ABSTRACT

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Since the 1970s multiple research efforts around the world have focused on identifying potential environmental, economic, and social impacts of development. It is well understood that local project assessment approaches fail to identify, or worse quantify, indirect or cumulative effects, when they do not provide an appropriate baseline framework to understand the local and the regional environment as a connected entity. A conceptual approach based on several environmental assessment and spatial analysis tools suggests that we need to consider multi-scale methods that can help describe the different processes that occur within a region. This would help project managers and researchers to better evaluate ongoing regional policies by retrieving a wide characterization of the application and impacts of policies within the whole geographical spectrum. Within each policy assessment, these methods could evolve into a framework for environmental management practices at both local and regional scales that could be updated with new information through time. We analyze two regional policy case studies: poverty targeting in Sri Lanka, and payments for ecosystem services in Costa Rica.

Scale and Strategy in Environmental Assessment of Regional Development Policies

by
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DEDICATION

To the memory of my grandparents:
Alfredo Arce and Hermelinda Rengifo

To the memory of a very good friend:
Enzo Chumbe Ferrari

To my parents: Ruben and Luisa

To my siblings: Carmen, Ruben, and Alfredo

And especially to my beloved wife:
Ginger Gail Deason

BIOGRAPHY

Luis Eduardo Carrasco Arce, was born in Callao, Peru in 1970. He received his BSc in Forest Sciences from the Agrarian National University "La Molina" in Lima (Peru) in 1995 as well as a professional degree of Forest Engineer in 1996. In 2002, he earned his MSc at North Carolina State University, studying the evolution of the quality of environmental impact statements for highway projects carried out by the North Carolina Department of Transportation. Luis has extensive professional expertise in environmental impact assessment. He worked for three years for Mondina S.A., a Peruvian based environmental consulting firm, before starting his master's studies. During this period, he programmed and conducted environmental impact studies (EIS) for oil exploration projects in different locations of the Peruvian Jungle. He also conducted environmental monitoring of seismic operations which included among other functions: water quality monitoring, forest inventory, waste management, and environmental education. Besides being fluent in English, Luis is also fluent in Spanish, his native tongue, and has conversational command of French.

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I have met so many people during the time that took me write this dissertation that it would probably be unfair to pretend to mention them all, as I am sure I will forget some of their names. I would like, though, to acknowledge very much the help of Dr. Gary Blank, my adviser, whose patience, guidance, and trust were very important to me during the whole dissertation process. I also would like to extend my appreciation to Dr. Erin Sills, whose very high standards of work pushed me to write a better dissertation. I also would like to thank Dr. Subhrendu Pattanayak and Dr, Heather Cheshire for their help and attention to detail with regards to my academic work.

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During the years of my dissertation work, two people at least recognized the difficulties of the conditions under which I was doing my dissertation, and may have thought at some point that I could give it all up. One of them was Dr. Dan Robison, whose honesty, flexibility, pragmatism, and professional support from the very beginning helped me focus my efforts on achievable objectives. The other person was Ginger Deason, my wife, who knows better than anyone else all what we put aside and supported me every single day, so I could finish this almost senseless journey and to whom I am forever in debt.

I am very sure I missed several names and for that I apologize beforehand.

Luis

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Chapter II

Chapter III

LIST OF ACRONYMS

EIS: Environmental Impact Study (for project-EIS)

EIA: Environmental Impact Assessment (project-EIS)

EA: Environmental Assessment

GIS: Geographic Information Systems

GLM: Generalized Linear Model

HLM: Hierarchical Linear Model, Multilevel Linear Model

ICI: Indirect and cumulative impacts

ICIA: Indirect and cumulative impacts assessment/analysis

LCA: Life cycle assessment/analysis

OLS: Ordinary Least Squares

PES: Payments for Ecosystem Services

PSA: Pagos por Servicios Ambientales (Spanish for Payments for Ecosystem Services)

SEA: Strategic Environmental Assessment/Analysis

PROLOGUE

When I started my master's studies I thought I knew exactly the main purpose of my intention of going back to school. I was going to get a Master's in Forestry at NCSU, and after being accepted I thought I had everything already planned. After all, I thought the time spent in environmental consulting was going to give me enough guidance in order to go through the master studies without much problems. Of course, I was wrong, and I just needed as much guidance as any other new comer or as in my case as a “returner” to school. I mention this as even though I learned a lot while working in a professional setting, it was hard to adapt to academic research as it is “commonly” perceived. By “commonly” I mean the intensive study of a subject matter until there's nothing else to say about it. In a simple graphical way this means that if you start an analysis by standing on the bottom of a pyramid, by the end you should be at the top. This approach is certainly valid and has served its purposes along time, especially when trying to demonstrate cause-effect problems. However, in environmental sciences, and specifically in environmental practice, several question are related to find relationships among elements of different disciplines. For instance, a road, neighbors, a stream, businesses, air, groundwater, a forest, wildlife. All of these individuals may have not being treated in one document if not for different regulations promulgated during the last forty years, and as diverse as they are, they need to be studied by different disciplines. The difficulty, or the challenge, come when we need to connect these results, ideas, models, etc. in order to make sense of the whole issue, in other words, to have the big picture. How can we tackle that?

