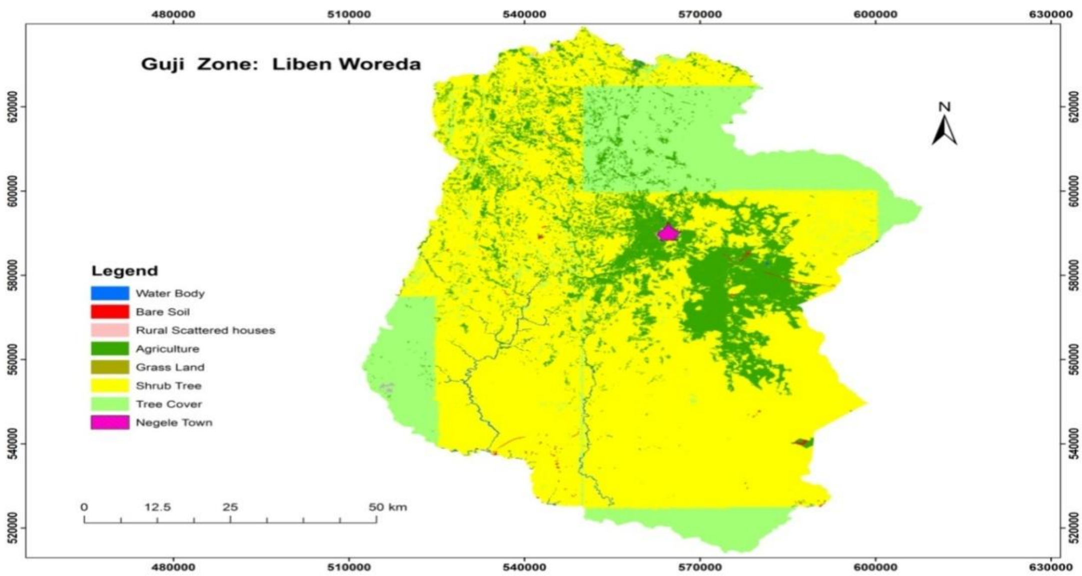

Figure 4.12: Liben woreda Land use / Land cover map of 2006

Table 4.1: Guji Zone Liben Woreda Land Use/Land Cover Classes

Land use/Land covers	Area (ha)	Area (%)
Agriculture	103413	13.94
Bare Soil	453	0.06
Grass Land	245	0.03
Rural Houses	361	0.05
Shrub Tree	482650	65.07
Tree Cover	8204	1.11
Water Body	1265	0.17
others	145130	19.57
Total Woreda Area	741721	

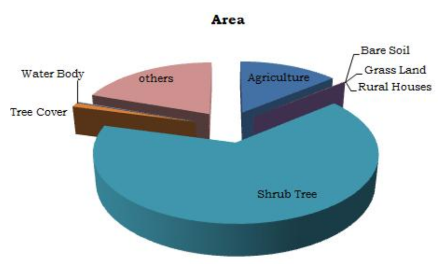

Figure 4.13: Area coverage of the classes in Liben woreda

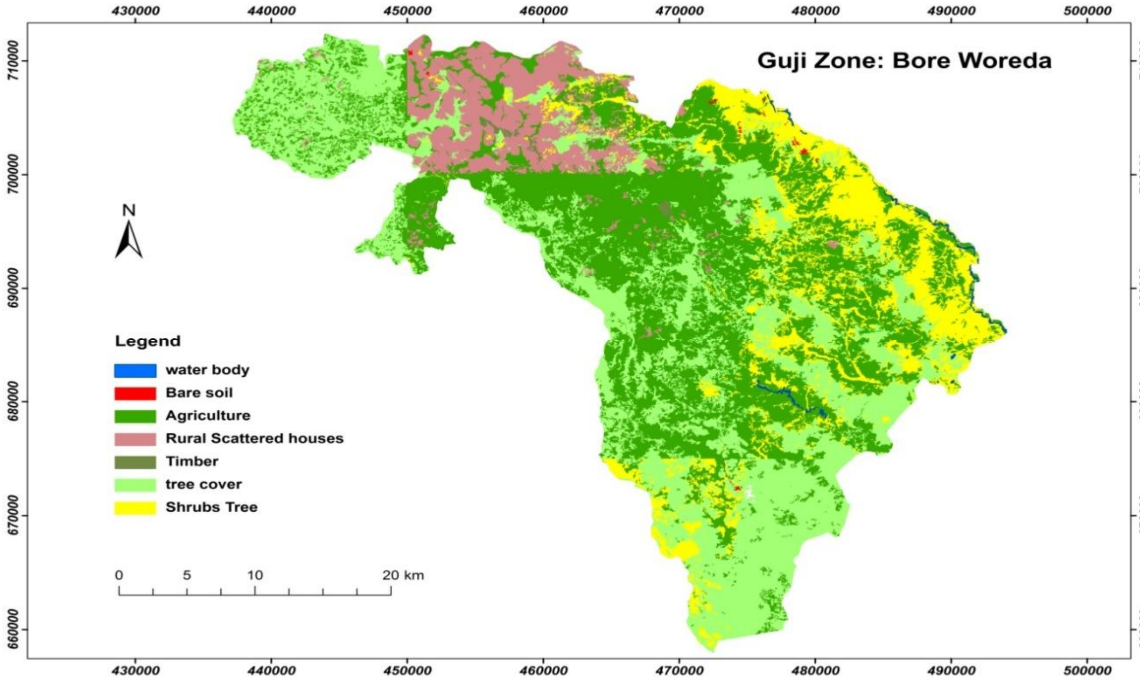

Figure 4.14: Guji Zone Bore woreda Land use/land cover map of 2006

Table 4.2: Guji Zone Bore woreda Land Use/Land Cover Classes

Land use/land covers	Area (ha)	Area (%)
Bare soil	410	0.50
Rural Houses	11879	14.40
Shrubs Tree	32551	39.47
Timber	140	0.17
tree cover	36637	44.43
water body	773	0.94
Other	77	0.09
Total woreda Area	82468	

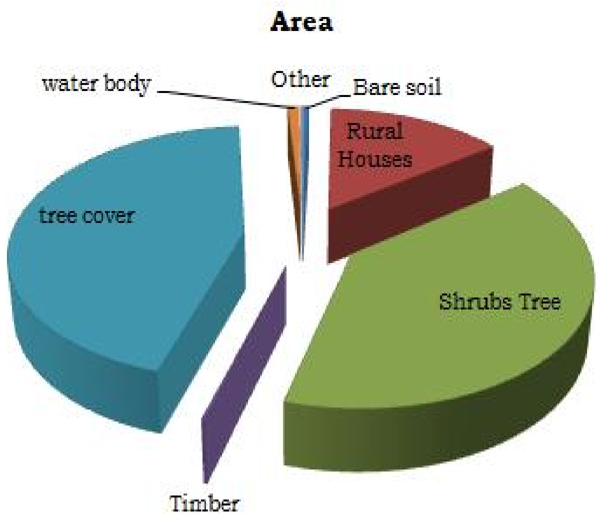

Figure 4.15: Area coverage of the Classes in Bore woreda

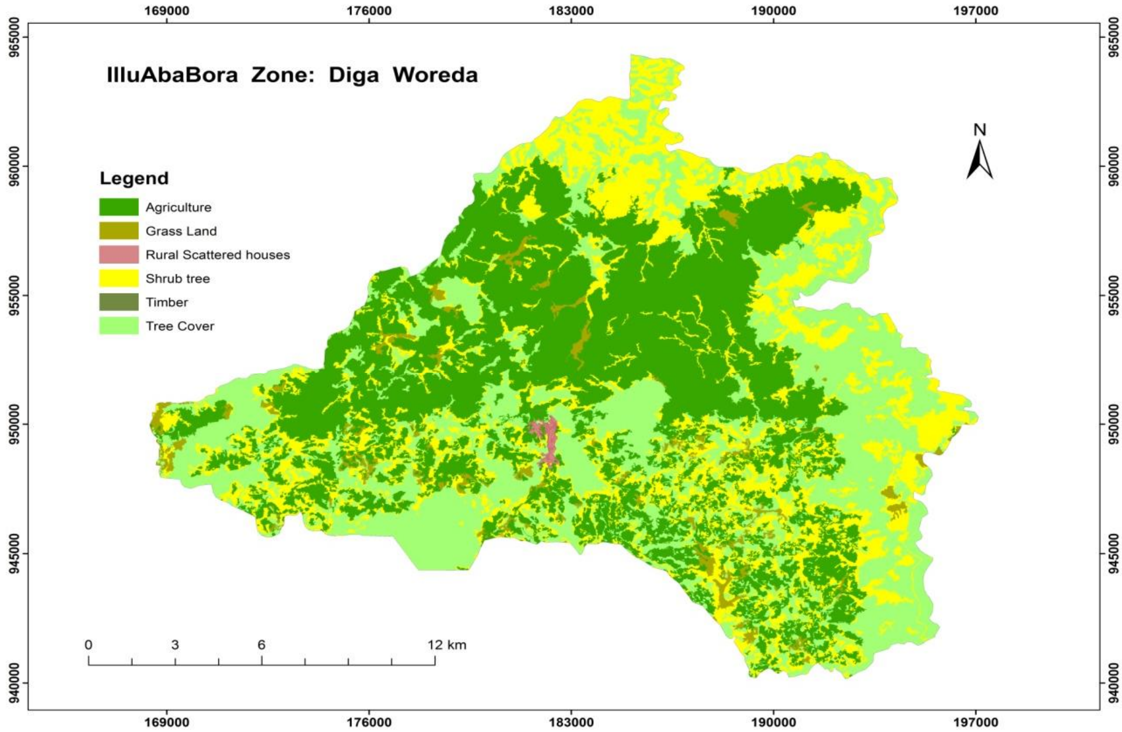

Figure 4.16: Diga woreda Land use / Land cover map of 2006

Table 4.3: IluAbaBora Zone Diga woreda Land Use/Land cover classes

Land use/land covers	Area (ha)	Area (%)
Agriculture	14831	41.88
Grass Land	937	2.64
Rural Houses	81	0.23
Shrub tree	8072	22.79
Tree Cover	11184	31.58
Other	308	0.87

