Land Degradation's Implications on Agricultural Value of Production in Ethiopia: A look inside the bowl

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Abstract: This paper estimates the effect of land degradation on the value of agricultural production in Ethiopia. While land degradation is widely recognized as reducing agricultural potential, few studies have explicitly measured its effects on the value of production. Ethiopia is particularly vulnerable to the effects of land degradation with one of the highest rates of soil erosion in Africa. This study integrates a fine resolution environmental map with a geographically coded plot level farmer survey (n=6,301) to compare farm characteristics, production and an index of land degradation that captures soil, water and ecological quality. Because land degradation may be endogenous to agricultural production choices, unlike much previous work, this analysis explicitly controls for this potential endogeneity using bequest and cooking energy as instrumental variables. To further improve the efficiency of the estimates, we account for the spatial nature of the land degradation process. After controlling for endogeneity and allowing for farmer adaptation, we find that land degradation reduces agricultural value by 7 percent. This value is significantly smaller than the estimate when endogeneity is not accounted for. Finally, the estimates from the regression were used to generate a vulnerability map. By identifying those regions or sectors of Ethiopia most at risk of losing agricultural value from land degradation, this paper provides important information to policy makers to target soil conservation measures.

Key words: land degradation, instrumental variables, spatial patterns of land degradation

1 Introduction

Land degradation has significant costs, particularly in developing countries (Rosegrant and Ringler, 1997).[1] It not only reduces farm productivity affecting livelihood and regional economies, it also leads to reduced biodiversity and stream sedimentation affecting water quality, storage and marine resources. Land degradation in most developing countries is becoming a major constraint to future growth and development (Raina, Joshi and Kolarkar, 1991; Reddy 2003). About 40-75% of the world's agricultural land's productivity is reduced due to land degradation (IFPRI, 2000).

Ethiopia is reported to have the highest rates of soil nutrient depletion in sub-Saharan Africa, with soil erosion estimated to average 42 tons per hectare per year on cultivated land (Stoorvogel and Smaling, 1990; Pender, Gebremehedhin, Benin and Ehui, 2001). This land degradation has many causes. Ethiopia has a long history of drought, which greatly contributed to land degradation. The Antsokia Valley of the Northern Shewa in the highlands was called the "dust bowl" in 1984. And past studies have shown that the frequency and spatial coverage of droughts have increased over the past few decades (Lautze et al, 2003). In addition to this, the combined effects of deforestation, overgrazing, expansion of cropland and unsustainable use of natural resources has contributed to land degradation (Descheemaeker, Raes, Nyssen, Poesse, Muys, Haile and Deckers, 2011). These soil-depleting activities have been exacerbated by the historical and changing patterns of land ownership relating to ethnic groups (Berry (2009). The frequent redistribution of land leads to tenure insecurity thereby reducing the incentive to engage

[1] According to Scherr and Yadav (1996), "land" includes not only the soil resource, but also water, vegetation, landscape, biodiversity and microclimatic components of an ecosystem. Global Land Degradation Information System (GLADIS), developed by Food, Agriculture Organization (FAO) in 2010, measures land degradation as the overall processes of defining ecosystem services relating to biomass, soil, water, biodiversity and vegetation, and thermal regime aspects. Scherr and Yadav (1996) define land degradation as a decline in the productive capacity of the land or its potential for producing environmental services.

in land conservation practices. Other studies have shown that land degradation is affected by the use of firewood and animal dung for household energy sources (Gebreegziabher et al., 2006). The use of fuel wood stoves has led to deforestation, and dung and crop residues stoves remove these sources of soil fertility and maintenance from the soil.

The cost of loss of soil and essential nutrients due to unsustainable management in Ethiopia is estimated to be about $139 million annually (Bojo and Cossells, 1995; Suttclife, 1993; Berry, 2009)). Berry (2009) stressed that this cost is about 3-4% of the agricultural GDP but where 85% of the rapidly growing population depends on agriculture; even this small percentage is critical. Dreschel and Gyiele (1999) estimated a range of losses through soil degradation using nutrients studies in areas of high and low nutrient loss. The total loss per hectare in areas of low soil nutrient loss is about 400 birr (46$) and 4,736 birr ($544) per hectare in areas of high soil nutrient loss or about 10-11% of the agricultural GDP. On the other hand, Sonneveld (2002) simulated several scenarios for the potential production from agricultural land in Ethiopia. Sonneveld found that the loss of agricultural value due to land degradation between 2000-2010 is about $7 billion (or increased by about 12.62%). These previous studies relied on crop simulations with very limited data on farm and farming practices and only measured the direct costs of soil erosion on yield. Moreover, the wide range of estimates reflects substantial uncertainty of the impact of land degradation on agricultural production. Nevertheless, these studies illustrate the magnitude of the problem (Berry, 2009).

Attempts have been made to analyze the vulnerability of Ethiopian farmers to environmental shocks in studies using panel datasets. Panel data sets is characterized by sequential observations for the same sample, thus, usually give the researcher a large number of data points, increasing the degrees of freedom and reducing the collinearity among explanatory variables, hence improving the efficiency of econometric estimates. For example, Dercon (2004), Dercon et al (2005) and Dercon and Krishnan (2000) analyzed vulnerability of Ethiopian farmers in an ex ante approach while Skoufias and Quisumbing (2003) used an ex post approach. However, longitudinal data are hard to find. These four studies have only used a small data pool of 15 villages. Deressa, Hassan and Ringler, 2009 stressed that while they are informative and methodologically sound, the use of a small data set reduces the ability to represent the vast agroecological and socio-economic diversity of Ethiopia and limits the ability to compare vulnerability of specific regions.

The processes of land degradation are site specific and differ in type, intensity and coverage. Kharin, Orlovskii, Kogai and Makulbekova (1986) emphasized a need to characterize and map land qualities to allow for more specific development plans such as aid and public investments. In response, our paper aims to estimate the role of land degradation on agricultural production and use the results of this estimation to project the effects of land degradation on agricultural value of production across Ethiopia. This approach allows us to identify regions or sectors in the community that are more susceptible or vulnerable to land degradation and where land degradation has the potential to cause the greatest economic harm. This information can help policy makers to target aid, extension and policy to those who need it most.

2 Literature Review and Contributions of the Study

Biophysical crop growth simulation is the predominant tool used to assess the impact of the environment on agricultural productivity. Examples of large-scale simulation models include Decision Support System for Agro-technology Transfer (DSSAT) by Nelson et al (2009), Agro-PEGASUS by Deryng, Sacks and Ramankutty (2009) and Future Agricultural Resources Model

(FARM) by USDA (1995). DSSAT simulates the impact of climate change on global food availability and malnutrition while Agro-PEGASUS simulates growth as a function of temperature, soil moisture and fertilizer level. FARM, on the other hand, projects the effects of rainfall and temperature on agricultural productivity through a computable general equilibrium (CGE) model of world agricultural economy. The advantage of the biophysical crop growth simulation approach is that the crop varieties and fertilizer applications can be fixed and the productivity effects can be simulated to generate large scale estimates with little data. A limitation of this approach is that these models assume that farmers will not change their crop and technology choice in response to changes in resource availability or climate (Hertel and Rosch, 2010). Moreover, crop simulation relies on data from agronomic experiments which may not be replicable on a country-wide scale. Mendelsohn, Nordhaus and Shaw (henceforth MNS) (1996) stress that since agronomic experiments are set up in a controlled environment, they fail to account for farmer adaptation leading to overestimation of the sensitivity of crops to environmental changes.

An alternative to the crop simulation method is to estimate statistical relationships between crop yields and environmental changes such as temperature, rainfall and/or soil erosion either based on cross-sectional or time series data. The advantage of this method is that it can be readily implemented for large geographic areas, implying that it can be applied at a national or global spatial resolution (Hertel and Rosch, 2010). However, in most regions of the world, time series on yields and climate are limited in length. The limited data results in large standard errors and significant uncertainty about the likely impacts of environmental changes on yields. MNS (1994) proposed the *Ricardian Approach* which uses cross sectional data to estimate a hedonic model of farmland pricing. This model is based on the notion that a tract of land capitalizes the discounted value of all future profits or rents that can be derived from the land. The advantage of the Ricardian method is that it relies on cross sectional variation to estimate the effect of climate on future land rents, while allowing for the implicit choices of landowners regarding the allocation of their land among competing uses instead of directly modeling farmer decisions. A criticism however is that previous Ricardian models do not take into account the embedded investment such as large government irrigation schemes to mitigate the effects of changing rainfall and temperature. The proponents of Ricardian models assumed that cross sectional, or short panel studies provide adequate variability in yields to isolate their expected changes in the long run. Furthermore, most of these studies do not control for unobservable, location-specific characteristics that may be correlated with the environment and agricultural productivity and therefore bias the estimated effect of these environmental characteristics.

We see several contributions of this paper. First, unlike previous studies such as (Dercon ,2004); Dercon et al, 2005); Dercon and Krishnan, 2000); Skoufias and Quisumbing, 2003) which used small data pool of 15 villages, this study uses a comprehensive cross-sectional data collected from 162 villages in the Nile Basin of Ethiopia. This approach enables us to represent the vast agroecological and socio-economic diversity of Ethiopia (Deressa, Hassan and Ringler, 2008).

Second, although comprehensive environmental data have been made available more than 35 years ago through regional surveys, national censuses and global satellite observation, these data have been gathered on different sampling frames and thus, have large differences in scopes and levels of processing. Integrating these data sets fails to preserve the finest scale of data. Thus, most studies have resorted to simulations or quantitative interpolation of environmental characteristics from agronomic experiments (Tol, 2002, Mendehlson and

Williams, 2004). To our knowledge, this study is the first attempt to link a fine resolution global environmental map containing land degradation information with a geographically coded farmer survey for Ethiopia. Our paper demonstrates the vast possibilities of integrating datasets coming from different sources by geographical location.

Third, while most studies in the literature used changes in yield to measure the impacts of environmental changes, vulnerability can be better measured by looking at the production potential of the land because some plots may have intercropping with more than one crop measured in different units and may also grow some perennials and raise livestock. A few studies have used land prices to consider the effect of land degradation on agricultural potential, known as the Ricardian approach. As noted above, the Ricardian approach benefits from including the effect of farmer crop and technology responses to changes in resource quantity and quality. However, because this study considers the effect of land degradation in a developing country, one might worry that land markets are not significantly developed for price to truly reflect the discounted future value of all agricultural production. Instead of using yields or land values, this study uses the agricultural value of production to measure agricultural potential. Further, this study uses a broader measure of land degradation, including environmental measures such as biodiversity, water quality, soil quality, and biomass.

Fourth, unlike much previous work (see Nkonya et al., 2008 for an exception), this study recognizes the endogeneity of land degradation; which if not addressed, potentially leads to biased estimates of the effect of land degradation. While agricultural production depends on the quality of the soil, biomass content, water quality etc., the quality of the environment is also influenced by agricultural practices on farm. Moreover, agricultural practices are a function of the socio-economic situation of the farmers, and in turn the socio-economic situation of farmers depends on crop output. These two processes combine to form a “complicated feedback loop” between farm production and resource quality (Lipper and Osgood, 2001). Because these two forces influence each other, a problem of endogeneity arises, complicating the estimation process.

Fifth, this paper explicitly takes into account the spatial nature of the problem[2]. In performing regressions on Geographic Information System (GIS) data, spatial autocorrelation should be included in the statistical model (Anselin 1988). Ignoring spatial autocorrelation in a linear regression can lead to inefficient parameter estimates and greater chance of erroneously finding insignificant coefficient estimates (Anselin, 2002).

Finally, an important contribution to the literature is to map projected effects based on the statistical parameters derived from estimations. From the results of the first stage regression, land degradation can be predicted for different groups, regions or sectors. Using the second stage regression, the actual value per grid of the merged map is multiplied by parameter estimates of the model. The values of the computed agricultural production value can then be projected onto a map. These results are valuable to policy makers in developing site-specific plans as to target some aid or extension to areas that are most degraded and areas where agricultural value is at risk or vulnerable to land degradation.

3 Conceptual Framework: A Model of Agricultural Value of Production

The basic premise for our study is that land degradation alters the production function for agriculture. Farmers are assumed to choose combination of inputs that maximizes their returns given their production function.

[2] Schlenker, Hanemann and Fisher, 2006 is one of the first papers to consider spatial correlation when estimating the effect of environmental change on the future value of agricultural production.