To describe this idea in a better way, environmental assessment has been done by collecting enormous amounts of disparate data; mostly coming from external sources such as older reports and some being produced for the sake of a development project. These data are disparate in most cases but for one particular detail, space. And it would be simple to just say space, but the mere aspect of dealing with space in a formal analysis, such as in a dissertation brings out several aspects that need to be taken into account when dealing with spatial data.

That is, space is not fixed, and its concept may be only defined in our minds, and consequently represented by different models, and the way we conceptualize it will affect our analyses, and our results, and at the end the lessons that everyone gets of such studies. On the other hand, the data that we use will need to adjust or be adjusted to our main "spatial concept" in order to be useful for our goals. In environmental assessment practice this is important since we know by experience that "our spatial concept" may not always be the proper one or coincide with those of our colleagues.

So, how does this story relate to the obstacles I found to adapt to the academic world? Basically, the scope that one would need to adopt in order to tackle the span of environmental assessment is in fact very large, and may not be perceived as focused research. This becomes even more complicated when trying to incorporate spatial elements into the analysis.

However, from environmental and economic reasons, trying to improve this discipline is very crucial. Every day, funding coming from national, state and international development agencies goes to project development, policies and programs implementation. In an important portion of these ventures, there is an environmental component that needs to be assessed from different angles, in which we could identify transdisciplinary elements struggling to fit together. In this sense I am not referring that we need improvements in the theoretical side, since environmental assessment has been mostly an application process and not an experimental one in the strict sense of the word. Methods that have been used in environmental assessment may have been adapted from already existing methods when data were available or improvised by practitioners when data were insufficient.

In recent years, research on environmental assessment has focused in different aspects such as proper methodology, analysis of alternatives to development projects, scale issues, data issues, and also: purpose. The latter one is probably the most important one. Environmental assessment practice deals with a broad spectrum of administrative burden and stakeholders interests, that in many cases it has been referred as a complex administrative permitting system. This perception, brought up by people involved in the process, has pushed a great deal of research on how to improve environmental assessment practice. Recently, assessment of cumulative and indirect impacts, has been incorporated with more or less success in environmental assessment. It is perceived that indirect and cumulative impacts may usually cross the boundary of a local project and interact with other similar effects across scales. Consideration of these issues has made environmental assessment become more complex, bringing the need of using a top-to-bottom approach as opposed to bottom-to-top one. Methods that consider this approach are strategic environmental assessment and strategic environmental analysis which I introduce in detail in chapter 1. This multitool and adaptable approach has been applied with different results in several countries already. The literature of SEA, however, is mostly conceptual, and puts a lot of emphasis in communication issues among stakeholders and goal targeting since the very beginning of a project planning. The idea is to bring the stakeholders together and define strategies that can make a policy work better for everyone, without failing to meet its main target or minimizing cross-scale negative effects. However, there is very little written about how to implement SEA as a multi-scale approach. By this I mean what type of information will be needed and of what level of complexity. SEA, by definition targets regional and subregional levels, in order to define concrete actions at the local level. We can try to imagine an scenario in which we have aggregated data at two scales: regional and subregional, plus disaggregated data at the local level. In economic terms, collecting all these data for a time frame relevant to our decision making and actions would be a very expensive task, and brings a lot of technical issues. However, advances in spatial analysis technology and its widespread use can help providing a technical platform based in spatial data and different analysis tools. With these possibilities in mind, I have tried to fill a hole in this subject, using different case studies that in different ways use spatial data and/or have a scale component in order to identify a policy strategy.

By no means I pretend to have solved a research question or a practical need. This would be nearly impossible for only one person since environmental assessment was not meant to be a one-man-show, but actually the product of interdisciplinary interaction. And, even in the interdisciplinary area, we still have a lot of room for improvement. With all these limitations, I expect this work to be useful for those interested in environmental assessment practice regardless of their core discipline. Otherwise, I just hope the experience of this work will at least make of me a better professional.

Thank you,

Luis E. Carrasco

CHAPTER I - SCALE ELEMENTS IN ENVIRONMENTAL ASSESSMENT OF REGIONAL POLICIES

Luis Eduardo Carrasco

1 ABSTRACT

Since the 1970s multiple research efforts worldwide have focused on identifying potential environmental impacts of development. It is well understood that local project assessment approaches fail to identify or quantify indirect or cumulative effects when they do not provide an appropriate baseline framework to understand the local and the regional environment as a connected entity. A conceptual approach based on several environmental assessment and spatial analysis tools suggests that we need to consider multi-scale methods that can help describe the different processes that occur within a region. This would help project managers and researchers to better evaluate ongoing regional policies by retrieving a wide characterization of the application and impacts of policies within the whole geographical spectrum. Within each policy assessment, these methods could evolve into a framework for environmental management practices at both local and regional scales that could be updated with new information through time. We analyze two regional policy case studies: poverty targeting in Sri Lanka, and ecosystem services in Costa Rica.