Total woreda Area 35414

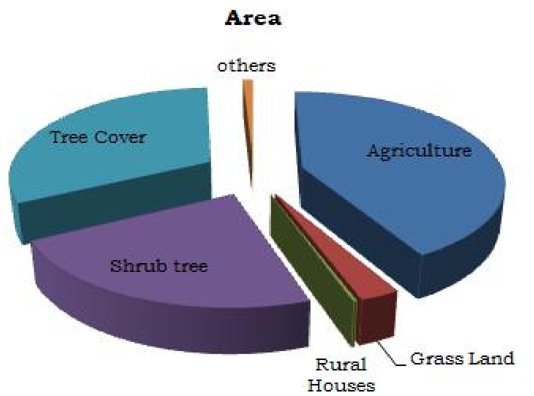

Figure 4.17: Area coverage of the classes in Diga woreda

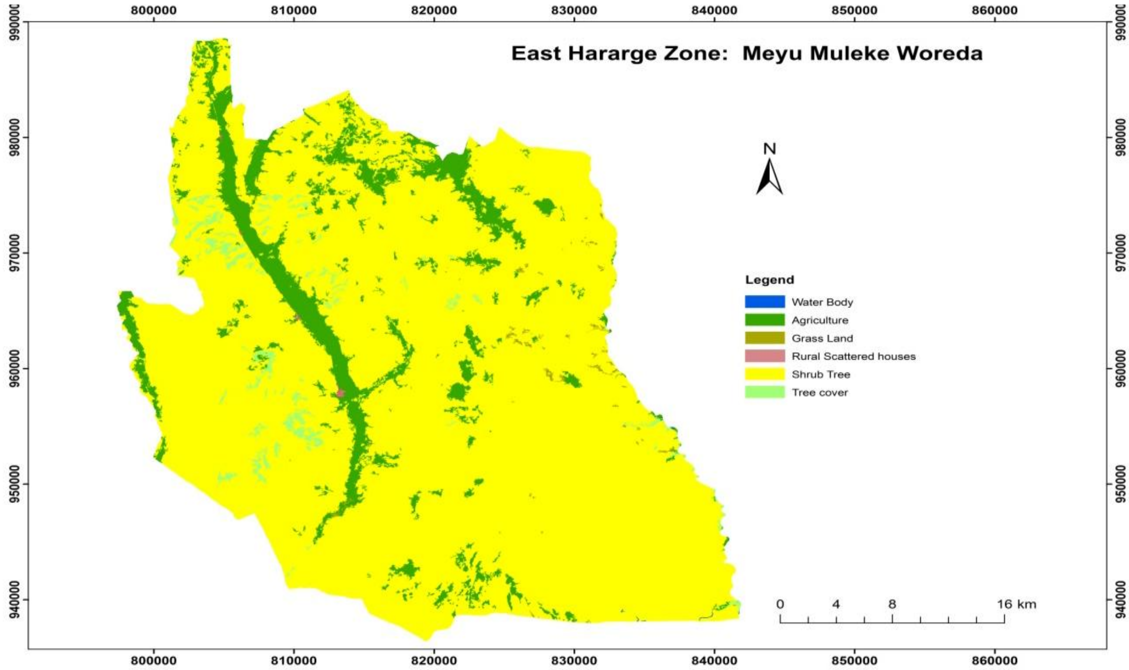

Figure 4.18: Meyu Muleke woreda Land use/land covers map of 2006

Table 4.4: East Harerge Zone Meyu Muleke woreda Land use/land Cover classes

Land use/Land covers	Area (ha)	Area (%)
Agriculture	13932	9.85
Grass Land	349	0.25
Rural Houses	49	0.03
Shrub Tree	124925	88.35
Tree cover	2129	1.51
Water Body	10	0.01

Total woreda Area 141395

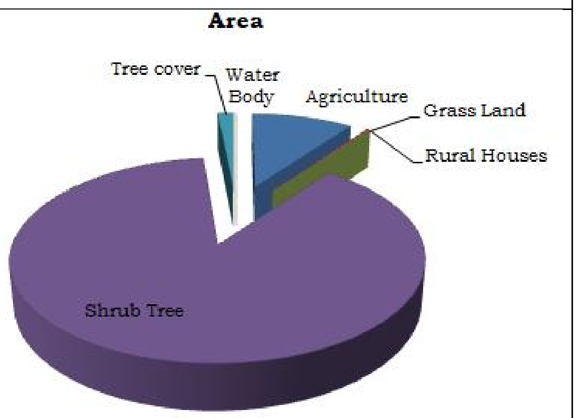

Figure 4.19: Area coverage of the classes in Meyu Muleke woreda

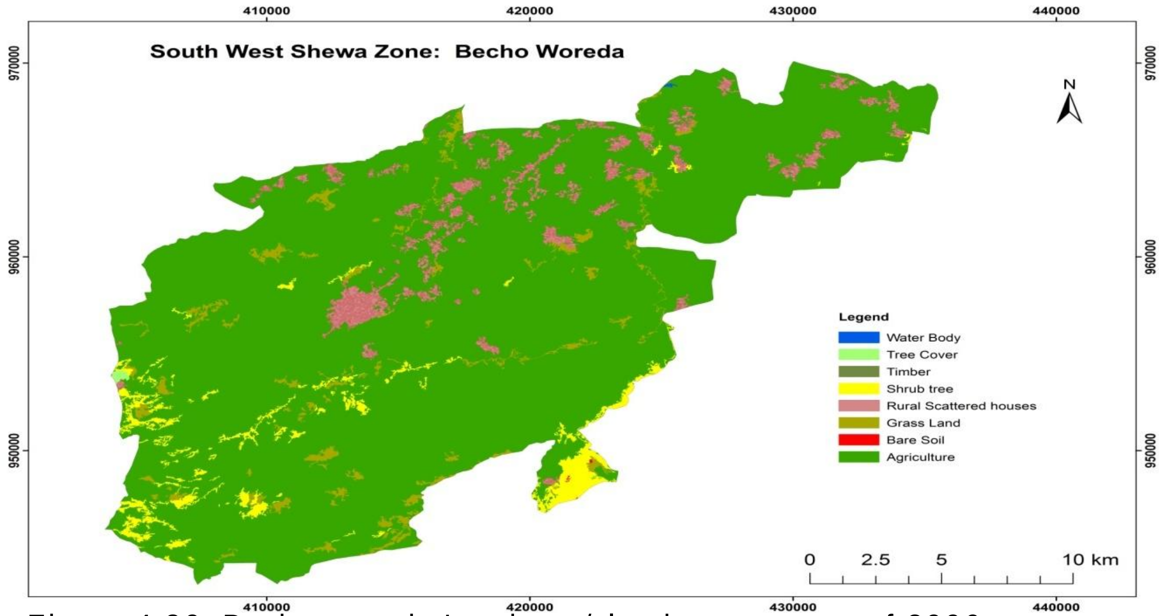

Figure 4.20: Becho woreda Land use/ land covers map of 2006

Table 4.5: South West Shewa Zone Becho Woreda Land use/cover Classes

Land use/Land covers	Area (ha)	Area (%)
Agriculture	39336	90.12
Bare Soil	4	0.01
Grass Land	1202	2.75
Rural Houses	1710	3.92
Shrub tree	1359	3.11
Tree Cover	29	0.07
Water Body	8	0.02
Total woreda Area	43648	

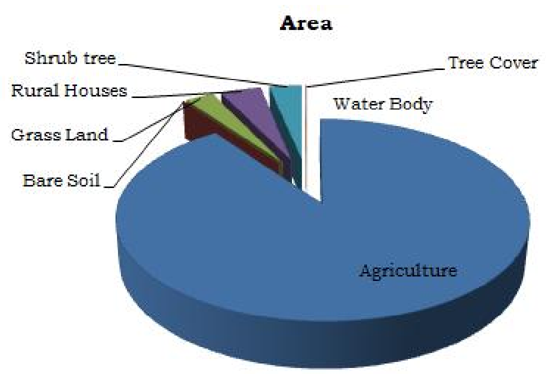

Figure 4.21: Area coverage of the Classes in Becho woreda

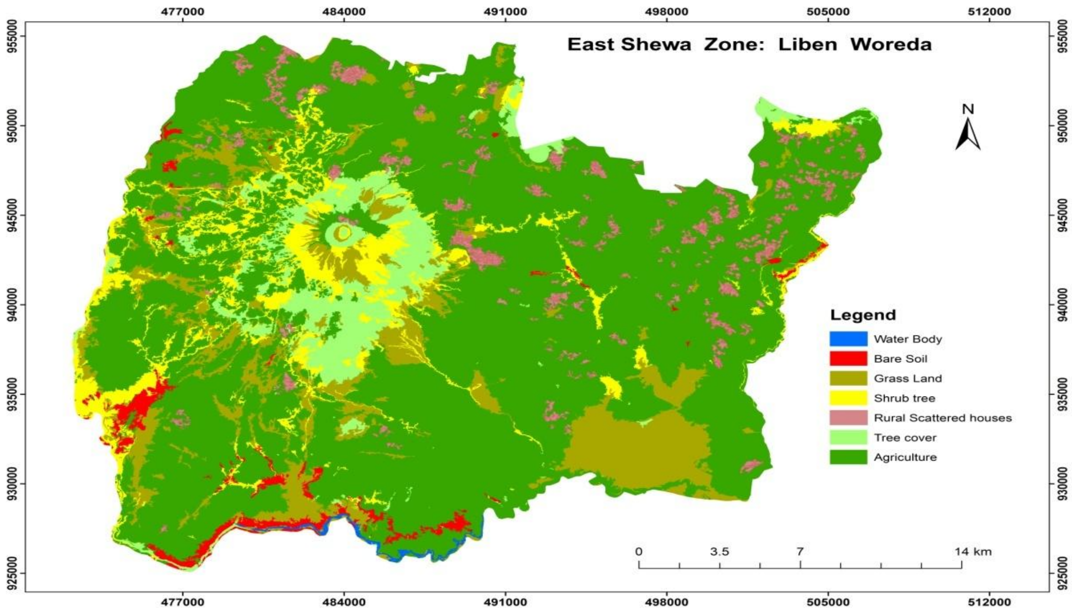

Figure 4.22: East Shewa Zone Liben woreda Land use/Land cover map of 2006

Table 4.6: East Shewa Zone Liben woreda Land use/cover Classes

Land use/Land covers	Area (ha)	Area (%)
Agriculture	47072	67.13
Bare Soil	1269	1.81
Grass Land	10008	14.27
Rural Houses	2198	3.13
Shrub tree	5302	7.56
Tree cover	4005	5.71
Water Body	177	0.25
others	93	0.13
Total woreda Area	70124	

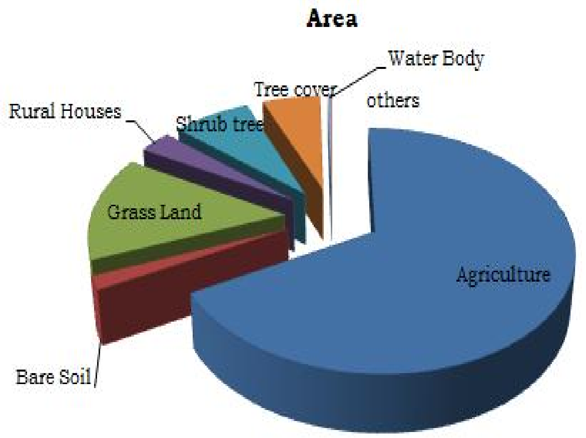

Figure 4.23: Area coverage of the classes in Liben woreda

- Selected woredas:- Medium poverty rate

Figure 4.24 shows the Hararge zone, Chiro woreda land use/land cover. According to the research in this woreda agriculture is dominant (62%), shrub tree cover (34%). But this woreda is characterized medium poverty indices. Figure 4.26 shows East Wellega zone selected woredas Limu, Gutu Gida, and Gudeyabela woredas are categorized Low level of poverty indices.

Gidakermu woreda is categorized on high level poverty indices. Sibusire woreda characterized Medium level poverty indices and in this woreda Agriculture is dominant (77%), Shrubs (18%). The results are described in detail by table 4.7 and 4.8. In addition to the area extent of the woredas are shown on figure 4.25 and figure 4.27.