Let $\pi_{h,p,k}$ denote the returns measured as the agricultural value of production associated with the k^{th} potential use of land $\left(k=1,...,N_k\right)$, in household h, plot p. Now let $\omega_{h,p}$ be the vector of input prices and let $C_{h,p}=C\left(C_{h,p,1},...,C_{h,p,N}\right)$ be vector of fixed costs and $p=C\left(p_1,...,p_N\right)$ be the vector of output prices. Let $z_{h,p}$ denote the characteristics not only of the farm but the farmer as well and $e_{h,p}$ denote environmental characteristics including the degree of land degradation. Then the returns associated with the k^{th} use of land can be represented by the function

$$\bar{\pi}_{h,p,k}=\pi_k\left(p_k,\omega_{h,p},e_{h,p},z_{h,p}\right)-C_{h,p,k} \qquad (1)$$

So for a given the value of agricultural productivity of a piece of land, say, θ, the corresponding agricultural productivity becomes $\theta\pi_{h,p,k}$. This output variable depends on environmental characteristics including land degradation, $e_{h,p}$, and a vector of farm characteristics, farmer's demographics, land tenure characteristics farmer's input and farming choices choices and socio-environment pressures included in $z_{h,p}$. Equation (1) implies that agricultural production potential or value of agricultural production, $\theta\pi_{h,p,k}$, depends on the quality of the soil, biomass content, water quality etc included in $e_{h,p}$

However, there are two issues we take into account in this framework. First, is the "complicated feedback loop" between farm production and resource quality (Lipper and Osgood, 2001) and second is the spatial nature of the land degradation problem.

The quality of the environment, such as land degradation, is influenced by agricultural input and investment decisions on farm. Moreover, agricultural input and farming decisions are a function of the socio-economic situation of the farmers, and in turn the socio-economic situation of farmers depends on crop output. Because these two forces influence each other, a problem of endogeneity arises, complicating the estimation process. When such problems arise, one way to approach the problem is to look for variables which proxy the effect of the endogenous variable of interest, but which are exogenous to the system. So we need to find instrumental variables that are known to affect land degradation but not agricultural value of production. Figure (1) illustrates this relationship.

Also, some input and investment choices farmers make such as crop choice, inputs and whether to adopt soil conservation measures may depend on unobserved farmer and plot characteristics. Thus, input and investment choices may be endogenous as well. In this paper, we disregard these variables and follow the assumption made in Ricardian models that farmers put their land to its best, or most profitable, use. Typically farmers at particular sites take environmental characteristics such as soil type, slope, elevation, temperature among other things as given and adjust their inputs and farming practices accordingly.

Second issue to account for in this framework is the spatial nature of the processes of land degradation. Neighboring farms could affect a farm household's practices as found in Evenson (1989), Bantilan and Davis (1991) and Alston, Norton and Pardey (1995). We modify equation (1) to include the spatial nature of the land degradation problem.

$$\bar{\pi}_{ha,pa,ka} = \pi_{ka}\left(p_{ka}, \omega_{ha,pa}, e_{ha,pa}, z_{ha,pa}, e_{hb,pb}, z_{hb,pb}\right) - C_{ha,pa,ka} \qquad (2)$$

Equation (2) represents the returns associated with the k^{th} use of land for a given farm household *a* to include neighboring farm household *b* characteristics.

4 Data Sources and Description

This study is based on two data sets: Global Land Degradation Information System (GLADIS) data and household survey in Ethiopia. The two data sets are combined based on spatial location.

4.1 GLADIS DATA

The environmental variables used in this study come from GLADIS, which was developed in 2010 by the Food Agriculture Organization (FAO)'s Land Degradation Assessment Team (LADA). GLADIS contains multiple environmental measures to represent land degradation processes roughly over the last 23 years (1981-2003). In GLADIS, the geographic areas are divided into fine resolution grids of 0.05 degrees per grid cell.

GLADIS is the only global scale environmental degradation data currently available. These data are not available to the public yet, which makes this study the first to use these data. GLADIS is comprised of a series of global maps on the status and trends of the main ecosystem services which includes soil health, water quality, biodiversity, biomass and social components overlaid on a rainfall-corrected normalized difference vegetation index map.[3] Each of these ecosystem measures comes from a huge scientific database from experts worldwide. Significant amount of modeling and expert input has been involved since 2009 in the process of integrating different databases and finalizing the maps. These measures of ecosystem health are then mapped into a normalized radar trend diagram according to the parameters from the database. Figure 2 represents the database and Figure 3 represents a radar diagram trend map. Radar trend diagram is a semi-quantitative way of combining different parameters such as ecosystem services,

[3] Normalized Difference Vegetation Index (NDVI) is a numerical indicator to analyze remote sensing measurements to assess whether there is green vegetation present.

by using indexes 0 (worst) to 100 (best) and putting these indexes along each ecosystem service axis with equal weights. It allows the visualization of the capacity of an ecosystem to deliver specific goods and services under environmental conditions. When the values are put in a radar diagram, they represent the strength and weakness of any ecosystem. To be able to compare objects of different nature, a normalization procedure is required to rate all indicators on a same scale, 0 to 1. These indexes, thus, represent a unit free measure. For more details on how the radar trend diagrams are made, see GLADIS Technical Report (Nachtergaele, Petri, Biancalani, Lynden and Velthuizen, 2010).[4] Data on Ethiopia is extracted from these global maps.

As mentioned previously, this dataset represents the only global scale land degradation data at a fine resolution that is available to date. It does, however, have several fundamental characteristics that must be taken into account when used for data analysis. One is the scale of coverage. Although the grid size used was relatively fine, the information for that grid may also have been derived from database for larger polygons. In the case of the paper, however, a study of interactions between land degradation, agricultural value of production and socio-economic factors is possible using GLADIS data since enough spatial variations exist. In addition, this paper is an improvement from previous studies such as Schlenker, Hanemann and Fisher (2006) and Mendehlson, Nordhaus and Shaw (1994) whose papers used county-level scale environmental data. Second characteristic that needs to be taken into account in using GLADIS is time. GLADIS represent the cumulative amount of land degradation for the period 1981-2003, preventing time-series analysis. However, we argue that the problem of land degradation is a long run effect, and so having the land degradation index in a grid format which represents the average value over both space and time may capture the long run more effectively.

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[4] http://www.fao.org/nr/lada/index.php?option=com_content&view=article&id=180&Itemid=168&lang=e

4.2 Farmer Survey in Ethiopia and Climate Data

The household survey was carried out in the Nile basin within Ethiopia by the International Food Policy Research Institute (IFPRI) in the 2004-2005 crop year. It covered five major regions: Tigray, Amhara, Oromiya, Benishangul-Gumuz (BG) and Southern Nations, Nationalities and People's Regions (SNNPR). Amhara is the biggest region in the Nile basin of Ethiopia, covering 38 percent of the total area, followed by Oromiya (24 percent), BG (15 percent), Tigray (11 percent), and SNNPR (5 percent) (Ethiopian Ministry of Water Resources, 1998; Kato et al, 2009). The household sampling frame was developed to ensure representation at the district (woreda) level regarding the level of rainfall patterns, classes of agro-ecological zones, vulnerability of food production systems and the presence of irrigation. Twenty woredas were selected to ensure equal proportions falling into each class for the sample. One peasant association was selected from every woreda for a total 20 peasant associations. Further, random sampling was used to select 50 households from each peasant administration. The final dataset contains 1,000 households. Households may farm up to 19 plots, resulting in 6,301 plots in the total data. This household level questionnaire collected information about household endowment of assets, household composition, income and expenditures, and adoption of agricultural and land management technologies. A plot level survey collected information on all of the plots owned or operated by the household, including information about land tenure, plot quality characteristics, land management practices, use of inputs and outputs during BELG (fall, February to June) and MEHERE (summer, June to October). Each household has available geographic information via GPS code; and IFPRI for the purposes of this data has not utilized this feature of the survey yet. In addition to the farmer survey, IFPRI water research team's

Climate Research Unit of East Anglia database provided historical rainfall data and temperature from 1951-2005.

It is worth noting that most of the production system is located on the Ethiopian Highlands. The highland constitutes about 45 percent of the total crop area including 88 percent of the total population at an average density of 144 per km^2 and supports 70 percent of the livestock population of the country (Deressa et al, 2008). Thus, most analyses of the impact of land degradation in Ethiopia are focused on the highland zone of the country. Also, our analysis is implemented at the plot level to allow us to capture more spatial heterogeneity and also helps to control for plot level covariates that condition crop production and hence help to minimize the omitted variable bias that would confound household level analysis.

Figure 4 represents the distribution of data points from survey overlaid on an environmental map and Table 1 lists all the variables and their descriptive statistics.

5 Methods and Empirical Specification

5.1 Determinants of Agricultural Value of Production

Recall from Section 3, the basic hypothesis is that land degradation shifts the production function for crops thus affecting agricultural production potential (equation 1). More formally, agricultural value of production π by household h on plot p is determined by some environmental characteristics, socio-environment characteristics, land tenure characteristics, farmers' demographics and perception, farm characteristics and our variable of interest, land degradation. We estimate the following equation by ordinary least squares (OLS):

$$\pi_{h,p} = \beta_0 + \beta_1 z_1 + \ldots + \beta_k e_k + u \qquad (3)$$

where

$$\pi_{h,p} = agricultural\ value\ of\ production$$
$$z_1 - z_{k-1} = vector\ of\ characteristics$$
$$e_k = land\ degradation$$

While previous studies used yield to measure impact of environmental changes or degradation, Molua (2002) argued that vulnerability to environmental changes or degradation is better measured by looking at the production potential of the land and not by yield.

Ricardian models measured the production potential in terms of land values (Mendehlson, Nordhaus and Shaw, 1996; Mendelsohn, 2000; Schlenker et al, 2003; Molua and Lambi, 2006). Ricardian models argue that long–term accumulation of net revenue determines land values. However, as mentioned previously, land markets in most developing countries are not well developed. Ethiopia has a long history of land redistribution programs. Many researchers (Ahmed et al., 2002; Holden and Yohannes, 2002; Jayne et al., 2003) believed that the frequent land reallocation has been a source of tenure insecurity. Tenure insecurity may influence farmers' willingness to invest in practices that yield future returns such as land degradation prevention measures; while land rights and security also may influence land management and productivity by affecting farmers' access to credit (Place and Hazell 1993; Pender and Kerr 1999). Thus, land values may not truly reflect the discounted future value of all agricultural production.

In this study, we use agricultural potential as measured by local agricultural value of production. This measure of agricultural value of production is based on regional weighted averages of crop yields, cattle and small ruminants and forestry timber production expressed in international Geary-Khamis prices from FAOSTAT[5] (GLADIS, Global Land Degradation

[5] The Geary-Khamis dollar, also known as the "international dollar", is a hypothetical unit of currency that takes into account purchasing power of the U.S. dollar at a given point in time. It was proposed by Roy C. Geary in 1958 and developed by Salem Hanna Khamis in 1972. It shows how much a local currency unit is worth within the country's borders. It is used to make comparisons both between countries and over time. (FAOSTAT). This is

Information System Technical Report, 2008). Thus, the production estimates are not affected by variations in local prices. This data is in grid format where each grid represents the average value of agricultural production per 0.5 degrees grid for years 1981-2003. This measure reduces the effect of short run production and price shocks, where such shocks could bias our results. In our case, however, having the agricultural value of production in grid format represents average value not only over space but time as well. Thus, this measure captures the long run agricultural potential. In addition, because some plots may have intercropping with more than one crop, estimation of a single measure of production is difficult. This approach of aggregating all crops on a plot into a single measure of value of crop production rather than using individual crop yields has been used in many previous plot-level-based microeconometric studies in Ethiopia and sub-saharan Africa (Kato et al, 2009; Pender and Gebremedhin, 20007; Pender et al, 2001, 2004; Nkonya et al, 2004, 2005 and 2008; Benin, 2006; Jansen et al, 2006). A limitation of using an agricultural value of production measure is this measure might be correlated with distance of household to markets because we are using cross-sectional framework (Kato et al, 2009).

So what are the factors included in $z_1 - z_{k-1}$?

Environmental characteristics such as soil type, elevation, slope, and temperature or climate affects agricultural value of production. Crop production is said to be based largely on soils and soil scientists classify soils by different taxonomies. Certain types of soil may be more productive and fertile, thus affecting agricultural production.

On the other hand, socio-environment characteristics such as population density and access to major facilities such as roads and markets may also affect agricultural value of production. Access to markets and facilities are major determinants of crop choice and, thus,

widely used in studies comparing price levels across countries such as International Comparison Program (ICP) of Organization of Economic Cooperation and Development (OECD).

directly affecting the value of agricultural production (Pender, Nkonya, Jagger, Sserunkuuma, and Ssali. 2003). High value perishable cash crops are expected to be higher in areas with greater access to roads and markets; while more storable and transportable grain crops are more important to farmers who are farther from roads and markets (Huffman and Fukunaga, 2008). Boserup (1965), on the other hand, found that intensification of labor in agriculture is more prevalent in populated areas.

Farmer demographics and farm characteristics are also important determinants of agricultural value of production. Huffman (2001), Weir (1999), Kiome and Stocking (1995) stressed the impacts of education or schooling on agricultural productivity through significant increases in labor productivity. Masterson (2007) and Molua (2011) looked at gender bias in crop specialization, which directly translates to value of production. Male farmers tend to specialize more in cash crops while female farmers tend to focus on crops for household's needs. Current value of assets also affects agricultural value of production. Wealth or availability of assets such as livestock ownership (Liverpool and Winter-Nelson, 2010) serves as collateral thus increases farmers' ability to make agricultural productivity enhancing investments (Rosenzweig and Binswanger, 1993; Foster and Rosenzweig, 2010).

5.2 Potential Endogenous Variables: Land Degradation and Specific Input and Investment Choices

As discussed in the conceptual framework, in equation (3) land degradation, e_k, is likely a function of the socio-economic situation of the farmers, and in turn the socio-economic situation of farmers depends on agricultural output. This endogeneity may bias the estimated effects of land degradation on the agricultural value of production. Thus, we use instrumental variables to correct the potential endogeneity of land degradation. Also, recall in section 3, we assumed that specific input choice variables such as crop choice, amount of fertilizer and chemicals used, soil conservation decision etc. are homogenous. And we used the Ricardian model long run equilibrium assumption that is farmers put their land to its best, or most profitable, use. Farmers at particular sites take environmental characteristics such as soil type, slope, elevation, temperature among other things as given and adjust their inputs and farming practices accordingly. Thus, endogeneity of specific input and investment choice variables can be ignored. However, one might also be concerned that different farmers might have unobservable differences, such as unseen access to credit, that may lead them to adopt different farming practices. If these unobservables are correlated with land degradation, we may bias our estimates on the effect of land degradation. To consider this problem and to validate our homogeneity assumption, we look at the range of agricultural technologies used in our sample. and compare it with the Atlas of Ethiopian Rural Economy[6].

Looking at summary statistics of the data on farm practices, we find no variation. Furthermore, the statistics from the farmer survey data is consistent with the Atlas of Rural Ethiopian Economy. This justifies dropping these variables in the analysis. The IFPRI farmer survey data on crop choice show that 92.44% of the farm households plant cereals and grains i.e. barley, maize, millet (mashilla), wheat (duragna), teff and sorghum; whereas the Atlas reports that cereals and pulses are the main crops. We also observe very little variation in production technology in the survey. The vast majority of farms (95%) are rain-fed and only 26 out of 1,000 households have water pumps. Atlas reports that agriculture is mainly rainfed with minor use of a gravitational irrigation system. The IFPRI survey shows that farm tools and machinery do not greatly differ across farms. Only 14 farm households out of 1,000 own heavy machinery, i.e.

[6] http://www.ifpri.org/node/3763

tractors, ploughs and trailers. According to the Atlas, 83% of the farmers use of maresha17 with oxen as the preferred draft animal for soil cultivation. Approximately 75% of farmers have already adopted soil conservation practices in their farm. This practices includes fanya ju (terraces) and any combination of soil, stone and wood bunds, 94.16% do not use any improved seed variety. The combination of fertilizer and chemicals does not vary much either. Fertilizer use is characterized by the use of urea, manure and DAP (Diammonium Phosphate). 91.8% of the farmers use 2-4D herbicide. The Atlas reports that chemical fertilizers and pesticides, subsidized by the government are rarely used. Thus, the assumption of homogeneity of farmers is supported by the survey data and the published Atlas of Rural Ethiopia. This consistency combined with potential endogeneity, validate excluding specific farming choices from the analysis.

What are the factors that affect land degradation, e_k ?

Land has been under state ownership in Ethiopia since the 1975 national land reform, and there have been many redistributions and readjustments since then. Many researchers (Ahmed et al., 2002; Holden and Yohannes, 2002; Jayne et al., 2003) believed that the frequent land reallocation has been a source of tenure insecurity and a disincentive for the farmers to invest in conservation agriculture. Berry (2009) suggests that in the case of Ethiopia, an interesting cause of land degradation problem apart from the historical and changing patterns of land ownership is relating to ethnic groups. Ethiopia has a tiered government system consisting of a federal government overseeing ethnically based regional counties, zones, districts (woredas) and neighborhoods (kebele). These federal states are organized along ethnic boundaries; that is people belonging to different ethnic groups live within defined boundaries (Keeley and Scones, 2000). Bekele and Drake (2003) suggest that being a member of the majority ethnic group is expected to have a positive correlation with the conservation decision. If there are land tenure insecurity concerns, farmers from the minority ethnic groups are expected to be more concerned with tenure insecurity and practice less soil conservation (Bogale, Taeb and Endo, 2006; Norris and Batie, 1987). Hirsch et al (1999) suggest that ethnicity may inform the use of natural resources in relation to cultural and social dimensions conflict.

Farmers' assets also affect farmer's decision to make soil conservation investments. That is because assets serve as collateral which determines access to credit (Place and Hazell 1993; Pender and Kerr 1999). Reardon and Vosti (1995) emphasized the link between poverty and the environment in developing countries. That is, income and ownership of machinery and livestock (Liverpool and Winter-Nelson, 2010) are major determinants of farmer's investment in sustainable practices and that policy strategies should focus in conditioning variables that improves community wealth or enhance investment in conservation technologies. Similarly, Gebremehedhin and Swinton (2003) find that assets and income determine access to credit which in turn affect soil conservation investment. Pender and Kerr (1999), on the other hand, find that technical assistance programs are expected to contribute to productivity if the information dissemination is effective.

Environmental characteristics such as soil type, slope and elevation are also determinants of land degradation. According to Rola and Coxhead (2001), farming uplands has been one of the major causes of soil erosion in most developing countries. Certain types of soil are also more susceptible to erosion thus leading to loss of organic matter and pesticide runoff (Larson, Pierce and Dowdy, 1983; Mudgal, Anderson, Baffault, Kitchen and Sadler, 2010).

Farm characteristics such as improper irrigation and overdrafting are also known causes of land degradation (Sojka and Bjorneberg, 2007). When drylands are irrigated, water evaporates quickly, leaving behind previously dissolved salts. These salts can collect since there is little rain to flush the system. The salt in the soil inhibits the uptake of water by plant roots until the soil can no longer sustain vegetative cover leading to nutrient loss.

Other factors include gender and perception. Bhagowalia, Chen and Shively (2007) use a panel data in India to show that the choice of farm inputs varies by gender. Farms managed by women tend to be more degraded than male managed farms primarily because most conservation practices are labor intensive. Kiome and Stocking (1995), on the other hand, stressed that the farmer's perception of the dangers of soil erosion and attitudes towards conservation are increasingly recognized as a rational basis for soil conservation.

5.3 Addressing Endogeneity of Land Degradation: Instrumental Variable Approach

In the case of the model presented above, the relevant procedure to correct for endogeneity is the instrumental variable (IV) approach (Imbens and Angrist, 1994; Imbens, 2004; Heckman and Vytlacil, 2005). This approach involves looking for instrumental variables, iv_1, that satisfy two requirements: first, iv_1, is uncorrelated with the error term u and second, there is partial correlation between land degradation and agricultural production.

$$Cov(iv_1, u) = 0 \qquad (4)$$

$$z_k = \delta_0 + \delta_1 z_1 + \ldots + \delta_{k-1} z_{k-1} + \theta_1 iv_1 + r_k \ , \quad \text{where} \quad \theta_1 \neq 0 \qquad (5)$$

This approach is equivalent to two stage least squares. Equation (5) represents the first stage regression and is estimated by OLS. That is, land degradation is regressed as a function of exogenous variables. We test for partial correlation requirement for validity of IVs using t-test statistic derived after the OLS estimation.

The second stage is presented in equation (6). Agricultural value is a function of exogenous variables and the land degradation estimated from the equation (5). After estimating equation (5) by OLS, predicted land degradation is generated, $\hat{z}_k$, and then plugging this predicted value to equation (3) becomes:

$$\pi_{h,p} = \beta_0 + \beta_1 z_1 + \ldots + \beta_k \hat{z}_k + u \qquad (6)$$

Wooldridge (2010) shows that this process solves the identification problems and leads to consistent and efficient estimates. This method separates the land degradation induced decline in agricultural value of production from the socio-economic induced decline in agricultural value of production. Similar to previous equations, we estimate equation (6) by OLS unless it exhibits heteroskedasticity[7]. If it is heteroskedatic, we estimate equation (6) using Generalized Method of Moments (GMM).

Identification of the effects of the endogenous variables in the IV models and two stage models can be difficult unless one has instrumental variables that strongly predict the endogenous explanatory variables. There have been very few studies that used this approach because finding a good instrumental variable for land degradation is often difficult[8]. In this paper, we employ intergenerational bequest and the farm household's main source of energy as our instrumental variables.

7 The test for heteroskedasticity is done by Pagan-Hall test.

8 Lipper and Osgood (2001) mentioned in their paper that an example of such as instrumental variable for land degradation is the change in terms of trade of the nation weighted by the region's agricultural production. This variable may be a valid instrument because it can be assumed that an individual African nation has negligible effect on world prices. Moreover, there has been a good amount of literature linking pollution or environmental degradation to terms of trade (Copeland and Taylor, 2000). Another example is Pender et al (2003) who used land ownership and ethnicity as instrumental variables of soil erosion with the argument that people who own the land are most likely to invest in land degradation reduction measures than those who rent, but land ownership does not directly affect yield. Huffman and Fukunaga (2008) argued that land contracts such as percentage of sharecropping can be a good instrumental variable for sustainable farming.

We derive intergenerational bequest variable by interacting inherited land dummy with number of children. We argue that if the farmer's source of land ownership is through the inheritance[9] from his ancestors, he is more likely to want to pass it along to his children as well[10], and to pass it along in good condition. This interaction between ownership and the presence of children reflects more than just tenure security but the familial heritage connection to the land. Note that tenure and children are included separately in the second stage regression. Therefore, the effect of tenure and the effect of having children are explicitly captured in the regression on agricultural value and not used as instruments. Thus, we posit that intergenerational bequest or the desire to pass along the farmland to children affects land degradation but not the agricultural value of production per se.

Since the 1980s, research and development on cook stoves in Ethiopia has been extensive through the World Bank Energy Sector Assessment. In 2010, the Berkeley Lab and Technology Innovation for Sustainable Societies have spearheaded cook stove projects in Ethiopia. Gebreegziabher, Van Kooten and Van Soest (2006) proved the relationship between land degradation and the household's choice of energy source for domestic use. In Ethiopia, deforestation is a major problem and many peasants have switched from fuel wood to animal dung for cooking and heating purposes. However, this switching or substitution also diverts dung and crop residues from their high value uses in agriculture, such as soil fertility and maintenance, which can cause environmental damages as well (Gebreegziabher et al., 2006). Note that current value of assets and some measure of wealth such as livestock, gift income and

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[9] McConnell (1983) differentiated land tenure arrangements in modeling soil conservation decisions with time horizon into owned family farms, rented family farms and corporate farms. He showed that corporate and rented farms tend to use up soil faster than intergenerational family farms because of greater incentive for soil conservation.

[10] Rola and Coxhead (2001) showed that farmers with more dependents have strong bequest motive and find it preferable to engage in conservation measures.

aid are included separately in the second stage regression. Thus, the effect of wealth is captured in the regression on agricultural value of production not used as instruments. We posit that farm household's choice of energy for domestic use directly affects land degradation but not agricultural value of production. The only way choice of energy source affects agricultural value of production is through land degradation.

In finite samples, the results of estimation with weak instruments can be more biased than ordinary least squares (Deaton, 1997). We address this concern by testing the significance of the impact of excluded instruments on the predicted endogenous variables by "relevance test" (Bound et al., 1995). We test the validity of our restrictions by comparing the OLS and IV models using Hausman (1978) specification test and we investigate the robustness of the regression results to estimation by OLS, IV and reduced form (RF) approaches.

5.4 Spatially Weighted Estimation: Addressing Spatial Patterns in the Data

After correcting for endogeneity, it is important to address the spatial nature of land degradation in our analysis because of the fact that the neighboring farms could affect another farm household's practices as found in Evenson (1989), Bantilan and Davis (1991) and Alston, Norton and Pardey (1995).[11] To control for spatial autocorrelation in the model so that the estimates are both unbiased and efficient, we modify the model presented above, equation (6), by including supplementary explanatory variables. These variables are meant to represent the spatial dependency of the dependent variable. There are two major ways in which spatial autocorrelation can manifest itself: spatial lag or spatial error dependence.

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[11] It is important to note that spatial autocorrelation should be included only after endogeneity is corrected. If the spatial autocorrelation is due to unobserved variables, then this is a valuable technique to improve parameter estimates. However, if the spatial autocorrelation is due to endogenous variable in the model, i.e. land degradation, then this technique worsens endogeneity.