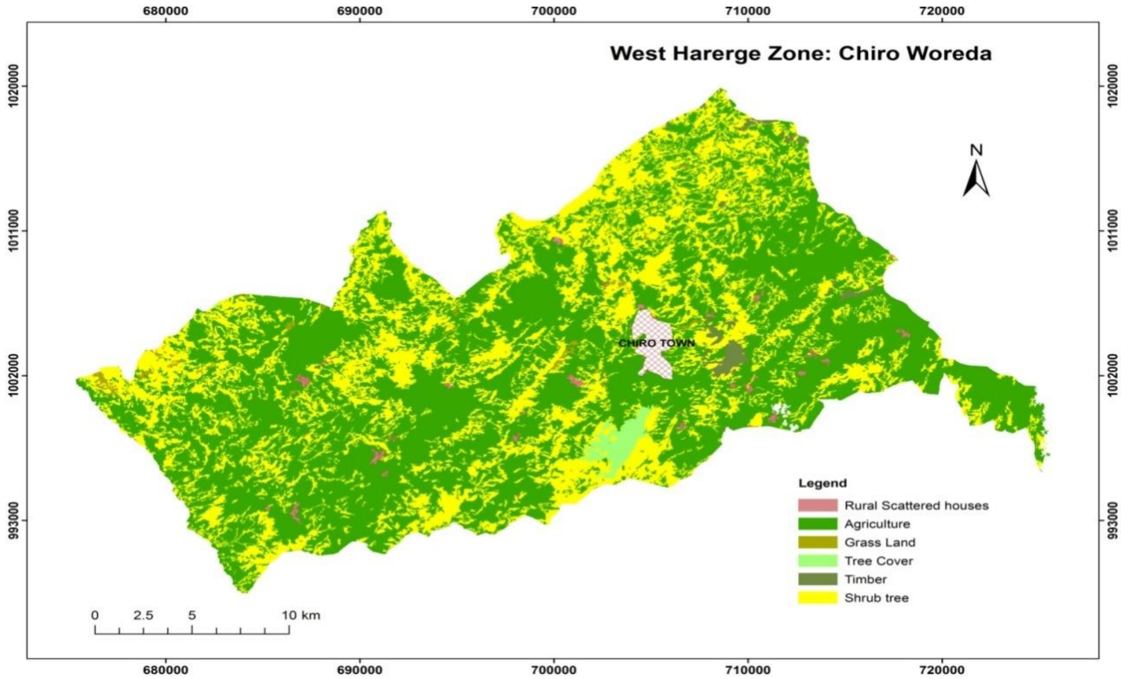

Figure 4.24 West Harerge Zone Chiro woreda Land use/ Land cover map of 2006

Table 4.7: West Harerge Zone Chiro woreda Land use/land cover Classes

Land use/Land covers	Area (ha)	Area (%)
Agriculture	44172	62.25
Grass Land	540	0.76
Rural Scattered houses	306	0.43
Shrub tree	24655	34.74
Timber	648	0.91
Tree Cover	641	0.90
Total woreda Area	70962	

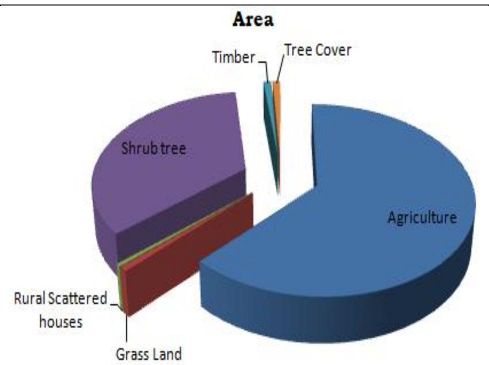

Figure 4.25: Area coverage of the classes in Chiro woreda

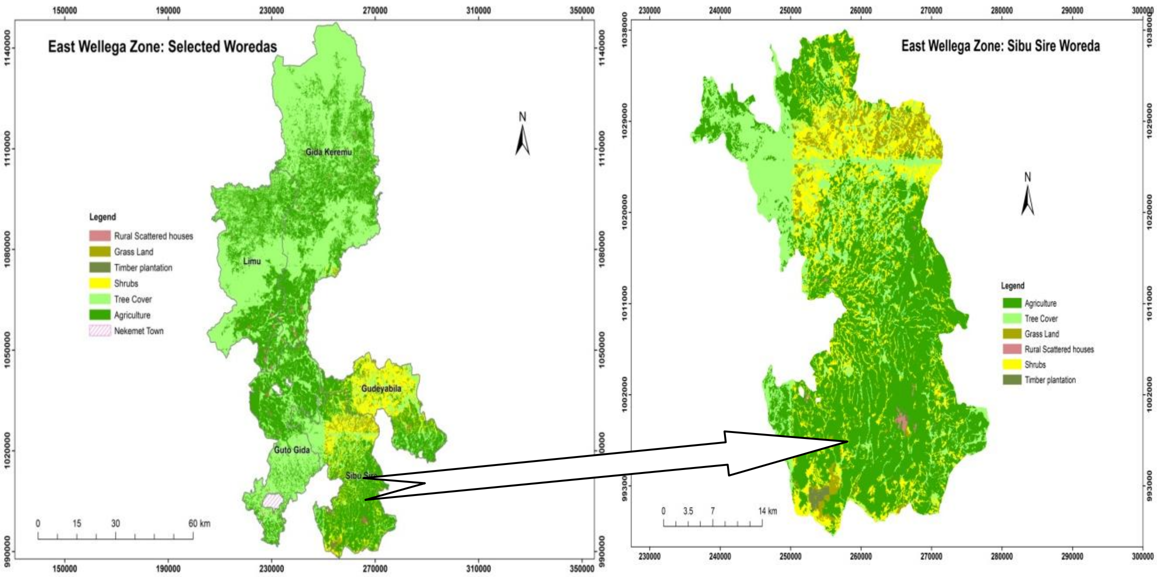

Figure 4.26: East Wellega Zone Sibu Sire woreda Land use/Land Cover map of 2006

Table 4.8: East Wellega Zone Sibu Sire Woredas Land use/land Cover Classes

Land use/Land covers	*Area (ha)*	*Area (%)*
Agriculture	80482	76.84
Tree Cover	4058	3.87
Grass Land	62	0.06
Rural Houses	485	0.46
Shrubs	18944	18.09
Others	713	0.68
Total woreda Area	104743	

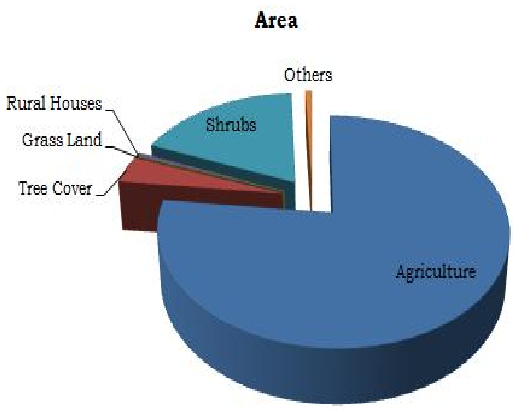

Figure 4.27: Area coverage of the classes in Sibu Sire woreda

- Selected woredas:- Low poverty rate

Figure 4.28, 4.30, figure 4.32 and figure 4.34 shows land use/land cover of North shewa zone Sululta woreda, Jimma zone- Mana, and Limukossa and Gomma woreda. In those Agriculture is dominant by 62, 47 36 and 34 percent respectively. Beside they are characterized by low poverty indices /rates. The results are described in detail by table 4.9, 4.10, 4.11 and 4.12.

In addition to the area extent of the woredas are shown on figure 4.29, 4.31, 4.33 and figure 4.35.

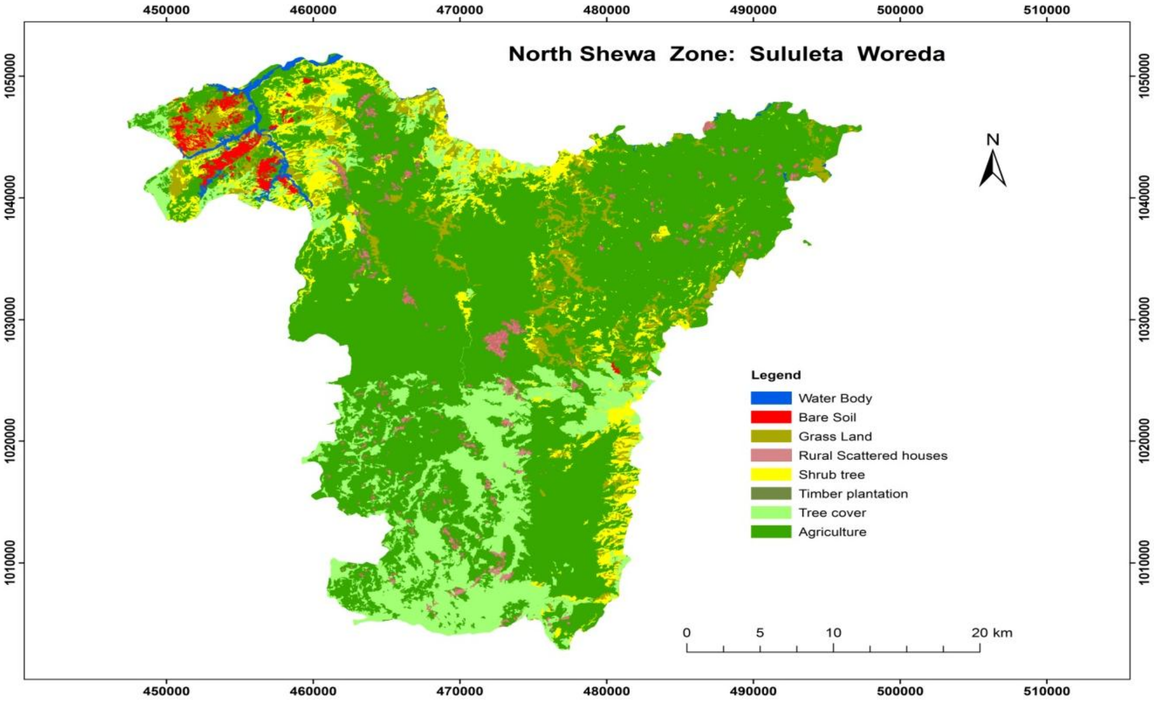

Figure 4.28: North Shewa Zone Sululta woreda Land use/land cover map of 2006

Table 4.9 North Shewa Zone Sululta Woreda Land use/Land Cover Classes

Land use/Land covers	Area (ha)	Area (%)
Agriculture	71242	61.88
Bare Soil	1519	1.32
Grass Land	6371	5.53
Rural Houses	1836	1.59
Shrub tree	9112	7.92
Timber plantation	10	0.01
Tree cover	5090	4.42
Water Body	19709	17.12
others	234	0.20