Spatial lag dependence refers to situation in which dependent variable in one area can be affected by dependent variable in nearby areas. This is commonly done using the spatial lag of the dependent variable. In this case, the spatial lag of the dependent variable is defined as the weighted mean of a variable for neighboring spatial units of observation (Anselin, 2002). In the case of this study, farming practices of farmers can exhibit clustering. Such a relationship can be modeled as a spatial lag model:

$$\pi_i = \delta_1 \sum_{j \neq i} w_{ij} \pi_j + \delta_2 \sum_{j \neq i} w_{ij} \left(z_{i1} + \ldots + \hat{z}_{ik} \right) + \beta_1 z_{i1} + \ldots + \beta_k \hat{z}_{ik} + u_j \qquad (7)$$

where π_i is the dependent variable for area i, δ is the spatial autoregressive coefficient, w_{ij} is the spatial weight reflecting the proximity of i and j, π_j is dependent variable for are j, $z_{i1} - z_{ik-1}$ is the matrix of exogenous explanatory variables, $\hat{z}_{ik}$ is the predicted land degradation for area i and u is the error term. The spatial weights matrix, w, represents the degree of proximity between each pair of spatial observations. Since the merged data in this study is a point data, the weights matrix is a continuous variable based on the average of characteristics of four nearest neighbors[12].

A second type of spatial dependence can be attributed to the error term of the model. In this case, the error for the model in one farm is correlated with the error terms in its neighboring farms (Anselin, 1988). This kind of spatial autocorrelation occurs when there are variables that are omitted from the regression model but in fact do have an effect on the dependent variable and they are spatially correlated. For example, institutional factors in one region may affect public

[12] Spatial weights matrix was generated in Geoda using 4 nearest neighbors. Contiguity matrices are not applicable in our case since it is a point data. This is done in household level because the gps point code is unique only to a household id so plot id cannot be used to generate the spatial weights matrix. Since the data is in plotid, the weights matrix was transformed by multiplying weights generated by household id by a matrix of 1's and 0's and generating its transpose to make the dimensions 5,497x5,497. This makes the weights matrix in plot level. This weights matrix conversion is done in R and multiplied to all the variables in the data as matrix then imported the weighted data back into Stata.

investments in agriculture, but it is not easy to include in the model. Since this type of local administration is likely to be spatially correlated, the error term in each location is likely to be correlated with the nearby locations. This can be expressed as

$$\pi_i = \beta_1 z_{i1} + \ldots + \beta_k \hat{z}_{ik} + \lambda_1 \sum_{j \neq i} w_{ij} \left(z_{i1} + \ldots + \hat{z}_{ik} \right) u_j + \lambda_2 \sum_{j \neq i} w_{ij} \pi_j u_j + u_i \qquad (8)$$

where π_i is the dependent variable for area *i*, λ is the spatial autoregressive coefficient, w_{ij} is the spatial weight reflecting the proximity of *i* and *j*, π_j is the dependent variable for area *j*, $z_{1i} - z_{ik-1}$ is the matrix of exogenous explanatory variables, $\hat{z}_{ik}$ is the predicted land degradation for area *i*, and *u* is the error term.

We test for spatial autocorrelation using standard Moran's Index (Anselin, 2002). Whenever there is spatial error or spatial dependence, an appropriate model is used to correct for the problem. For spatial dependence, the spatial lag model is used. In the case of spatial error, spatial error model is used. To select which model to use, we use Lagrange Multiplier test to assess the statistical significance of the coefficients in each model. Where spatial autocorrelation is likely, usually, the result of the test on each will be significant. The preferred model in such a case is the one with highest Lagrange multiplier test value (Anselin, 2002).

6 Results and Discussion

The results and discussion section is organized as follows: First, we estimate agricultural value of production using Ordinary Least Squares (OLS) without correcting for endogeneity. Second, we check for endogeneity of land degradation by looking at Wu-Hausman test. If endogeneity exists, we address it through Instrumental variable (IV) approach, equivalent to Two Stage Least Squares (TSLS). We, then, run the first stage regression by estimating land degradation as a function of the exogenous variables using OLS. Fourth, we correct for endogeneity by estimating agricultural value of production using IV to instrument for land degradation. This is equivalent to the second stage of TSLS, that is, using the predicted values of land degradation from the first stage, then regressing agricultural value of production as a function of predicted value of land degradation from the first stage and other control variables. Fifth, after correcting for endogeneity, we test for Moran's I and run the appropriate spatially weighted regression. Finally, we project the vulnerability maps, derived from the beta coefficient of land degradation multiplied by the characteristics per grid and discuss some important policy implications.

Before running the regressions, we tested for multicollinearity by looking at variance inflation factors and found it not be a serious problem for most explanatory variables. Also, a total of 173 households were dropped because of missing or incorrect GPS point code lying outside the map of Ethiopia. Appendix Table 1a and 1b reports the F statistics for testing for omitted variables bias and functional forms.

Table 2 shows regression results: OLS for agricultural value without correcting for endogeneity in first column, OLS for land degradation in the second column (equivalent to first stage of TSLS), Instrumental Variable regression for agricultural value in the third column (equivalent to second stage of TSLS), and the spatially weighted IV results in the fourth column.

Without correcting for endogeneity, the estimated effect of land degradation on agricultural value of production is about 9% with a large t-statistic and is significantly different from zero (1st column, table2). Note however, that this coefficient might be biased due to endogeneity. As pointed out in previous sections, agricultural productivity depends on the quality of environment and some farm and farmer characteristics, while the quality of the environment is also influenced by farm and farmer characteristics. And farm and farmer characteristics are influenced by the agricultural value of production they receive from the market. The test for endogeneity reveals a Wu-Hausman F statistic of 0.0035 which implies that land degradation is indeed endogenous in the system. To address this problem, we employ instrumental variable approach.

6.1 Results from the First Stage: What are the factors that affect land degradation?

The second column of table 2 presents the first stage regression of TSLS. We regress land degradation against all the explanatory variables including the candidates for instrumental variables. The two chosen instrumental variables (bequest and cooking energy) are significant satisfying the partial correlation requirement for validity of IVs. This validates McConnell's (1983) hypothesis that intergenerational family farms exhibit less severe land degradation because of more incentive to take measures to prevent soil erosion so farmers can pass it along to his children in good condition. Moreover, the significance of type of energy used in cooking stoves coincides with the findings of Gebreegziabher, Van Kooten and Van Soest (2006). They proved the relationship between land degradation and the household's choice of energy source.

Not surprisingly, soil type and temperature increase the degree of land degradation. High temperature drylands and desert increase the degree of land degradation. Soil types have mixed result. Histosols are type of wet soil that requires drainage to become productive. In the regression result, histosol turned out to be negative, thus reducing land degradation. This is consistent with an earlier finding by Binswanger Pingali 1988 study on African farming systems and how soil types influences the choice of farming system/degradation. Aridisol, on the other hand, requires irrigation and entisols require fertilizer. Results show that aridisol and entisol increases land degradation. Nitrate leaching and improper irrigation system have both been shown to increase land degradation. In fact, looking at the farm characteristics variables, we find that irrigation has a strong positive impact on land degradation. Improper irrigation and overdrafting are known causes of land degradation. Farmers control the flow of water and hence erosion occurs to a greater extent on irrigated plots. Moreover, when drylands are irrigated, water evaporates quickly, leaving behind previously dissolved salts which can collect. The salt in the soil inhibits the uptake of water by plant roots until the soil can no longer sustain vegetative cover leading to nutrient loss. Distance of farm from home is also positive and significant. This is consistent with the finding by Huffman and Fukunaga (2008). Because the farther the farms are to the farmer's home, monitoring becomes less frequent.

The positive effect of population density on land degradation is consistent with Malthusian theory as well as previous studies in Ethiopia (Pender, Gebremedhin, Benin and Ehui, 2001; Grepperud, 1996). While the significance of the variable access to information agrees with Kiome and Stocking (1995) that changes in farmer's perception of the dangers of soil erosion and attitudes towards conservation reduce land degradation.

In addition, percentage of the land sharecropped is negative and significant suggesting that as the percentage of land sharecropped increases, land degradation decreases. This is consistent with the findings of Huffman and Fukunaga (2008). Sharecropping increases farmers' incentive to invest in soil conservation measures, thus, reducing land degradation. The dummy variable for inheritance also decreases land degradation.

Farmer characteristics that were found significant include membership to big ethnicity (increases degradation), children (reduce degradation), gender (females tend to conserve more), farming years (decreases degradation), livestock (increases degradation), and aid income (decreases degradation). Membership to majority ethnic group increases land degradation and is somehow related to population pressure. As mentioned previously, Ethiopia is organized into federal states along ethnic boundaries. This is not consistent with findings that stress bigger ethnic groups cause communal pressure in protecting the land (Bekele and Drake, 2003; Bogale, Taeb and Endo, 2006; Norris and Batie, 1987). Meanwhile, the effects of farming years and gender are due to the differences in perception of land degradation. Farming years may increase farmers' awareness of land degradation problems and potential solutions. Thus, contributing to preserving quality of land (Kiome and Stocking, 1995). Finally, while livestock ownership measures asset and can also serve as collateral (Liverpool and Winter-Nelson, 2000), livestock density on farm also causes disturbance of the topsoil and vegetation leading to increased land degradation.

6.2 Results from the Second Stage: What are the implications of land degradation on agricultural value of production?

The factors that affect agricultural value of production are presented in the 3rd column of table 2. After controlling for endogeneity, the coefficient on land degradation decreased to 7%. This suggests that eliminating the endogeneity-induced bias decreases the effects of land degradation. In other words, not accounting for endogeneity will overestimate the impacts of environmental degradation to agricultural value of production. In monetary terms, this is equivalent to $7.63 per hectare (FAOSTAT website)[13]. If all of the agricultural lands are degraded, the loss for the country as a whole is $267 Million. And where 85% of the population

[13] FAOSTAT Website, Data for 2009: Average Value of Production for the whole country = $8,901,719,000, Total hectares devoted to Agriculture = 34,985,000 hectares; Average Value of Production Hectares devoted to Agriculture=34,985,000 hectares; Average Value of Production per hectare=$254.443; Loss per hectare from Land Degradation=$7.63; Loss for Ethiopia if all lands are degraded=$267,050,650; Farming population=85% of total population or $69,700,000; Loss per farmer=$3.83 or 65.82 Birr; Minimum wage per month=$18.62 or 320 Birr

depends on agriculture, this loss is substantial. Moreover, comparing this value to the recent estimates found in the literature mentioned in the introduction (see page 2, paragraph 3), this 7% reduction in the agricultural value of production is equivalent to about 3.64% loss in the the GDP. 3.64% falls in the lower bound of range of effects of land degradation to agricultural production (Note: 52% of the GDP is agriculture).

The Sargan statistic[14] from this regression is valued at 1.32 with chi-square statistic of 0.1894, which shows the validity of the instruments. The test for heteroskedasticity (Pagan-Hall test) suggests that disturbance is homoskedastic.

A surprising result is the irrigation intensity variable. One would expect the value of this variable to be positive. However, IV regression implies that the irrigation intensity decreases the value of agricultural production. This is interesting because irrigation intensity as shown in the first stage also causes substantial increase in land degradation. This, then, goes back to the question – 'are they using irrigation strategy that is suitable to their environmental situation?'.

Environmental characteristics that are found to be very significant include soil types, elevation (decreases agricultural value of production), temperature (decreases agricultural value of production) and environmental shock (decreases agricultural value of production). None of the land tenure characteristics were significant.

Population density positively affects agricultural value of production. This is consistent with studies that find the beneficial effect of population, i.e., through increased market demand leading to higher value of agricultural production (Tiffen et al, 1994). The negative effect of distance from facilities, such as bridges, roads and market is embodied in the central relationship

[14] Sargan statistic is the test of validity of instrumental variables and testing for overidentifying restrictions. The hypothesis being tested with the Sargan statistic is that Ivs are uncorrelated to residuals if they are truly exogneous and are therefore acceptable instrumental variables. If null hypothesis is confirmed (not rejected) then the instruments pass the test.

that von Thunnen emphasized, which says that as distance increases, transportation cost increases as well, thus reducing the agricultural value of production. And this increase in transportation cost reduces price received by farmers for their products and economic rent (Carr, 1997). Positive impact of access to information through extension agent visits implies that farmers who are more disposed to new ideas and concepts provided by extension agents and other informants are able to adjust their production which eventually increases the value of their production (Demir, 1976 and Nkonya, 1997).

Farmer demographics that significantly affect agricultural value of production on a given plot include gender of household (increases agricultural value of production), children (increases agricultural value of production), farming years (increases agricultural value of production), current value of assets and livestock (increases agricultural value of production), aid (decreases agricultural value of production). The effect of gender can be attributed to gender bias in crop specialization and productivity. Male household heads specialize in agricultural cash crops while female household heads are more concerned with households' food supply (Masterson, 2007; Molua, 2011). Aid, however, decreases agricultural value of production. This could represent the loss in incentive to invest in productivity enhancing strategies if aid comes in more frequently.

6.3 Testing for Spatial Autocorrelation and Spatially Weighted Regression: Do neighboring farms affect each other's production?

The Moran's I statistic in Figure 5 shows the cluster maps and significance map of agricultural value of production which verifies the presence of spatial correlation. However, the Moran's-I statistic does not differentiate between types of spatial dependence, so We conduct Lagrange-Multiplier tests and find that a spatial lag is significant at the 10% level. A spatial lag implies that neighboring farms affect one another, thus exhibit some clustering or "spill-over effect". In the last column of table 2, we include spatially weighted characteristics in the regression, which represent the average characteristics of the four nearest neighboring plots. Note that we use the predicted land degradation which is our correction for endogeneity.

Including variables about neighboring farms' characteristic does not substantially change our finding that land degradation decreases the value of agricultural production to 0.0652, but it improved the efficiency of our estimates. Hence, the results for the similar variables in IV regression are the same. The result implies that land degradation not only affects the value of agricultural production directly, but also indirectly by influencing the neighboring agricultural production. Thus, by using a spatial lag model, we can observe both the direct and indirect effects of land degradation. This subsection focuses more on the neighbor's characteristics that were added in this regression.

The neighboring farms' land degradation reduces the agricultural production value of the farm. This shows that land degradation, similar to most environmental problems, is a spatial problem related to negative externalities. Similarly, environmental characteristics such as soil type, and slope are also significant. Other variables that are significant are literacy and irrigation intensity, positive and negative respectively, suggesting presence of "spill- over effect" in terms of farming knowledge's positive externality and negative externality from improper irrigation.

6.4 Vulnerability Maps and Policy Implications

Figure 6A shows the agricultural value of production vulnerability map. The projection is based on the coefficient of land degradation from previous subsection, i.e. β_{LD} from second stage, multiplied by the actual agricultural value of production. The darker areas represent those areas where agricultural production is most vulnerable to degradation. This vulnerability map is similar to crop productivity elasticity of soil erosion map derived from simulations in Sonneveld (2002). However, Sonneveld (2002) only looked at soil erosion and used limited farm and farmer characteristics data that were in regional units. To make site-specific policies, it is important to know the specific characteristics of the vulnerable areas.

Figures 6B, 6C, and 6D show the characteristic-induced vulnerability based on variables that were found to significantly affect agricultural value of production in the previous subsection (Table 2). The characteristics we chose to reiterate on and relate to policy are slope, soil type, and irrigation intensity. The darker areas represent vulnerability induced by the specified characteristic.

Figure 6B shows the slope-induced vulnerability. It represents the estimated effect of slope on land degradation at any single point or the marginal effect of an extra unit of slope. Areas on steeper slopes are more vulnerable to agricultural value of production losses from land degradation. Figure 6C, on the other hand, represents soil type induced vulnerability. This varied across the map of Ethiopia because some soil types maybe vulnerable while others are not. For example, while Aridisols and Entisols are productive types of soil, farms with this soil type experience high degradation. Entisols are productive only if combined with fertilizer and Aridisols are dry and usually useless without irrigation. Thus, effort towards “proper” irrigation and fertilizer subsidy are important policies to think about. Moreover, “proper” irrigation is important because irrigation intensity also contributes to land degradation. Figure 6D represents irrigation-induced vulnerability. In low-rainfall areas, grass strips, waterways, and trees are less capital inducive water saving technologies.

Other important results from this paper that pose important policy implications are the significance of the type of energy used in cooking as one of the instrumental variables, literacy, access to information measured as the number of visits by extension agents and ethnicity. The significance of type of energy used in cooking stoves suggests a two-pronged policy to stem deforestation and to disseminate more efficient stove technologies. Moreover, these results suggest that extension programs and farmer training are promising programs to benefit Ethiopian farmers. Households acquire specific human capital that affect farming decisions and outcomes and indicate the importance of accounting for these strategies in empirical research on land management. Membership in bigger ethnic groups (Amhara and Oromo) reduces land degradation while membership to a smaller group increases land degradation. As mentioned previously, federal states of Ethiopia are organized along ethnic boundaries (Keeley and Scones, 2000) and that ethnicity may affect conservation behaviors (Bekele and Drake, 2003; Bogale, Taeb and Endo, 2006; Norris and Batie, 1987). These correlations may require investigation and the understanding of the socio-cultural outlook of the different ethnic groups related to natural resource use and design conservation interventions that suit particular settings.

7 Conclusion and Suggestions for future studies

This study estimates the impact of land degradation on agricultural value of production in Ethiopia using cross section farm household data and environmental characteristics map. This study integrates a fine resolution global environmental map containing land degradation information with a geographically coded farmer survey for Ethiopia without any information loss in the process.

We use instrumental variable approach to control for endogeneity of land degradation and find that the effect of land degradation exhibits upward bias if endogeneity is not accounted for. We find that land degradation reduces agricultural value to 7 percent. In monetary terms, this decline is equivalent to $7.63 per hectare. And if all of the agricultural lands are degraded, the loss for the country as a whole is $267 Million. Where 85% of the population depends on agriculture, this loss is substantial. We also find that the type of energy used in cooking stoves and bequest variables are good instruments for land degradation. The significance of type of energy used in cooking stoves suggests a two-pronged policy to stem deforestation and to disseminate more efficient stove technologies.

To account for the spatial nature of the problem of land degradation, we accounted for spatial autocorrelation and found significant clustering or spill-over effect. The coefficients' efficiency were improved which makes our estimates more reliable. Having established the spatial nature of the problem of land degradation, it is worth noting that other river basin countries in sub-saharan Africa: Tanzania, Rwanda, Burundi, Congo, Kenya, Uganda, Eritria, Sudan and Egypt might be affected as well. Ethiopian highlands is one of the catchment of Nile River. The source of water from Ethiopian highlands discharge into the Nile, thus soil erosion in the watershed area could become sediment yield entering the rivers affecting the other countries as well that depend on the Nile river.

Limitation of the study is not taking into account the time component of the land degradation process. Recommendation for future studies is developing more waves of the survey with GPS point codes, as well as developing more GLADIS maps to be able to analyze the problem through a panel approach. Nevertheless, the paper demonstrates the vast possibility of analysis we could generate by geographically combining different datasets.

The spatial cross section analysis of the data implies that the strategies to reduce land degradation's effect on agricultural value of production must be location-specific. The vulnerability maps imply that to have site specific development plans such as aid and extension, it is important for policy makers to know the areas that are most degraded and areas where agricultural value is at risk or vulnerable to land degradation. Moreover, the characteristic of the land that induces land degradation is also important so that interventions are tailored to local circumstances.

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Tables

Table 1. Variable Definitions and Summary Statistics

Variable Name	Definition	Source	Mean	Std	Min	Max
Agricultural Value of Production	continuous variable, normalized from 0 to 1	GLADIS	0.2562263	0.1457332	0	0.52445
Land Degradation	continuous variable, normalized from 0 to 1	GLADIS	0.6591157	0.1578695	0	0.753843
Candidates for Instrumental Variables						
Bequest = Inheritance*Children	Interaction term between inheritance as the source of ownership dummy and number of children	IFPRI	1.092151	2.147391	0	12
"Bad" Cooking Energy	=1 if source of energy is animal dung, fuel wood or both, =0 otherwise	IFPRI	0.6243453	0.484329	0	1
Environmental Characteristics						
Histosol Soil (useless without drainage)	=1 if Histosol Type of Soil, =0 otherwise	GLADIS / USDA	0.2709094	0.444464	0	1
Aridisol Soil (useless without irrigation)	=1 if Aridisol Type of Soil, =0 otherwise	GLADIS / USDA	0.0068243	0.0823333	0	1
Entisol Soil (useless without fertiizer)	=1 if Entisol Type of Soil, =0 otherwise	GLADIS / USDA	0.2590065	0.43812	0	1
Slope	increasing continuous variable in %, (1-0 to 2%, 2-2 to 16%, 3->16%)	GLADIS	3.458868	1.891157	0	8
Elevation	elevation in MASL units	IFPRI	2782.969	9527.373	0	220000
Average Rainfall (1951-2005)	continuous variable; in mm	IFPRI	971.8406	206.9701	211.14	1216.21
Average Temperature (1951-2005)	continuous variable; in degrees Celsius	IFPRI	18.74625	2.295955	14.0061	24.7505
Env Shock	=1 experienced hail, drought or flood shock; =0 otherwise	IFPRI	0.4449501	0.4970038	0	1
Socio-Environment Characteristics						
Population Density	number of inhabitants per kilometers sq	GLADIS	1932.725	1022.399	0	3000
Access to Basic Facilities	average distance in kilometers of farm to roads and bridges and market where they sell output	IFPRI	5.79087	4.373555	0.05	45
Access to Information	number of visit times of entension agents (2004-2005) cropping season	IFPRI	5.467826	8.088444	0	60
Farm Characteristics						
Irrigation Intensity	normalized intensity of irrigation	GLADIS	0.691466	0.513001	0	1
Distance of farm from home	distance of farm from home in kilometers	IFPRI	1.09207	3.368073	0	100
Area	total plot area in hectares	IFPRI	0.4677371	9.405884	0	625
Land Tenure Characteristics						
Inheritance Dummy	=1 if source of ownership is through inheritance; =0 if government redistribution	IFPRI	0.3739089	0.4838783	0	1
Land Certified	=1 if land is certified; =0 not certified	IFPRI	0.1986986	0.3990523	0	1
Land Owned	=1 if land is owned; =0 not owned	IFPRI	0.8531979	0.3539366	0	1
Rent	annual rent of land in Birr	IFPRI	204.9958	30.06293	1	1200
Sharecrop	percentage share of land being sharecropped	IFPRI	49.99623	6.638499	0.2	300

Continued Table 1. Variable Definitions and Summary Statistics

Variable Name	Definition	Source	Mean	Std	Min	Max
Farmer Demographics						
Big Ethnic Group	=1 if member of Oromo or Amhara, =0 otherwise	IFPRI	0.4445326	0.4969533	0	1
Children	number of children	IFPRI	4.253465	2.226205	0	12
Gender	=1 if male; =0 female	IFPRI	0.0800511	0.271397	0	1
Farming Years	number of farming years	IFPRI	24.46769	12.62777	1	68
Literacy	number of years of education	IFPRI	4.924933	1.347396	0	13
Total Sick days	number of sick days for the household who work on farm	IFPRI	1.089351	8.277076	0	195
CV Assets	total current value of assets (i.e. farm tools and machineries)	IFPRI	2567.226	6946.504	0	200195
CV Livestock	total current value of livestock	IFPRI	994.8111	1949.011	0	17499
Gift income	gift income received in Birr	IFPRI	78.72254	308.7018	0	3442.5
Aid	aid both cash or food in Birr	IFPRI	19.00135	92.30292	0	1400
Neighbor's Characteristics						
Neighbor's Land Degradation	continuous variable, normalized from 0 to 1	GLADIS	0.6125237	0.3590624	0	0.973684
Neighbors Histosol Soil (useless without drainage)	=1 if Histosol Type of Soil, =0 otherwise	GLADIS / USDA	0.32546	0.43628	0	1
Neighbor's Aridisol Soil (useless without irrigation)	=1 if Aridisol Type of Soil, =0 otherwise	GLADIS / USDA	0.078392	0.045372	0	1
Neighbor's Entisol Soil (useless without fertiizer)	=1 if Entisol Type of Soil, =0 otherwise	GLADIS / USDA	0.342517	0.395759	0	1
Neighbor's Slope	increasing continuous variable in %, (1-0 to 2%, 2-2 to 16%, 3->16%)	GLADIS	1.715086	0.502328	0	2.923858
Neighbor's Elevation	elevation in MASL units	IFPRI	15878.62	9937.9	0	37036.99
Neighbor's Population Density	number of inhabitants per kilometers sq	GLADIS	1932.725	1022.399	0	3000
Neighbor's Farming Years	number of farming years	GLADIS	33.225475	18.3077175	0	63.5579
Neighbor's Literacy	number of years of education	IFPRI	3.86759	1.2436	0	11
Neighbor's Irrigation Intensity	normalized intensity of irrigation	GLADIS	0.43522	0.27383	0	1