Total woreda Area 115122

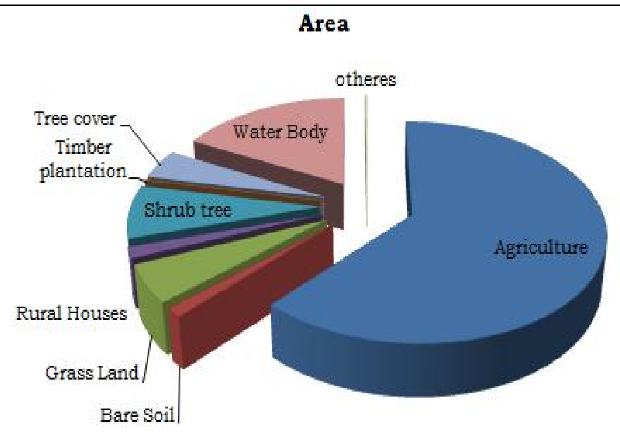

Figure 4.29: Area coverage of the classes in Sululta woreda

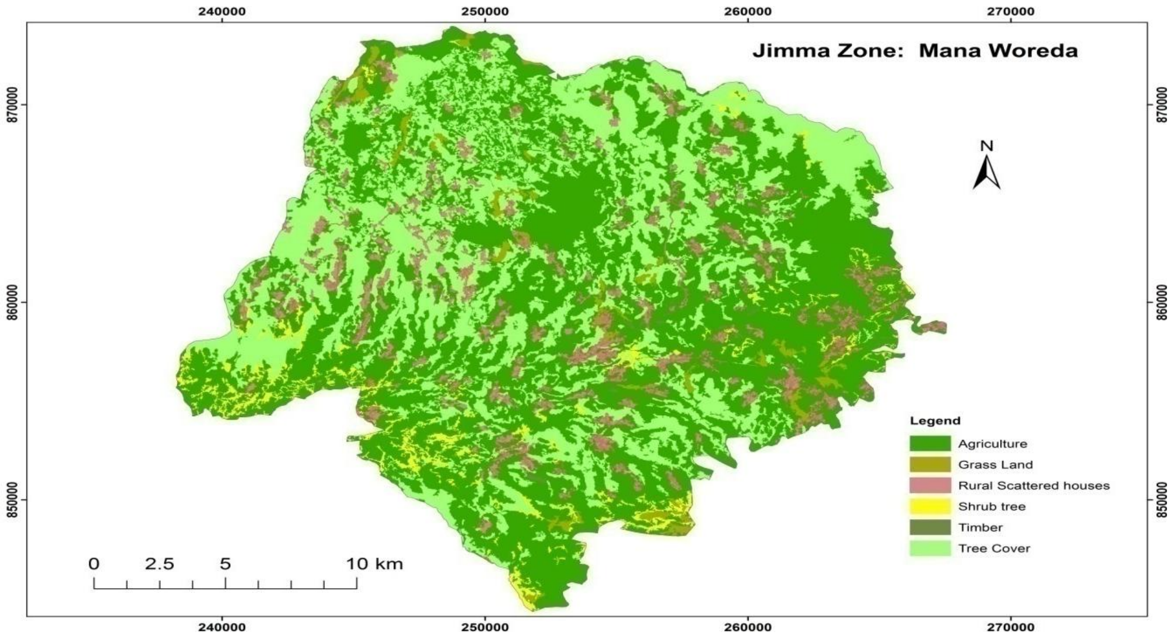

Figure 4.30: Jimma Zone Mana woreda Land use/Land cover map of 2006

Table 4.10: Jimma Zone Mana Woreda Land use/land Cover classes

Land use/Land covers	Area (ha)	Area (%)
Agriculture	23478	47.45
Grass Land	1314	2.66
Rural Houses	3467	7.01
Shrub tree	1801	3.64
Tree Cover	19419	39.25
Total woreda Area	49479	

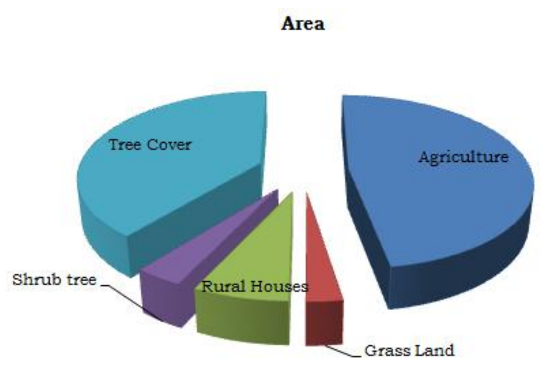

Figure 4.31: Area coverage of the classes in Mana woreda

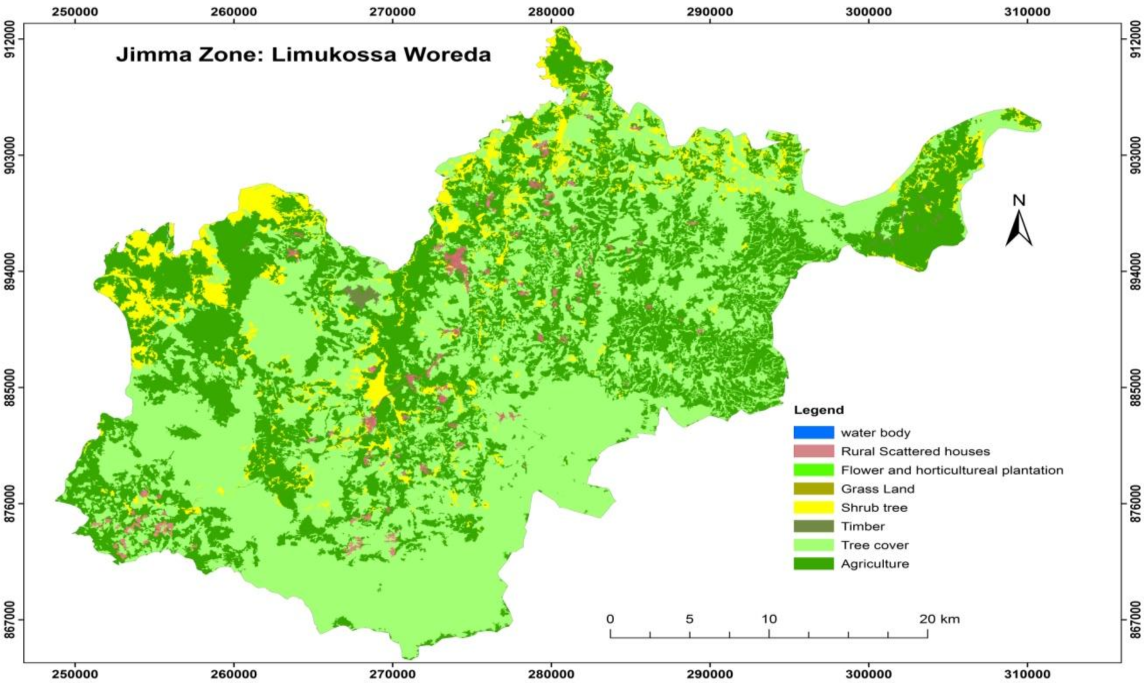

Figure 4.32 Jimma Zone Limukossa woreda Land use/land Cover map 0f 2006

Table 4.11: Jimma Zone Limukossa Woreda Land use/land Cover Classes

Land use/Land covers	Area (ha)	Area (%)
Agriculture	46815	35.57
Flower and horticultural plantation	1.538	0.0012
Grass Land	30	0.02
Rural Houses	1030	0.78
Shrub tree	9634	7.32
Timber plantation	393	0.30
Tree cover	73692	55.99
water body	10	0.01
Total woreda Area	131605	

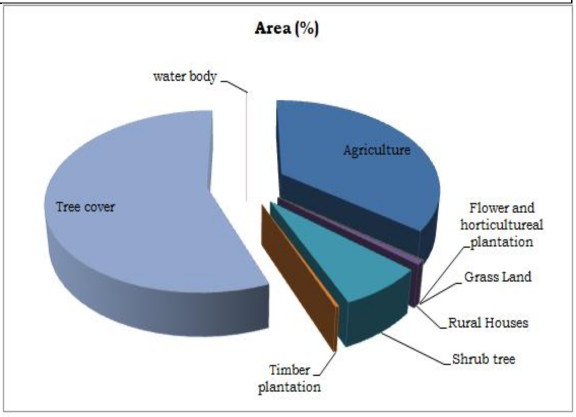

Figure 4.33: Area coverage of the Classes in Limukossa woreda

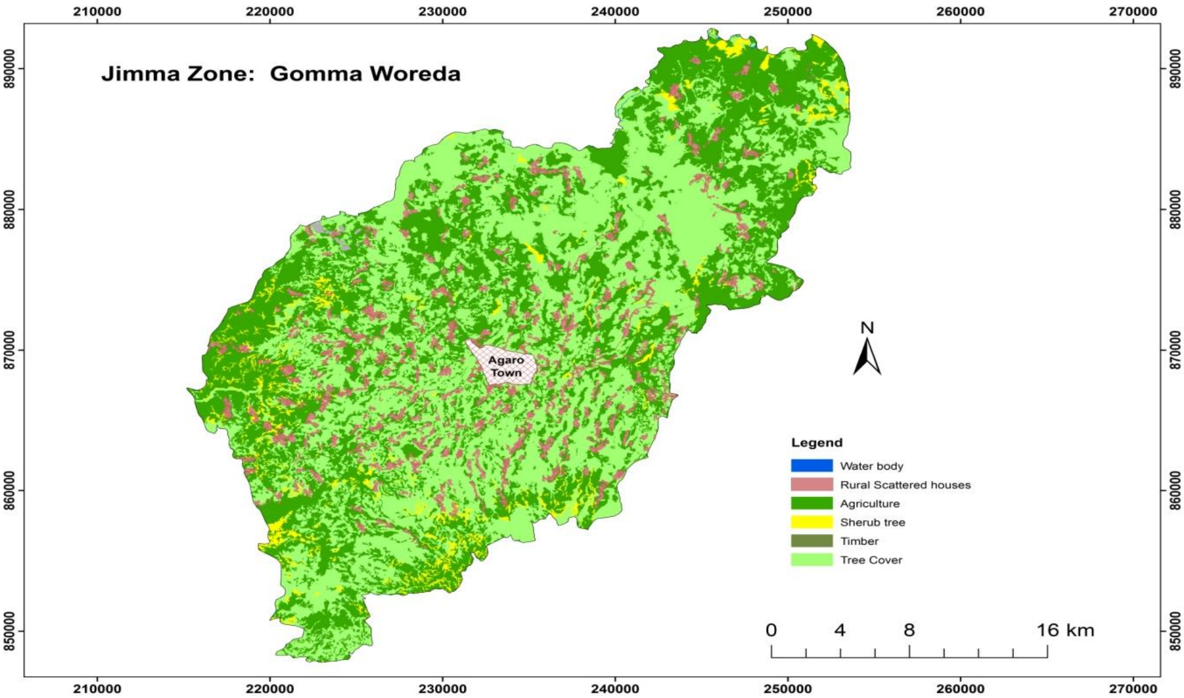

Figure 4.34 Jimma Zone Gomma woreda Land use/Land cover map of 2006

Table 4.12: Jimma Zone Gomma Woreda Land use/land Cover Classes	

Land use/Land covers	*Area (ha)*	*Area (%)*
Agriculture	29747	34.40
Rural Houses	5502	6.36
Shrub tree	2723	3.15
Tree Cover	48474	56.06
Water body	24	0.03
Total woreda Area	86469	

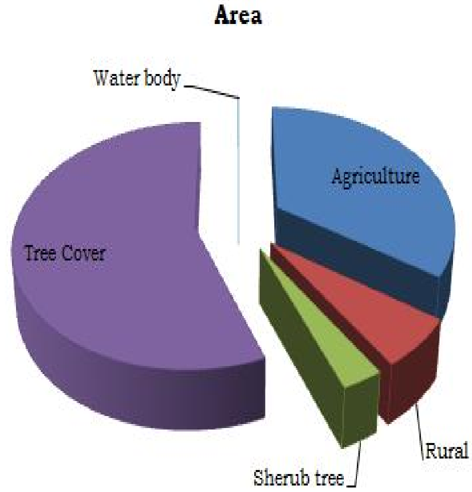

Figure 4.35: Area coverage of the classes in Gomma Woreda

Discussion

Poverty Mapping is the methodology for providing a detailed description of the spatial distribution of poverty and inequality within a country. It combines individual and household (micro) survey data and population (macro) census data with the objective of estimating welfare indicators for specific geographic area as small as village or hamlet. (Fzavidis, Nikos 2010). In different countries' government have indicated that the use of the poverty maps has helped highlight poor areas that had previously gone unnoticed as well as helping to substantiate intervention in areas previously assumed to be poor but for which there was no supporting evidence. The poverty maps provide an easily understandable format and are an important communication tool (one that is easier to interpret than spreadsheets or tabular data) to focus attention on poor groups and to encourage integration of the issue of poverty in policy and program design.