Table 2. Regression Results

	OLS without correcting for endogeneity	*First Stage Regression*	*Instrumental Variable Approach*	*Spatially Weighted Regression*
	Agricultural Value of Production	Land Degradation	Agricultural Value of Production	Agricultural Value of Production
Land Degradation	-0.0921*		-0.0729*	-0.0652***
	(0.02510)		(0.05740)	(0.04910)
Candidates for Instrumental Variables				
Bequest	-0.00108	-0.0104*		
	(0.00123)	(0.00617)		
"Bad" Cooking Energy	-0.0311	0.219***		
	(0.00411)	(0.10700)		
Environmental Characteristics				
Histosol Soil	0.0504***	-0.0441***	0.0261**	0.0258***
	(0.00364)	(0.00175)	(0.01300)	(0.00285)
Aridisol Soil	-0.0682***	0.0331**	-0.232**	-0.256***
	(0.02560)	(0.01290)	(0.11000)	(0.09830)
Entisol Soil	-0.0595***	0.0302***	-0.203***	-0.245***
	(0.00367)	(0.00180)	(0.07890)	(0.06573)
Slope	-0.000405	0.00045	-0.00405	0.0120
	(0.00221)	(0.00111)	(0.00573)	(0.00255)
Elevation	-2.34E-08	1.26E-09	-2.68E-08	-3.24e-06**
	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Average Rain	0.0289**	0.0276**	0.106*	0.1735**
	(0.02200)	(0.01110)	(0.09250)	(0.08373)
Average Temperature	-0.0194***	0.0208***	-0.0755*	-0.110***
	(0.00418)	(0.00209)	(0.05560)	(0.00923)
Environmental Shock	-0.00720**	-0.00271	-0.0224**	-0.0294***
	(0.00340)	(0.00171)	(0.01080)	(0.01640)
Socio-Environment Characteristics				
Population Density	4.87e-06*	7.41e-05***	0.000350*	0.0200***
	(0.00000)	(0.00000)	(0.00019)	(0.00773)
Access to Basic Facilities	0.000387	0.000767	-0.00407*	-0.00292***
	(0.00035)	(0.00018)	(0.00220)	(0.00068)
Access to Information	0.000157	-0.000351*	0.00146*	0.00103*
	(0.00022)	(0.00011)	(0.00107)	(0.00062)
Farm Characteristics				
Irrigation Intensity	-0.102***	0.0183***	-0.0151**	-0.134***
	(0.00210)	(0.00103)	(0.01474)	(0.07060)
Distance of farm from home	-0.00166	0.000648***	-0.00466	0.000858
	(0.00041)	(0.00020)	(0.00197)	(0.00090)
Area	-0.00126	0.00295***	-0.0153	0.00726
	(0.00215)	(0.00108)	(0.00936)	(0.00109)
Land Tenure Characteristics				
Inheritance Dummy	0.00769	-0.0105***	0.025	0.027
	(0.00579)	(0.00291)	(0.01800)	(0.02890)
Land Certified	0.0270***	0.00943***	-0.0162	0.00608
	(0.00374)	(0.00188)	(0.02660)	(0.02960)
Land Owned	0.000387	-0.0015	0.00613	0.187
	(0.00378)	(0.00190)	(0.01040)	(0.12000)
Share of Land Sharecropped	-0.0000111	-0.0000147**	0.0000622	0.000226
	(0.00004)	(0.00001)	(0.00011)	(0.00020)
Annual Rent	0.000016	0.0000227	-0.0000776	0.0000563
	(0.00019)	(0.00010)	(0.00049)	(0.00008)

Table 2. Continued Regression Results

	OLS without correcting for endogeneity	*First Stage Regression*	*Instrumental Variable Approach*	*Spatially Weighted Regression*
	Agricultural Value of Production	Land Degradation	Agricultural Value of Production	Agricultural Value of Production
Farmer Demographics				
Big Ethnic Group	-0.000066	0.00609***	-0.0183	0.0538
	(0.00384)	(0.00193)	(0.02040)	(0.01160)
Children	0.00360***	-0.000752*	0.00897***	0.00407***
	(0.00077)	(0.00039)	(0.00326)	(0.00144)
Gender	-0.0128*	-0.00467*	0.0818**	0.0282**
	(0.00480)	(0.00242)	(0.01700)	(0.01310)
Farming Years	0.000921***	-0.000119**	0.00156***	0.00418**
	(0.00011)	(0.00005)	(0.00043)	(0.00327)
Literacy	0.000248	0.00160***	-0.0074	0.00451
	(0.00096)	(0.00048)	(0.00487)	(0.00144)
Total Sick Days	-0.000105***	-0.00000943	-0.0000608	-0.000541
	(0.00002)	(0.00001)	(0.00007)	(0.00046)
CV Assets	8.14e-07***	-0.000000106	1.28e-06**	2.12e-06**
	(0.00000)	(0.00000)	(0.00000)	(0.00000)
CV Livestock	9.70e-06***	0.000000864**	0.00000677*	3.98e-06***
	(0.00000)	(0.00000)	(0.00001)	(0.00000)
Gift Income	0.00000503	0.00000469	-0.0000167	-5.10e-05
	(0.00001)	(0.00000)	(0.00002)	(0.00003)
Aid	-5.99e-05***	-1.89e-05***	-2.13e-05**	-1.93e-05**
	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Neighbor's Characteristics				
N's Land Degradation				-0.423**
				(0.1670)
N's Histosol Soil				0.0324**
				(0.01100)
N's Aridisol Soil				-0.345**
				(0.21400)
N's Entisol Soil				-0.0967***
				(0.0200)
N's Slope				-0.0280*
				(0.0156)
N's Elevation				0.426
				(0.1440)
N's Literacy				0.0941***
				(0.0280)
N's Irrigation Intensity				-0.0487**
				(0.0195)
Constant	0.397***	0.1522***	0.125**	1.127***
	(0.02)	(0.08)	(0.11)	(0.1034)
Observations	6,301	6,301	6,301	6,301
Adj R-squared	0.392	0.76	0.489	0.514
Underidentification test			1.17[a]	1.11[a]
Chi-sq(2) P-val			0.43	0.562
Overidentification test			1.32[b]	0.98[b]
Chi-sq(2) P-val			0.1894	0.3576

[a] Anderson Canonical Correlation LM Statistic
[b] Sargan Statistic
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figures

Figure 1. "Complicated Feedback Loop": Land Degradation and Agricultural Value of Production

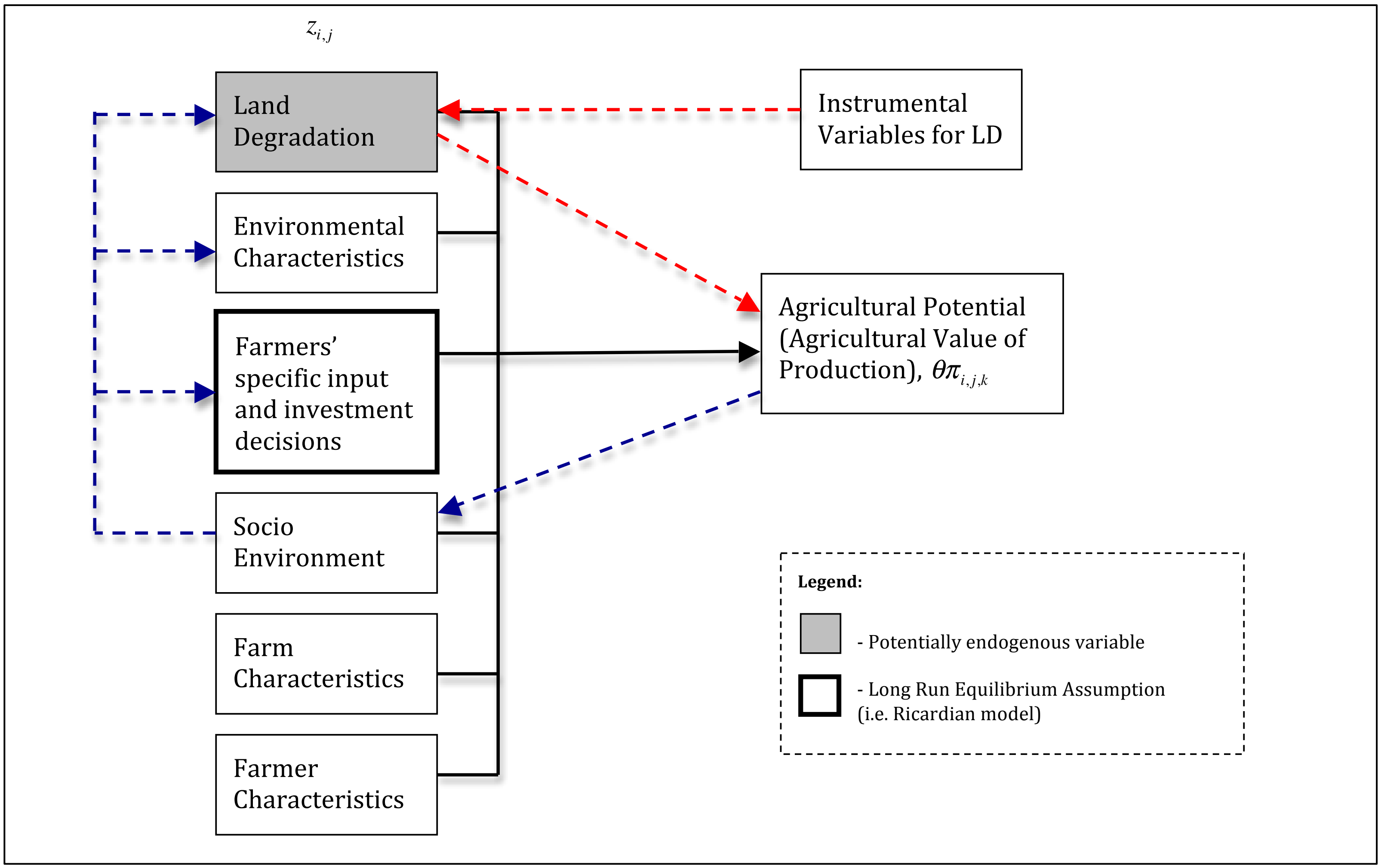


Figure 2. GLADIS Description of Axes

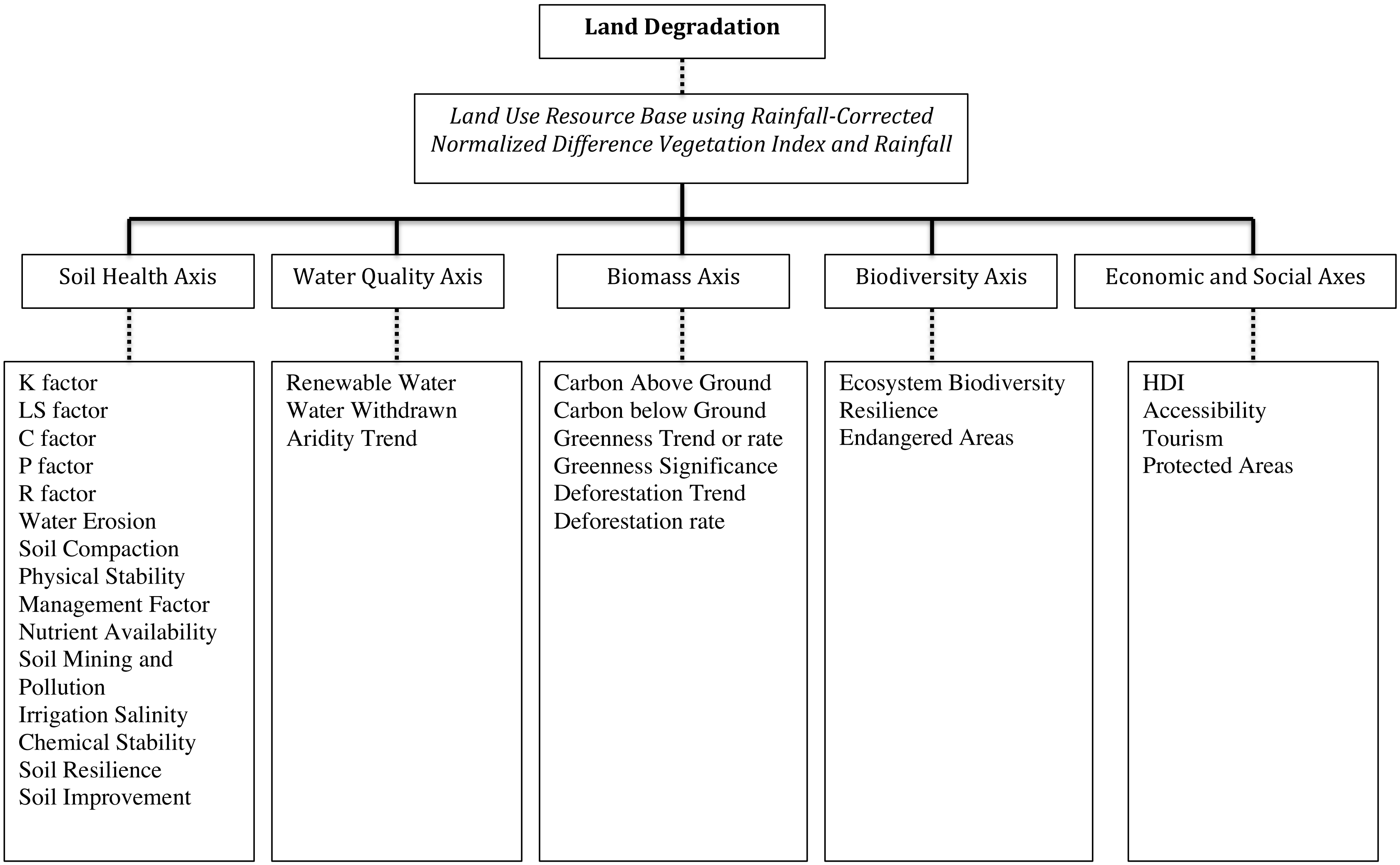
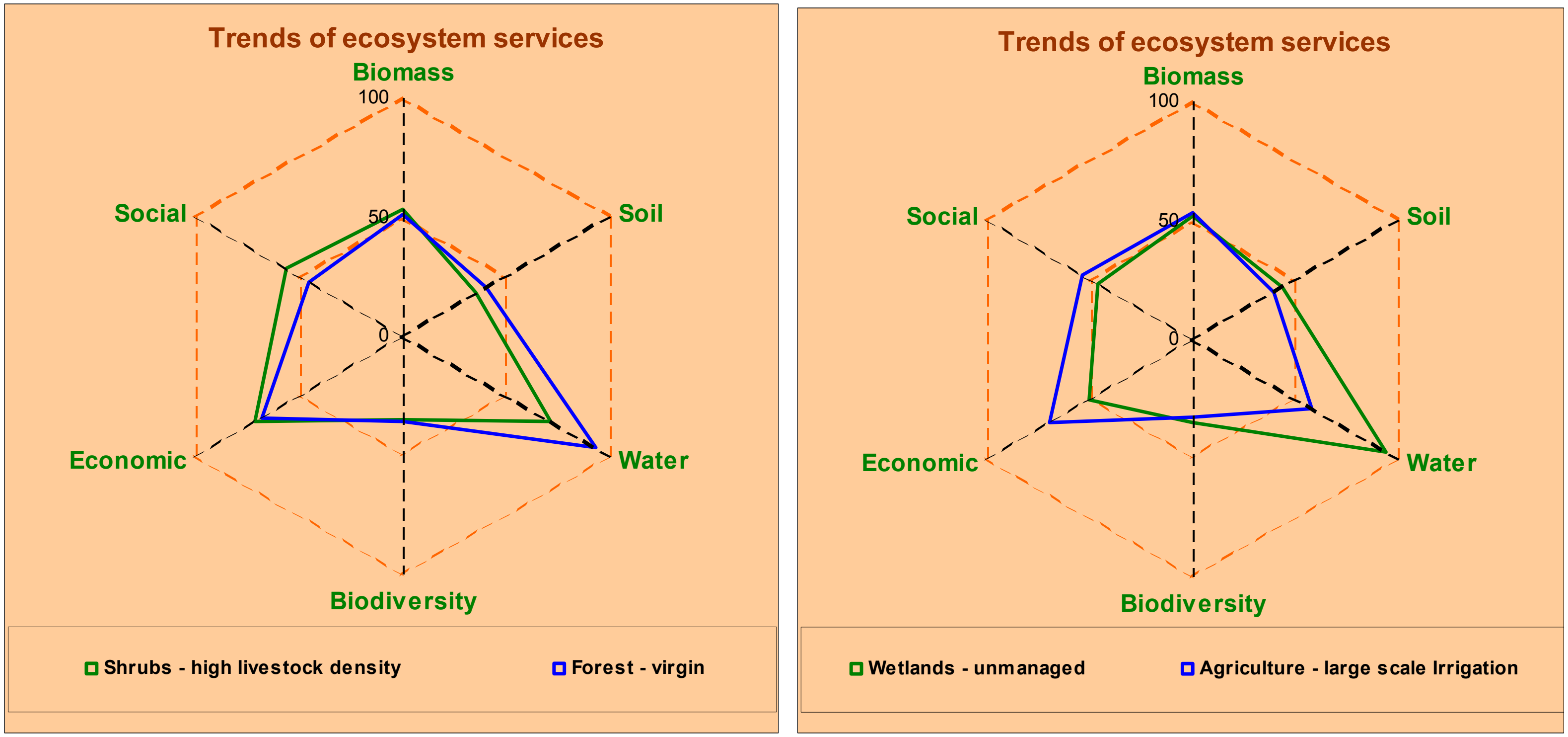
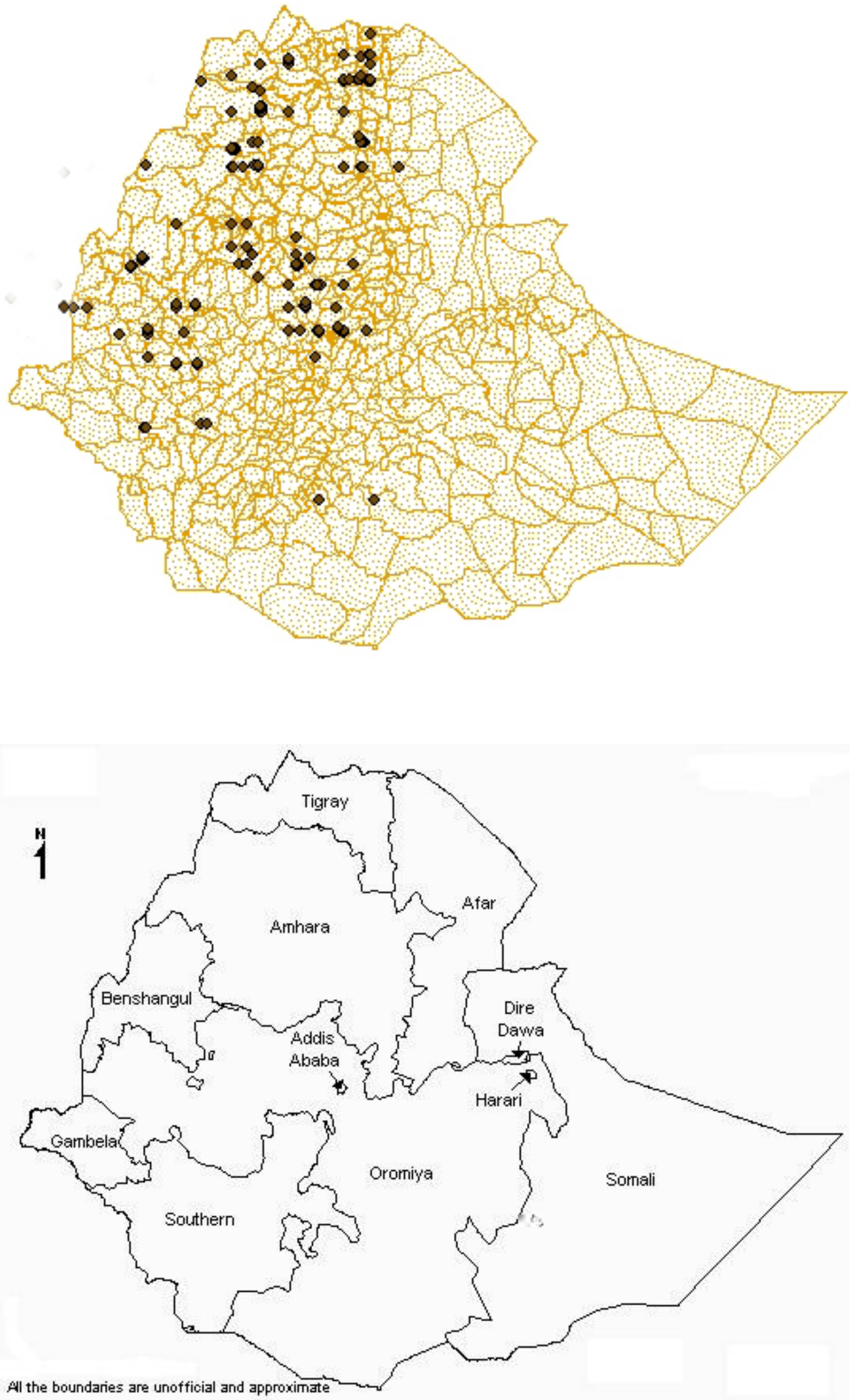


Figure 3. GLADIS Radar Trend Diagram : LD Trends in Different Land Use Systems



Source: GLADIS Technical Report No 17, LADA Network, FAO

Figure 4. Gladis and IFPRI Merged Data and Ethiopia State Map



Source: http://www.fao.org/DOCREP/005/AC627E/AC627E08.htm

Figure 5. Cluster and Significance Maps of Land Degradation induced Agricultural Value of Production and Moran's I-statistic

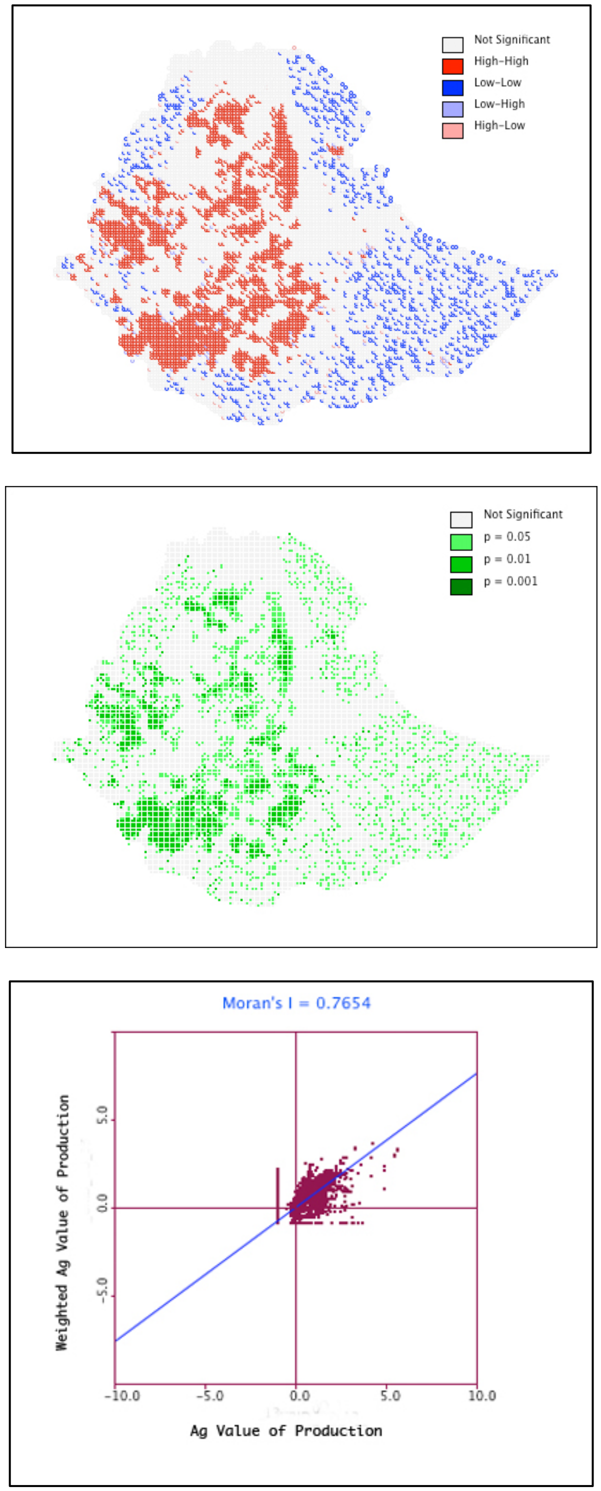


Figure 6. Vulnerability Map and Characteristic Induced Land Degradation

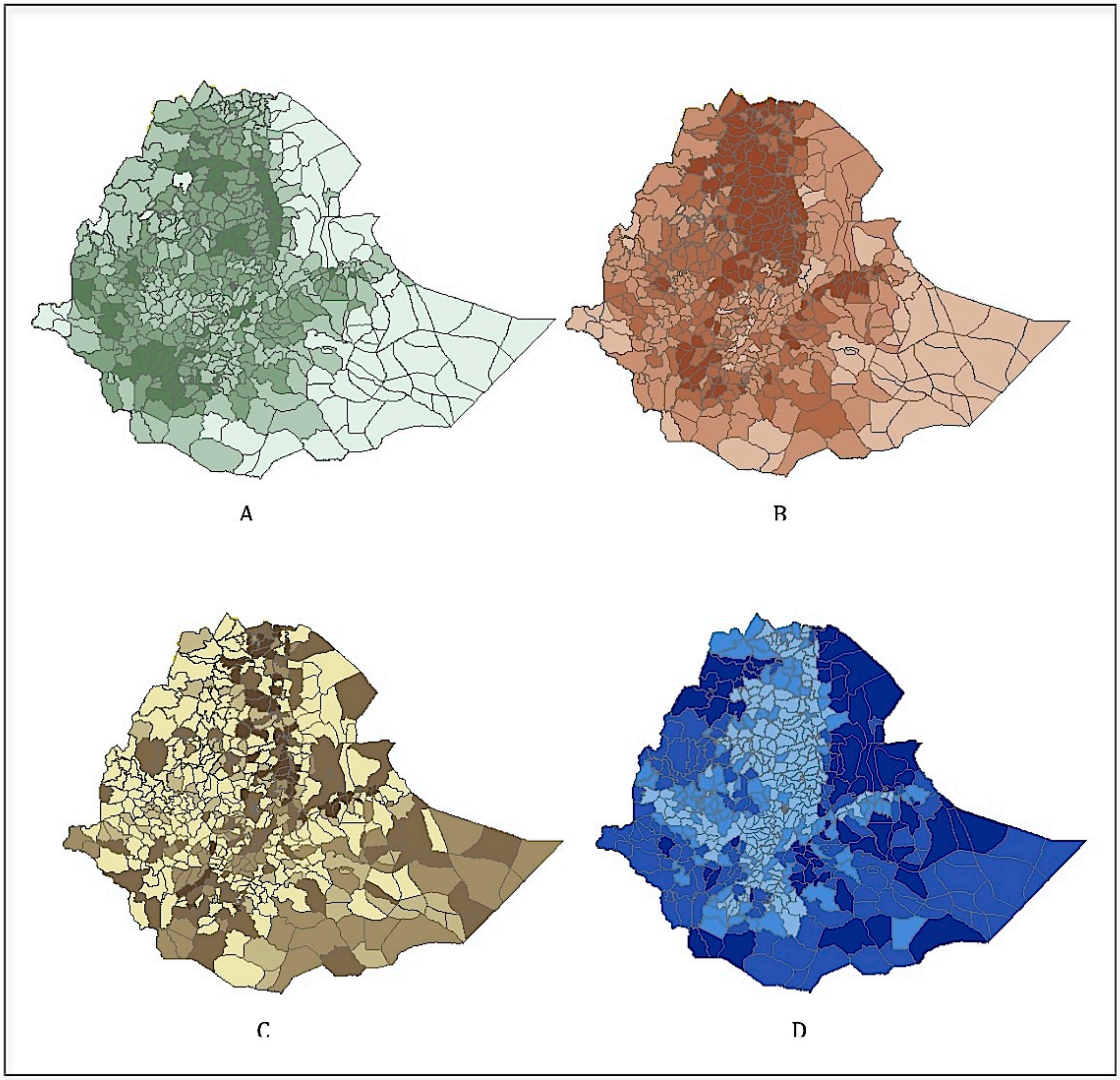


Figure 6A represents agricultural value of production vulnerability to land degradation. Mathematically, marginal effect of land degradation on agricultural value of production multiplied by actual agricultural value of production. i.e. β_{LD} from 2nd stage $\times$ AgValProdn