How is poverty maps used?

The most obvious use of a poverty map is to identify areas in a region in which development has been lagging behind. Regional disparities of living standards exist in most countries. Maps that show indicators of well-being can help identify those regions that may benefit most from additional resources, for example through investments in public infrastructure that will improve economic opportunities for the local population. Poor areas may also be selected to receive some form of direct transfer payments, for example in the form of subsidized credit, funds for public works, food-for-work programs, or direct local administrative budget subsidies. (Deichmann, Uwe. January 1999). Beside, poverty mapping has two primary uses:-

The first is spatial identification of the poor, on which this paper concentrates. It has in many instances served to target social, agricultural, emergency and environmental phenomena. Poverty maps have been crossed with environmental and agricultural-system maps in order to use visual spatial analysis to determine correlations.

The second use is to create, as a by-product, explanatory and dependent spatial variables for use in multivariate analysis in combination with recently developed tools that permit the spatial dimension to be incorporated in multivariate examination of poverty issues. (Davis 2003).

In addition to welfare indicators developed from SAE, spatial analysis tools and geographical information systems (GIS) have opened up new possibilities to integrate poverty indicators and their correlates into national- or broad-scale poverty assessments (Deichmann, 1999, Stoorvogel et al., 2004). For example, measures of distance and accessibility are rarely found in censuses but can be derived from maps of facilities, services and the transportation network (Higgs and White, 2000). Numerous efforts have been developed to provide measures of climate variability, topography or soil fertility (Antle, 1996, Jones and Thornton, 1999, CIAT, 2005, Hijmans, et al., 2005).

Location is a powerful determinant of poverty. Spatial patterns of inequality between and within countries have become an important focus of the development community, and research on patterns of poverty and inequality across districts, municipalities, and communities has accelerated over the past decade. With spatial variables increasingly recognized as determinants of poverty (Bedi et al. 2007, Hyman et al. 2005). Poverty maps have become more popular due to many reasons (Henninger and Snel 2002). Also Poverty maps are powerful tools for:-

- Visualizing the location of the poor and in describing their conditions,
- Poverty maps help in identifying priority areas and how to target anti-poverty programs.

- Poverty maps make possible the integration of data from various sources such as surveys and administrative-based data and from different disciplines like social, economic and environmental data. Thus, different dimensions of well being can be examined and integrated.

The role of Geographic Information Systems (GIS) in poverty assessment has increased in importance, particularly as a means of generating explanatory variables and because of its data integration and spatial analysis capabilities.

This research used small area estimation methods. Small area estimation method developed by Elbers et al., 2003.Some studies illustrate the use of the SAE (Small Area Estimation) procedure to calculate a welfare indicator relevant to rural areas and food security concerns. In addition to welfare indicators developed from SAE, spatial analysis tools and geographical information systems (GIS) have opened up new possibilities to integrate poverty indicators and their correlates into national- or broad-scale

poverty assessments (Deichmann, 1999, Stoorvogel et al., 2004). For example, measures of distance and accessibility are rarely found in censuses but can be derived from maps of facilities, services and the transportation network (Higgs and White, 2000). Numerous efforts have been developed to provide measures of climate variability, topography or soil fertility (Antle, 1996, Jones and Thornton, 1999, CIAT, 2005, Hijmans, et al., 2005).

In terms of poverty maps and poverty mapping approaches this paper describes the spatial distribution of poor in maps; the small area estimate methodology approach to poverty mapping. There for in Oromiya region most of the poor's are concentrated on the eastern part of the region. This indicated that factors such as climatic variability, soil characteristics, water availability affect the productivity of land it have a massive impact on the welfare of the population. Fluctuations in these factors contribute to a change in levels of poverty.

According to MOFED 2008, in Ethiopia, growth reduces poverty and thus, as a general rule, policies and interventions that increase growth will reduce poverty. Growth in regions such as Oromiya is especially desirable as this region had the largest number of poor people (9.3 million), accounting for One-third of all Ethiopians living in poverty in 2004/05.

CHAPTER FIVE

5.0 Conclusion and Recommendation

5.1 Conclusion

Poverty mapping is a powerful tool to illustrate the geography of poverty at the small area level; it can help identify pockets of poverty. Its use can be broadened by combining it with other GIS databases such as human development, agriculture, and transportation. Geographical presentation of these development indicators can be valuable for designing and planning poverty alleviation strategies.

Some of the causes of poverty in Ethiopia

Ethiopia is one of the World's poorest countries. Poverty in Ethiopia is more prominent in the rural areas as compared to the urban areas. The situation worsened recently because of sharp increase in the prices of food and fertilizers on world markets, which made it more difficult for poor households in Ethiopia. According to World Bank explanation poverty can occur because of the next factors.

- Arid conditions leading to irregular production in the agriculture sector.
- Improper marketing strategies of agricultural products.
- Degrading ecology
- Technological knowhow being poorly developed.
- Transportation facilities are poorly developed.
- Failure of the rural people in participating in awareness programs meant for them
- Absence of sufficient rainfall
- Shortage of food products owing to several conditions
- Absence of proper socio economic infrastructure. This includes lack of potable water, proper education and health programs.

(.http://finance.mapsofworld.com/economy/ethiopia/poverty.html)

Therefore, beside the above factors the livelihoods of the peoples in the Oromiya region are based on a number of key assets including natural resources such as water and land. In rural area these assets are essential to meet the basic needs of food, water, dignity and general well-being. Various pressures and access considerations are undermining the security of these assets leading to diversification activities which in turn encounter their own challenges.

The variation in poverty at the woreda level shows several interesting geographical patterns. In this thesis to analyze the distribution of poverty indices, by using this method one of these is by using spatial statistics tools; Hotspot analysis. Spatial Statistics and the Hot Spot Analysis tool can help to solve resource allocation problems, including in the field of emergency management and awareness. By using this method I verified the factors that are causes of poverty in Oromiya regions are arid conditions, transportation facilities, Absence of sufficient rainfall, Absence of proper socio economic infrastructure this includes lack of potable water, proper education and health programs are also caused of poverty in Oromiya.

To sum up, as many expected, the western and most of central part of the region are relatively well-off, while most extreme poor areas are located in the Easter part and southern part of the region. Overall the result, there is clear spatial pattern between rural poverty and tap water /clean water/ accessibility, poverty and road, Climate Poverty linkages (poverty and agro-ecology, and poverty and rainfall), Travel Time map and poverty. All indicate that poor area have low infrastructure like road, water accessible and the people spent more time to travel to the nearest city and also the area that poor have not favorable climate condition and less rainfall value.

Land use of the selected woredas was produced after the poverty maps were finalized, because Oromiya is a big region so cannot be processed image with the specific time therefore I selected woreda that have high, medium and low value on poverty head counts. Therefore from the selected woreda most of the woredas who has very high poverty indices are found in the eastern part of the region. Whereas the woredas who have less poverty level but they are the area which has more productive area therefore it needs further research.

Therefore, for the requirements of Government planners, policy makers and implementers, the poverty maps were intended to meet the following objectives:

- To develop maps useful for locating the poor, identifying their characteristics or describing their conditions.
- To review the available poverty measures in the Oromiya Region.
- To explore the role of poverty maps in the context of interventions for poverty reduction.

5.2 Recommendation

Recommendation has been set based on the observations and findings. It is recommended that the government and other actors implement sustainable and effective intervention measures such as the following:

- To counteract the soil and poverty, Gender and Poverty, Electrification and Poverty, Access to Education and Poverty, Poverty and Market Accessibility, poverty and land use in Rural Areas in the Oromiya region.
- Such factors call for additional studies climate change and its variability have extreme consequences that affect poor people vulnerable communities who have limited options for adaption, therefore it must be need further counteract with climate change and poverty mapping.
- The national or regional government should aim to address the underlying drivers of vulnerability. This means implementing poverty reduction and development policies that: promote people in rural area's livelihoods; enhance access to vital infrastructure, resources and services in rural areas; enhance the security of living standard of the peoples; restore and protect the environment agricultural lands; create more efficient markets and help control population growth.
- In order to build capacity, access to resources must be improved and in order to build their assets need to be better secured living standards.

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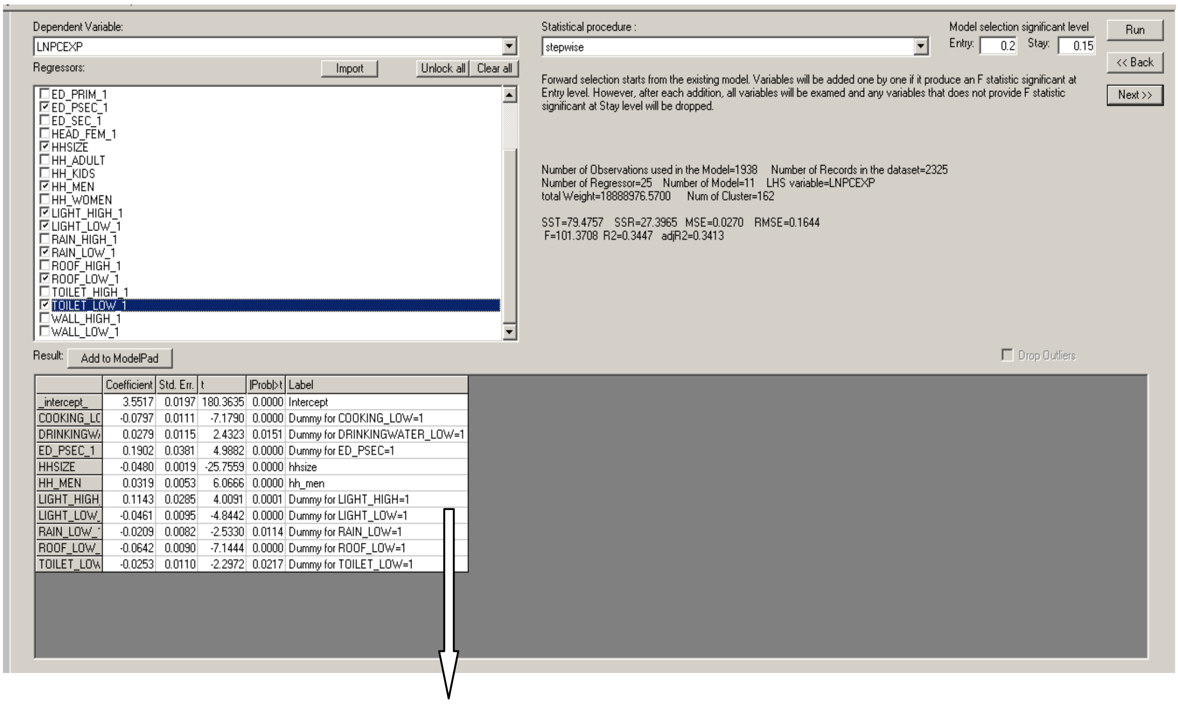
ANNEX

Annex 1. Consumption model

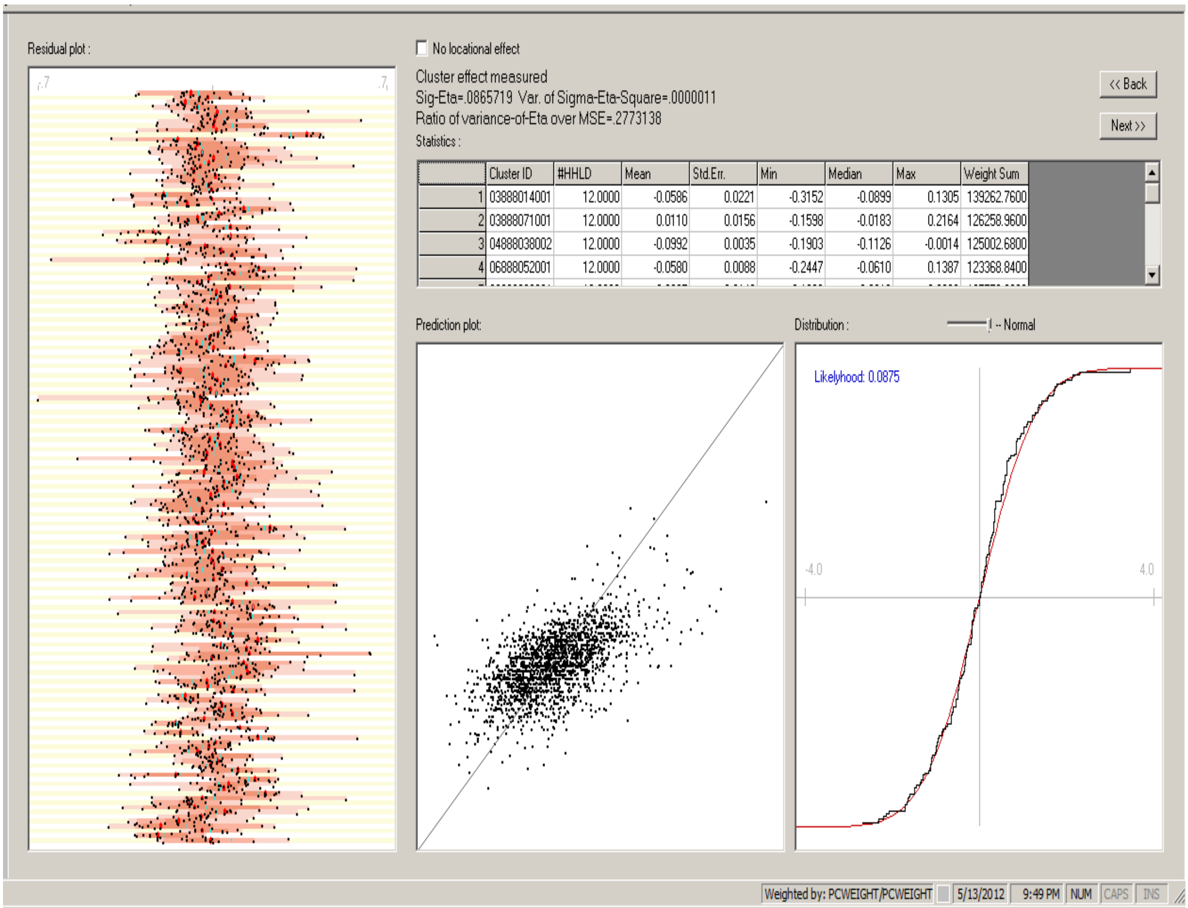


	Coefficient	Std. Err.	t	|Prob|>t	Label
intercept	3.5517	0.0197	180.3635	0.0000	Intercept
COOKING_LC	-0.0797	0.0111	-7.1790	0.0000	Dummy for COOKING_LOW=1
DRINKINGW/	0.0279	0.0115	2.4323	0.0151	Dummy for DRINKINGWATER_LOW=1
ED_PSEC_1	0.1902	0.0381	4.9882	0.0000	Dummy for ED_PSEC=1
HHSIZE	-0.0480	0.0019	-25.7559	0.0000	hhsize
HH_MEN	0.0319	0.0053	6.0666	0.0000	hh_men
LIGHT_HIGH	0.1143	0.0285	4.0091	0.0001	Dummy for LIGHT_HIGH=1
LIGHT_LOW_	-0.0461	0.0095	-4.8442	0.0000	Dummy for LIGHT_LOW=1
RAIN_LOW_	-0.0209	0.0082	-2.5330	0.0114	Dummy for RAIN_LOW=1
ROOF_LOW_	-0.0642	0.0090	-7.1444	0.0000	Dummy for ROOF_LOW=1
TOILET_LOW	-0.0253	0.0110	-2.2972	0.0217	Dummy for TOILET_LOW=1

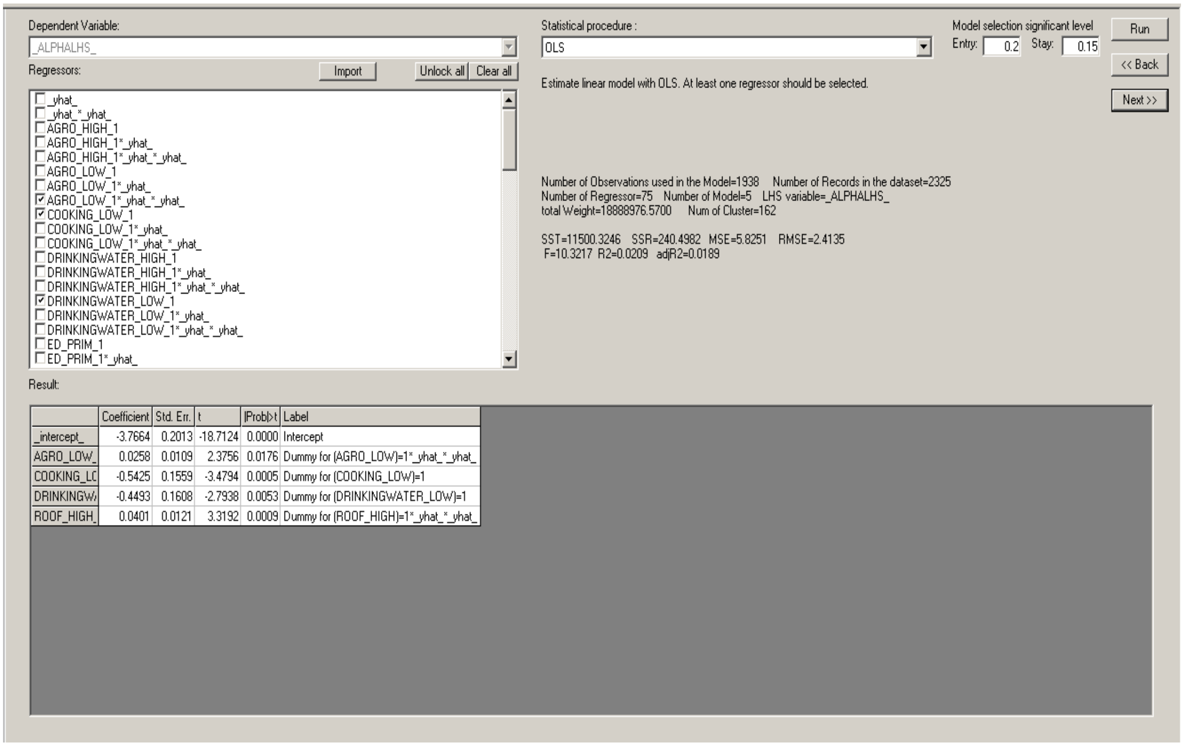
ANNEX 1. Tables -1 consumption model result

	β
Household Characteristics	
Household Size	-0.048
Number of men in household	0.032
Head education - post secondary	0.190
Housing Characteristics	
Roof - low quality	-0.064
Toilet facility - low quality	-0.025
Lighting source - high quality	0.114
LIghting source - low quality	-0.046
Cooking fuel - low quality	-0.080
Drinking water - low quality	-0.028
Weather	
Annual rainfall - below average	-0.021
R-squared	0.35