Figures 6B, 6C, and 6D represent the estimated effect of slope, soil type and irrigation on land degradation, respectively. Mathematically, 6B is the marginal effect of an extra unit of slope times the actual slope at that point. i.e. β_{slope} from 1st stage $\times$ Land Degradation. Likewise for 6C and 6D.

Appendix Tables

Appendix Table 1a. Test for Omitted Variable Bias First Stage of Regression

	LD1	LD1a	LD2	LD3	LD4	LD5	LD6
Candidates for Instrumental Variables							
Bequest	-0.001**		-0.001*	-0.001*	-0.001*	-0.002***	-0.0104*
	(0.0010)		(0.0010)	0.0000	0.0000	0.0000	(0.0062)
"Bad" Cooking Energy	0.031***		0.046***	0.006***	0.006***	0.005***	0.219***
	(0.0030)		(0.0030)	(0.0020)	(0.0020)	(0.0020)	(0.1070)
Interact Instruments		2.107***					
		(0.0710)					
Environmental Characteristics							
Histosol Soil			0.019***	-0.053***	-0.045***	-0.044***	-0.0441***
			(0.0030)	(0.0020)	(0.0020)	(0.0020)	(0.0018)
Aridisol Soil			0.025	0.029**	0.029**	0.026**	0.0331**
			(0.0230)	(0.0130)	(0.0130)	(0.0130)	(0.0129)
Entisol Soil			0.070***	0.026***	0.026***	0.028***	0.0302***
			(0.0030)	(0.0020)	(0.0020)	(0.0020)	(0.0018)
Slope			0.001	0.001	0.001	0.001	0.00045
			(0.0020)	(0.0010)	(0.0010)	(0.0010)	(0.0011)
Elevation			0.000	0.000	0.000	0.000	1.26E-09
			(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Average Rain			0.162***	0.032***	0.026**	0.024**	0.0276**
			(0.0200)	(0.0110)	(0.0110)	(0.0110)	(0.0111)
Average Temp			0.075***	0.025***	0.023***	0.022***	0.0208***
			(0.0040)	(0.0020)	(0.0020)	(0.0020)	(0.0021)
Environmental Shock			-0.019***	-0.005***	-0.001	-0.003	-0.00271
			(0.0030)	(0.0020)	(0.0020)	(0.0020)	(0.0017)
Socio-Environment Characteristics							
Population Density				6.97e-05***	6.92e-05***	7.39e-05***	7.41e-05***
				(0.0000)	(0.0000)	(0.0000)	(0.0000)
Access to Basic Facilities				-0.001	-0.001	-0.001	0.000767
				(0.0002)	(0.0002)	(0.0002)	(0.0002)
Access to Information				0.000	0.000	0.000	-0.000351*
				(0.0001)	(0.0001)	(0.0001)	(0.0001)
Farm Characteristics							
Irrigation Intensity					-0.018***	-0.018***	0.0183***
					(0.0010)	(0.0010)	(0.0010)
Distance of farm from home					0.001***	0.001***	0.000648***
					0.0000	0.0000	(0.0002)
Area					0.003**	0.003**	0.00295***
					(0.0011)	(0.0011)	(0.0011)
Land Tenure Characteristics							
Inheritance Dummy						0.015***	-0.0105***
						(0.0020)	(0.0029)
Land Certified						0.009***	0.00943***
						(0.0020)	(0.0019)
Land Owned						-0.002	-0.0015
						(0.0020)	(0.0019)
Share of Land Sharecropped						-0.0000152**	-0.0000147**
						(0.0000)	(0.0000)
Annual Rent						0.0000231	0.0000227
						(0.0001)	(0.0001)

Continued Appendix Table 1a. Test for Omitted Variable Bias First Stage of Regression

	LD1	LD1a	LD2	LD3	LD4	LD5	LD6
Farmer Demographics							
Big Ethnic Group							0.00609***
							(0.0019)
Children							-0.000752*
							(0.0004)
Gender							-0.00467*
							(0.0024)
Farming Years							-0.000119**
							(0.0001)
Literacy							0.00160***
							(0.0005)
Total Sick Days							-0.00000943
							(0.0000)
CV Assets							-0.000000106
							(0.0000)
CV Livestock							0.000000864***
							(0.0000)
Gift Income							0.00000469
							(0.0000)
Aid							-1.89e-05***
							(0.0000)
Constant	0.149***	0.165***	0.104***	0.010***	0.055***	0.055***	0.052***
	(0.0020)	(0.0010)	(0.0040)	(0.0030)	(0.0040)	(0.0080)	(0.0080)
Observations	6,301	6,301	6,301	6,301	6,301	6,301	6,301
Adj R-squared	0.23	0.17	0.303	0.744	0.756	0.759	0.76
RESET Test= Ho: Model has no omitted variables							
F Statistic	3.93	0.5	0.684	0.2866	0.8341	0.7505	0.7341
Prob>F	0.00820	0.68030	0.00932	0.12680	0.13648	0.26483	0.74830

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix Table 1b. Test for Omitted Variable Bias Second Stage of Regression with Spatially Weighted Variables

	AgVal1	AgVal1b	AgVal2	AgVal3	AgVal4	AgVal5	AgVal6	AgVal7
Predicted Land Degradation	0.0651***		0.0786***	0.04032***	0.0842***	0.0801	0.0801	0.0652***
	(0.0328)		(0.0190)	(0.0210)	(0.0183)	(0.0246)	(0.0246)	(0.0491)
Predicted Land Degradation Squared		2.107***						
		(1.0710)						
Environmental Characteristics								
Histosol Soil			0.040***	0.218***	0.091***	0.066***	0.0261**	0.0258***
			(0.0040)	(0.0060)	(0.0090)	(0.0110)	(0.0130)	(0.0029)
Aridisol Soil			-0.110***	-0.197***	-0.113***	-0.092***	-0.232**	-0.256***
			(0.0300)	(0.0280)	(0.0270)	(0.0270)	(0.1100)	(0.0983)
Entisol Soil			-0.093***	-0.169***	-0.090***	-0.067***	-0.203***	-0.245***
			(0.0040)	(0.0040)	(0.0060)	(0.0080)	(0.0789)	(0.0657)
Slope			-0.011***	-0.007***	-0.005**	-0.004*	-0.00405	0.0120
			(0.0030)	(0.0020)	(0.0020)	(0.0020)	(0.0057)	(0.0026)
Elevation			-2.68E-08	-2.68E-08	-2.68E-08	-2.68E-08	-2.68E-08	-3.24e-06**
			0.0000	0.0000	0.0000	0.0000	(0.0000)	(0.0000)
Average Rain			-0.027	0.061**	-0.013	-0.027	0.106*	0.1735**
			(0.0260)	(0.0240)	(0.0230)	(0.0230)	(0.0925)	(0.0837)
Average Temp			-0.022***	-0.065***	-0.019***	-0.028***	-0.0755*	-0.110***
			(0.0040)	(0.0050)	(0.0060)	(0.0070)	(0.0556)	(0.0092)
Environmental Shock			-0.008**	-0.017***	-0.021***	-0.014***	-0.0224**	-0.0294***
			(0.0040)	(0.0030)	(0.0030)	(0.0030)	(0.0108)	(0.0164)
Socio-Environment Characteristics								
Population Density				0.000346*	0.000420*	0.000533*	0.000350*	0.0200***
				(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0077)
Access to Basic Facilities				0.004***	-0.001	0.001	-0.00407*	-0.00292***
				(0.0002)	(0.0002)	(0.0002)	(0.0022)	(0.0007)
Access to Information				-0.002***	0.00146*	0.00146*	0.00146*	0.00103*
				(0.0001)	(0.0001)	(0.0001)	(0.0011)	(0.0006)
Farm Characteristics								
Irrigation Intensity					-0.086***	-0.098***	-0.0151**	-0.134***
					(0.0040)	(0.0050)	(0.0147)	(0.0706)
Distance of farm from home					-0.002***	-0.002***	-0.00466	0.000858
					0.0000	0.0000	(0.0020)	(0.0009)
Area					-0.004*	-0.003	-0.0153	0.00726
					(0.0020)	(0.0020)	(0.0094)	(0.0011)

Continued Appendix Table 1b. Test for Omitted Variable Bias Second Stage of Regression with Spatially Weighted Variables

	AgVal1	AgVal2	AgVal3	AgVal4	AgVal5	AgVal6	AgVal7	AgVal8
Land Tenure Characteristics								
Inheritance Dummy						-0.005	0.025	0.027
						(0.0030)	(0.0180)	(0.0289)
Land Certified						0.035***	-0.0162	0.00608
						(0.0040)	(0.0266)	(0.0296)
Land Owned						-0.002	0.00613	0.187
						(0.0040)	(0.0104)	(0.1200)
Share of Land Sharecropped						0.0000622	0.0000622	0.000226
						(0.0001)	(0.0001)	(0.0002)
Annual Rent						-0.0000776	-0.0000776	0.0000563
						(0.0005)	(0.0005)	(0.0001)
Farmer Demographics								
Big Ethnic Group							-0.0183	0.0538
							(0.0204)	(0.0116)
Children							0.00897***	0.00407***
							(0.0033)	(0.0014)
Gender							0.0818**	0.0282**
							(0.0170)	(0.0131)
Farming Years							0.00156***	0.00418**
							(0.0004)	(0.0033)
Literacy							-0.0074	0.00451
							(0.0049)	(0.0014)
Total Sick Days							-0.0000608	-0.000541
							(0.0001)	(0.0005)
CV Assets							1.28e-06**	2.12e-06**
							(0.0000)	(0.0000)
CV Livestock							0.00000677*	3.98e-06***
							(0.0000)	(0.0000)
Gift Income							-0.0000167	-5.10e-05
							(0.0000)	(0.0000)
Aid							-2.13e-05**	-1.93e-05**
							(0.0000)	(0.0000)

Continued Appendix Table 1b. Test for Omitted Variable Bias Second Stage of Regression with Spatially Weighted Variables

	AgVal1	AgVal2	AgVal3	AgVal4	AgVal5	AgVal6	AgVal7	AgVal8
Neighbor's Characteristics								
N's Land Degradation								-0.423**
								(0.1670)
N's Histosol Soil								0.0324**
								(0.0110)
N's Aridisol Soil								-0.345**
								(0.2140)
N's Entisol Soil								-0.0967***
								(0.0200)
N's Slope								-0.0280*
								(0.0156)
N's Elevation								0.426
								(0.1440)
N's Literacy								0.0941***
								(0.0280)
N's Irrigation Intensity								-0.0487**
								(0.0195)
Constant	0.135***	0.169***	0.137***	0.126***	0.380***	0.401***	0.125**	1.127***
	(0.0030)	(0.0030)	(0.0050)	(0.0050)	(0.0120)	(0.0200)	(0.1100)	(0.1034)
Observations	6,301	6,301	6,301	6,301	6,301	6,301	6,301	6,301
Adj R-squared	0.173	0.123	0.30	0.401	0.457	0.464	0.489	0.514
RESET Test= Ho: Model has no omitted variables								
F Statistic	133.23	266.73	40.198	2.52	1.3778	0.9283	0.8632	0.7342
Prob>F	0.00000	0.00000	0.09726	0.05640	0.11830	0.22648	0.67390	0.56473

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1