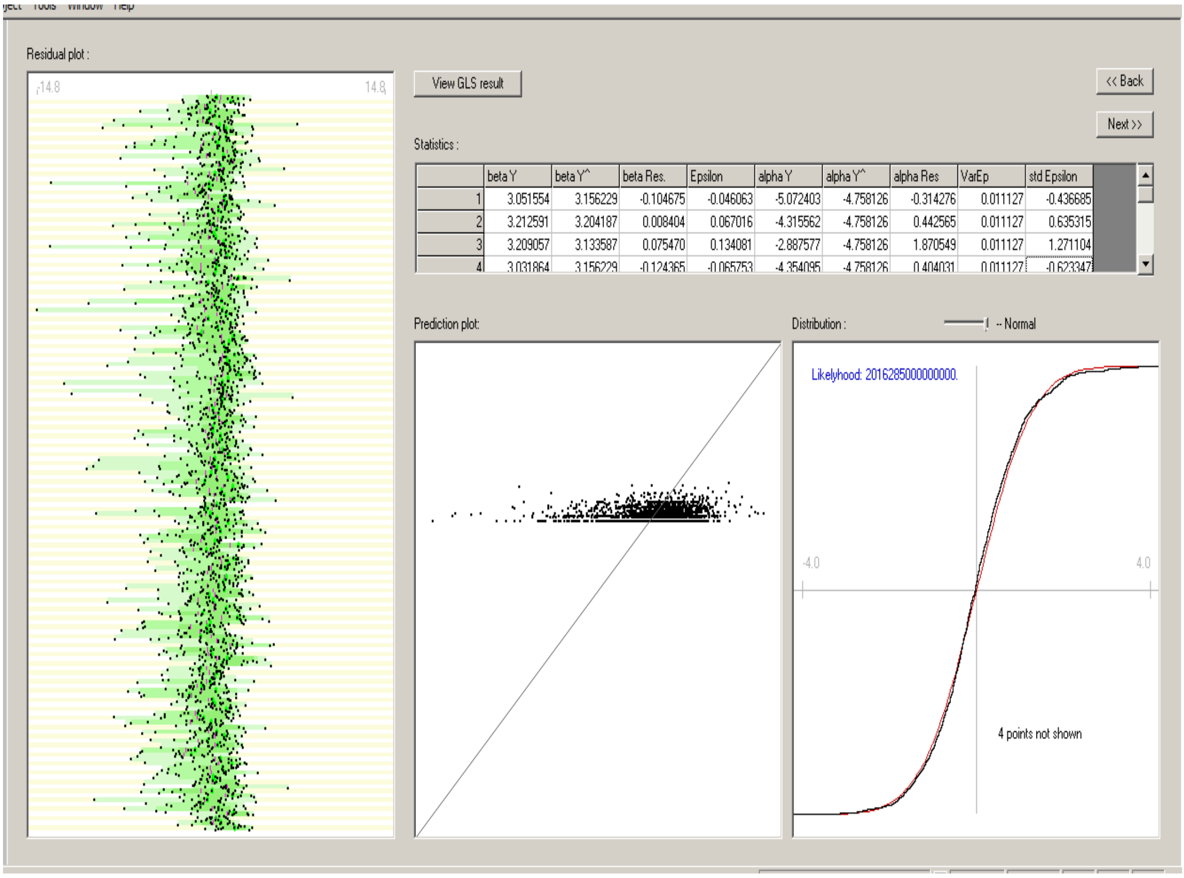
Annex 2. Cluster effect



Annex 3. Idiosyncratic model



Annex 4. Household effect



Annex 5 Tables -2 Mean Per Capita Expenditure and Poverty Estimates

Woreda code	Population	Min_Y	Max_Y	Mean	StdErr	avg_FGT0
40101	126,083	13.3942	67.6361	24.3776	0.49975	0.3353615
40102	130,909	13.3673	68.8718	24.798	0.5217	0.2882231
40103	74,623	13.3737	72.927	25.4349	0.56139	0.2506588
40104	75,584	13.4401	69.5124	25.4779	0.58929	0.2379291
40105	51,800	13.549	70.428	24.6335	0.54609	0.2988181
40106	42,813	13.3753	65.9644	24.9745	0.5935	0.2750656
40107	69,856	13.3956	68.8318	25.3979	0.5646	0.2582679
40108	48,561	13.4353	57.5876	24.302	0.47646	0.3197218
40109	96,253	13.3709	63.3943	24.0065	0.50946	0.3620694
40110	48,871	13.3721	64.1395	25.1988	0.61171	0.2772459
40111	60,513	13.3835	70.8966	24.1559	0.48962	0.350234
40112	38,858	13.3759	72.8732	24.749	0.53993	0.3027372
40113	59,793	13.3924	74.6765	25.575	0.61577	0.2469313
40114	67,262	13.3985	71.7178	25.2176	0.54018	0.2649588
40115	59,826	13.392	68.2113	24.5444	0.616	0.310362
40116	119,722	13.3695	73.6535	24.4184	0.50702	0.3298963
40118	76,013	13.3706	71.6462	24.7706	0.50746	0.3095387
40119	24,557	13.4145	73.2868	25.8527	0.70946	0.2268227
40120	47,537	13.5195	74.1746	25.2648	0.58031	0.2682727
40201	72,483	13.3773	69.1182	24.3432	0.5403	0.3256299
40202	36,280	13.3774	62.2596	23.6935	0.6181	0.3948701
40203	158,635	13.3709	74.6789	24.363	0.51867	0.3376348
40204	52,163	13.3676	70.6023	24.1511	0.52655	0.3590081
40205	47,886	13.3678	62.7924	24.2372	0.51138	0.3221644
40206	63,180	13.4346	66.0748	24.452	0.52189	0.3126833
40207	54,744	13.4224	64.6821	24.7232	0.55309	0.3102899
40208	41,012	13.4001	71.7998	24.2906	0.62962	0.3315366
40209	102,228	13.4304	71.1619	23.986	0.50403	0.3551365
40210	66,689	13.3733	74.6706	24.4791	0.52814	0.320039
40211	80,814	13.3935	67.132	24.4295	0.52416	0.3310689
40212	72,057	13.3692	71.2191	24.3006	0.54784	0.3394554
40213	89,906	13.374	73.5522	24.3671	0.53362	0.3272909
40214	86,329	13.3779	74.7303	24.2052	0.53812	0.3447888
40215	64,775	13.4483	63.6806	24.0945	0.55061	0.3396987
40216	49,103	13.3842	65.0579	24.1645	0.56345	0.3435398
40301	145,070	13.3714	71.9926	24.5486	0.48888	0.3228918
40302	76,611	13.4141	73.3711	24.4031	0.53233	0.3263402
40303	100,506	13.3671	73.3392	24.3102	0.55293	0.3318086
40304	39,466	13.4219	66.3758	24.1174	0.58896	0.3443723

Woreda code	Population	Min_Y	Max_Y	Mean	StdErr	avg_FGT0
40305	41,285	13.3788	62.3185	24.072	0.56502	0.3626266
40306	70,478	13.3691	70.2403	24.1332	0.57212	0.3536339
40307	73,708	13.3871	73.5646	23.8573	0.50356	0.3695333
40308	84,929	13.3891	65.6212	24.2268	0.53284	0.3321525
40309	52,851	13.3719	74.1785	25.0644	0.5698	0.2839748
40310	61,954	13.3852	72.8846	25.4461	0.55995	0.2443156
40311	64,266	13.4024	70.0889	24.6974	0.57186	0.3074975
40312	50,841	13.3726	66.5817	24.4188	0.53996	0.3264262
40313	22,902	13.3737	63.9664	24.4511	0.64715	0.3325497
40314	24,947	13.4501	58.9285	24.632	0.65719	0.2965644
40315	28,810	13.4201	65.1329	25.2296	0.61947	0.2663625
40316	42,667	13.4405	64.8586	25.3633	0.63843	0.2624514
40317	32,639	13.3707	64.872	23.7406	0.57984	0.3743491
40318	22,001	13.541	62.3171	24.0228	0.6323	0.3583555
40319	16,881	13.3708	69.0624	24.496	0.64129	0.3177851
40322	77,687	13.3757	71.7812	24.2577	0.53644	0.3409971
40323	56,106	13.373	74.5888	23.8381	0.54861	0.3773026
40324	36,705	13.4012	69.6703	24.5095	0.59391	0.3319725
40401	189,463	13.3751	73.1837	23.9043	0.45721	0.3571625
40402	161,338	13.3744	68.3407	24.9095	0.48648	0.2750872
40403	136,320	13.38	74.0402	24.3782	0.46177	0.3273039
40404	131,536	13.3791	63.2515	23.9551	0.50341	0.3484495
40405	165,391	13.3732	64.6598	24.1303	0.51069	0.3353812
40406	146,675	13.3898	67.9166	25.2461	0.53327	0.2553216
40407	213,023	13.3757	74.4868	25.911	0.53871	0.2312465
40408	112,395	13.4717	67.4279	24.0261	0.50717	0.3471857
40409	208,096	13.3839	63.4093	24.2977	0.51442	0.3184367
40410	288,457	13.3772	67.5389	24.3388	0.46697	0.3179602
40411	248,173	13.3732	67.1999	23.9653	0.47604	0.3497505
40412	92,313	13.3673	69.3377	23.4277	0.51963	0.4054368
40413	103,221	13.3818	60.1789	23.5128	0.47833	0.3955084
40414	112,068	13.4326	68.0257	24.4093	0.49545	0.3114033
40415	91,738	13.3951	66.436	24.0943	0.53422	0.3430647
40416	60,490	13.3925	71.3407	24.7199	0.55402	0.3087553
40501	104,595	13.3728	69.0373	24.7143	0.5197	0.310554
40502	202,716	13.3702	72.3048	24.4667	0.46509	0.3225364
40503	108,406	13.3676	74.5153	24.579	0.49377	0.3163225
40504	79,580	13.3699	63.8557	24.6248	0.52433	0.3011442
40505	156,962	13.3703	66.4944	24.3269	0.49061	0.3166213
40506	123,031	13.3936	70.1364	24.7321	0.5425	0.2867181
40507	97,243	13.3845	70.1989	23.9747	0.4751	0.359129

Woreda code	Population	Min_Y	Max_Y	Mean	StdErr	avg_FGT0
40508	84,248	13.4538	69.4374	23.9473	0.52632	0.3532926
40509	71,417	13.3805	70.2345	24.2983	0.52964	0.322517
40510	165,803	13.3756	72.249	24.322	0.4986	0.3200376
40511	86,934	13.4328	69.5307	24.6401	0.52901	0.2957818
40512	83,823	13.383	74.4935	24.8296	0.56619	0.2891223
40513	120,654	13.4686	70.8992	24.1976	0.48571	0.3312931
40514	140,627	13.3726	71.3812	24.4451	0.45466	0.3299805
40516	109,275	13.3674	68.6494	24.6533	0.53019	0.3179393
40517	119,999	13.3798	62.4279	24.6451	0.50283	0.2967394
40518	72,210	13.4387	62.2671	24.2354	0.51817	0.3269752
40519	57,389	13.3671	68.317	24.2581	0.58124	0.3391141
40520	25,593	14.2603	59.5481	25.8648	1.29106	0.2283366
40601	141,426	13.3707	73.1598	23.4559	0.40967	0.4117276
40602	181,217	13.3669	69.2331	23.4379	0.40314	0.4103352
40603	82,994	13.3754	65.706	23.3707	0.41794	0.4124659
40604	121,052	13.3722	71.5711	23.3425	0.43191	0.4211682
40605	99,143	13.3757	73.006	23.7022	0.42283	0.3759817
40606	67,312	13.3708	65.1417	24.3146	0.45918	0.3440574
40607	45,179	13.3697	60.5396	24.3705	0.50269	0.3300504
40608	97,529	13.3833	73.3879	24.1624	0.4343	0.3432691
40609	74,376	13.367	70.4973	23.9493	0.39807	0.3606194
40610	74,276	13.3743	68.9208	24.2474	0.38516	0.3387854
40611	80,808	13.3835	72.6921	24.4049	0.46261	0.3320288
40612	129,000	13.3751	71.1753	25.0647	0.51192	0.2754866
40614	54,992	13.379	70.0506	24.0144	0.49448	0.3512067
40615	53,658	13.3996	70.288	23.9504	0.4781	0.3606503
40616	35,138	13.4185	74.7373	24.1959	0.64253	0.3299587
40617	53,414	13.3801	71.6663	24.2882	0.44066	0.3344185
40701	81,740	13.3802	74.1848	25.6094	0.50964	0.308197
40702	142,112	13.3801	68.4792	23.8462	0.42494	0.3805508
40703	155,349	13.3686	73.5238	24.9732	0.45051	0.3129834
40704	117,080	13.381	69.4056	24.7443	0.43931	0.3041167
40705	86,902	13.3808	74.0811	24.6699	0.43676	0.3068203
40706	130,321	13.368	73.7479	24.8621	0.41806	0.3089096
40707	144,910	13.3732	67.0567	23.4517	0.4035	0.4078688
40708	141,405	13.3685	69.484	23.179	0.41471	0.434974
40710	58,748	13.3771	64.7498	23.3421	0.46864	0.4165117
40711	76,351	13.372	72.6111	23.5369	0.38751	0.3968038
40712	77,836	13.3728	74.4125	24.5942	0.44938	0.324235
40801	90,408	13.3672	74.1678	23.7247	0.44159	0.4053873
40802	84,112	13.3697	62.3986	23.2867	0.43	0.4324782

Woreda code	Population	Min_Y	Max_Y	Mean	StdErr	avg_FGT0
40803	172,176	13.3679	61.9198	23.2482	0.41475	0.4286625
40804	124,093	13.3736	74.1138	23.4371	0.4217	0.423106
40805	64,310	13.3946	71.4179	23.3983	0.4789	0.428024
40806	120,862	13.3669	73.4288	23.014	0.38889	0.4517806
40807	124,219	13.3699	72.5745	23.859	0.46384	0.3859218
40808	147,764	13.3789	62.4622	23.2705	0.40046	0.4219188
40809	89,291	13.37	63.7636	23.4136	0.464	0.4044677
40810	73,245	13.3681	62.0967	23.4506	0.41732	0.4082957
40811	47,929	13.3716	51.7959	22.666	0.45341	0.4855367
40812	165,210	13.3728	71.2883	23.4286	0.37703	0.4050359
40813	66,203	13.3767	68.1192	23.2445	0.48741	0.4278108
40814	163,823	13.3685	64.0115	23.1768	0.38421	0.4305319
40815	140,466	13.3691	65.732	24.1963	0.41764	0.3337656
40816	86,761	13.369	70.6603	24.3121	0.46246	0.3353195
40817	166,539	13.3902	63.8746	23.531	0.422	0.3905585
40818	180,695	13.3702	69.4245	23.789	0.40515	0.3716104
40819	76,365	13.3806	64.8515	23.2523	0.43767	0.4251164
40820	73,970	13.3685	74.463	23.9496	0.41998	0.3787315
40821	107,133	13.372	66.7822	23.7605	0.39667	0.3834353
40822	72,301	13.3703	61.6773	23.0672	0.41938	0.4382213
40823	73,952	13.3758	62.3732	23.3341	0.4329	0.4149124
40824	58,561	13.3803	55.7911	23.499	0.46956	0.3915731
40901	130,709	13.3737	73.1609	22.6468	0.40023	0.4902033
40902	133,939	13.3676	71.9976	24.0888	0.46252	0.3567761
40903	147,384	13.3837	71.4728	24.3581	0.46637	0.3219647
40904	151,698	13.3737	69.5078	23.8075	0.49082	0.3694746
40906	81,646	13.3748	73.5416	22.7807	0.46262	0.4809477
40907	122,335	13.369	69.8312	22.551	0.40585	0.5048994
40908	190,455	13.3765	66.6546	23.2275	0.39185	0.4297669
40909	198,095	13.3735	70.8895	22.735	0.3961	0.4802898
40910	151,156	13.3673	68.3156	23.1071	0.40169	0.4367052
40911	158,282	13.3855	66.4133	23.441	0.42367	0.4072388
40912	184,238	13.3748	66.6157	23.1453	0.39103	0.4360394
40913	169,912	13.3684	68.451	24.1294	0.49415	0.359594
41001	140,080	13.3684	67.7875	24.3794	0.43295	0.3376156
41002	116,638	13.3711	58.6329	23.6221	0.41814	0.389339
41003	151,931	13.3673	68.0895	23.3624	0.44247	0.4193003
41004	93,708	13.374	74.4483	23.4879	0.45164	0.4160135
41005	113,108	13.3721	68.6277	23.4755	0.41402	0.3983862
41006	271,018	13.3702	74.1032	24.8303	0.45426	0.3026457
41007	58,701	13.3715	64.2189	23.6947	0.497	0.3933879

Woreda code	Population	Min_Y	Max_Y	Mean	StdErr	avg_FGT0
41008	170,816	13.3685	70.8953	24.3917	0.41712	0.3281261
41009	252,269	13.3672	71.8596	24.0636	0.39366	0.3635408
41010	143,931	13.3704	72.6599	23.6503	0.40908	0.4028253
41011	242,140	13.377	74.27	23.9078	0.44298	0.3648071
41012	177,416	13.3692	72.7614	23.2878	0.41922	0.4239814
41013	238,966	13.377	71.4018	23.561	0.42265	0.3987869
41014	75,242	13.3718	62.9169	23.2212	0.42976	0.4246238
41015	87,063	13.3803	68.098	23.2428	0.47847	0.4282034
41016	240,173	13.3672	61.9708	23.3902	0.39318	0.4080605
41017	104,440	13.3669	67.1108	22.646	0.41322	0.4946033
41018	46,210	13.375	63.625	22.7927	0.50983	0.4778935
41104	102,110	13.3832	71.7178	23.2759	0.44109	0.4316564
41105	100,809	13.3683	58.1545	22.9011	0.42946	0.463709
41106	78,220	13.3713	74.3231	23.3343	0.43423	0.4289159
41107	62,521	13.3712	61.3882	22.5117	0.46988	0.5048815
41108	139,495	13.3669	74.1662	23.4101	0.40387	0.4184035
41109	118,594	13.3851	74.2869	24.0935	0.40429	0.3601517
41110	40,757	13.4988	53.2166	23.6652	0.49325	0.378003
41111	81,497	13.3677	62.7163	22.1529	0.46218	0.5450537
41112	89,670	13.3772	71.1405	22.755	0.41367	0.4881072
41113	97,532	13.3699	65.0964	22.2455	0.46676	0.5326608
41114	90,642	13.3971	74.7627	22.9238	0.41184	0.4589178
41115	28,961	13.379	57.2959	22.3184	0.51687	0.5227183
41116	83,106	13.3729	71.7765	23.6323	0.40385	0.3957221
41117	33,169	13.3682	55.5079	22.3792	0.51504	0.5178538
41118	65,846	13.3848	52.5335	22.4162	0.42411	0.5173995
41121	30,849	13.4092	57.4043	22.9669	0.50884	0.453308
41122	39,124	13.4107	70.2826	23.4236	0.50597	0.4076074
41123	0	13.3744	59.8411	22.3485	0.55062	0.5191545
41206	264,489	13.3762	71.8965	22.8962	0.40534	0.4640685
41207	102,165	13.3703	65.4059	22.4202	0.41636	0.5153823
41208	48,126	13.3711	53.6403	22.4009	0.55098	0.5158025
41210	31,162	13.3752	74.5479	22.8471	0.43481	0.4758624
41211	73,401	13.3691	74.3468	22.8956	0.43414	0.4663584
41212	70,501	13.3746	52.6981	22.5682	0.43575	0.4991031
41213	103,348	13.3771	70.2832	23.4335	0.38955	0.4121064
41215	147,327	13.3711	67.2321	22.0924	0.39113	0.553624
41216	50,601	13.3689	71.0504	22.9583	0.44967	0.4559779
41217	71,369	13.3693	60.3372	22.9534	0.38873	0.4606672
41301	122,056	13.376	71.1845	24.3587	0.49934	0.3136924
41302	93,624	13.4206	72.9249	24.5722	0.52596	0.2980765

Woreda code	Population	Min_Y	Max_Y	Mean	StdErr	avg_FGT0
41303	143,391	13.3762	74.3651	24.1078	0.49666	0.3343559
41304	84,336	13.3789	69.2938	23.9097	0.47966	0.3466308
41305	61,985	13.4482	67.5844	24.1794	0.49481	0.3257802
41306	132,294	13.3672	74.026	24.7058	0.47291	0.3158346
41307	81,015	13.401	72.8655	23.9608	0.56094	0.346683
41308	62,895	13.4165	59.5607	23.9984	0.55917	0.3423992
41309	74,016	13.3844	57.9338	23.8678	0.54473	0.3571498
41310	69,215	13.3939	60.7618	23.802	0.53664	0.3608267
41312	45,486	13.4165	60.6963	23.9477	0.57518	0.3435504
41313	43,607	13.3837	51.7565	23.275	0.44273	0.4157006
41401	176,238	13.3674	59.2005	22.8452	0.40142	0.4651738
41402	210,179	13.3765	73.1405	22.6625	0.37484	0.4848405
41403	110,034	13.3686	72.4423	22.6026	0.44865	0.4965371
41404	50,554	13.3746	58.1083	22.4346	0.46443	0.5174095
41405	206,372	13.3687	68.4791	22.6015	0.4029	0.498019
41406	227,362	13.3681	60.8026	23.4067	0.38809	0.4098718
41407	138,813	13.3682	70.4127	22.249	0.3934	0.535518
41408	56,896	13.3817	66.3462	23.2861	0.5354	0.4132695
41409	104,971	13.3896	57.7212	22.9006	0.42428	0.4610494
41410	50,179	13.3775	63.5458	22.2245	0.44493	0.5357058
41701	145,649	13.3819	72.3955	23.7086	0.45782	0.3706041
41702	149,804	13.3682	64.2583	23.5128	0.48005	0.401073
41703	260,129	13.3717	68.7025	23.9349	0.49487	0.3650517
41704	178,950	13.372	60.5135	23.7437	0.4708	0.3676103
41705	103,734	13.3758	73.1161	24.0793	0.49304	0.3389264
41706	186,907	13.368	73.243	23.9598	0.35004	0.3629939
41707	193,812	13.3816	63.1321	23.0312	0.38487	0.4468779
41708	144,549	13.3889	70.7032	23.5109	0.46426	0.3886647
41709	114,559	13.3735	64.7541	22.8025	0.44125	0.4738573
41710	138,717	13.3722	69.6865	23.256	0.3872	0.434426
41712	246,774	13.3696	74.6396	23.9565	0.50253	0.3693023
41801	95,976	13.3889	73.6099	24.9186	0.47914	0.2985041
41802	51,392	13.4359	62.1552	24.3135	0.52848	0.326284
41803	104,387	13.3721	66.2181	24.7286	0.52179	0.2889039
41804	65,396	13.3795	67.6046	24.4279	0.52463	0.3331542
41805	116,631	13.3754	66.6173	25.8456	0.53006	0.2183112
41807	77,156	13.3932	74.6778	26.2243	0.60669	0.2163913
41808	74,039	13.3851	72.357	24.7293	0.56	0.3012468
41809	85,904	13.4227	69.9246	25.2604	0.57267	0.2563726
41810	45,889	13.3818	71.2541	24.8932	0.60371	0.2991489
41811	51,448	13.3836	63.5329	24.4185	0.55814	0.310814

Woreda code	Population	Min_Y	Max_Y	Mean	StdErr	avg_FGT0
41901	74,989	13.4321	69.3721	24.744	0.54313	0.2889913
41903	98,084	13.3817	70.6262	25.2729	0.55312	0.2572808
41904	45,325	13.4118	72.3628	24.9791	0.55468	0.2682124
41905	48,316	13.4507	74.3415	26.8447	0.68469	0.2037622
41906	64,158	13.3693	63.5317	24.6843	0.52081	0.2942419
41907	55,580	13.3686	64.1805	24.8465	0.57181	0.2802625
41908	48,943	13.4026	58.865	24.6106	0.58528	0.3037779
41909	52,633	13.3759	68.6903	23.9263	0.47384	0.3764768
41910	67,017	13.385	74.4101	24.6949	0.53821	0.3101928
42001	63,889	13.4508	70.3174	27.4635	1.05856	0.1450539

Where: -

- Min_Y – the minimum of estimated y of all replications in that aggregation group.
- Max_Y- the maximum of estimated y of all replications in that aggregation group
- Mean – average of mean value of estimated y of all replications
- StdErr – average of standard error of estimated yavg_FGT0- average poverty indices