Keywords: Strategic Environmental Assessment, Environmental impact analysis, Environmental impact assessment, GIS, Multilevel analysis, Multiscale analysis, poverty targeting, payments for ecosystem services.

2 INTRODUCTION

Environmental Assessment (EA) has been applied to very localized projects to identify, evaluate, monitor and mitigate impacts of human development for almost four decades. As our understanding of environmental impacts complexity has increased, application of EA focused beyond local project boundaries to address environmental concerns of much broader areas. Numerous disciplines are used in EA to address these concerns with varied methodologies. Although the application of these methodologies is well intended, it is very challenging to include the spatial element as a dynamic component of the assessment of connected regional and local environmental issues. At the same time, extensive literature in EA suggests that impacts that occur at local scales and that can have effects at regional levels and vice versa should be addressed in a strategic way usually thought of as a "top-to-bottom" approach. This top-to-bottom approach is referred to as Strategic Environmental Assessment (SEA) and has been described in a theoretical context and applied in many countries. However, quantitative methodologies to put SEA into practice are still under development. Of these methodologies, Geographic Information Systems (GIS) are among the most promising ones because of the possibilities that these tools offer to integrate scale aspects into EA and more specifically into SEA.

Since the late 1980s, scientific literature has identified scale issues in GIS. However, the integration of convergent or divergent scale elements in GIS applied to EA could provide some avenues to enhance EA and SEA, when applied to regional policies. This dissertation presents the results of different scenarios where scale elements are included in spatial analysis methodologies applied to two case studies of regional policies.

3 OBJECTIVES

Analyze example case studies in which scale and strategy components are present and extract useful ideas relevant to (1) the application of environmental assessment to regional and subregional policies and (2) the use of geographic information systems in the context of environmental impact assessment.

4 METHODOLOGY

This study includes the meta-analysis of two case studies applying environmental assessment to programs, plans and policies. These two cases have a scale and strategic component in which analysis could contribute to understanding steps that are needed to improve SEA in treatment of cumulative and indirect impacts.

The two case studies topics are:

1. Poverty Mapping in South West Sri Lanka and
2. Payments for Environmental Services in Costa Rica

   In these two case studies, analysis of data available for use in GIS generates results and conclusions about a variety of questions posed. Moreover, these analyses performed demonstrate a number of important issues that emerge when GIS are brought to bear in environmental assessment as a strategic process.

From each case study important lessons are extracted regarding the following topics:

1. Type of environmental assessment
2. Type of impacts
3. Environmental impacts management processes
4. Policy theoretical scope, scale of implementation and scale of impacts
5. Scale of problems assessed
6. Metrics or indicators
7. Data characteristics
8. Analysis tools used
9. Resulting concepts concerning scale and strategy

The methods of analysis used in each case study are described specifically in each chapter that follows.

CHAPTER II - MULTISCALE ASSESSMENT OF POVERTY DISTRIBUTION

Luis Eduardo Carrasco

1 ABSTRACT

Recent adoption of GIS and GPS in socio-economic household surveys serves as an important innovation for poverty targeting. These tools can help provide information for city and policy planners even when detailed census data are not available. Because most geographic poverty-targeting studies have relied so far in non geo-referenced data, results are produced by averaging sample information within fixed administrative boundaries. This procedure may lead to interpretations that may not be spatially accurate. Most importantly, this type of analysis does not allow the researcher to explore or understand the varying geographical extension of particular indicators of socioeconomic processes. Distribution of geo-referenced socio-economic variables based in a hot-spot analysis using local indicators of spatial autocorrelation (Getis-Ord Gi*) and Voronoi Maps are presented here. We discuss the method's advantages and disadvantages, data requirements and potential applications in poverty targeting strategies.

2 INTRODUCTION

Poverty mapping is a relatively new tool that aims to provide accurate spatial environmental (ecological, social, and economic) information to researchers and policy makers. This information can be used to select areas (i.e. neighborhoods, districts, countries, regions) to be targeted for development projects, direct funding, food programs or other types of poverty alleviation solutions.

An underlying premise of poverty mapping is that poverty occurs in clustered areas. However, there is very little literature proving such clustering in a spatial statistics context. The consequence of having clusters of poverty is that targeting these areas could lead to more effective poverty reduction, as long as the clusters are very well determined.

Most poverty maps and efforts to target poverty on a geographic basis have used census or other types of data aggregated to fixed political units such as districts, states, or counties, etc. Previous research suggests that using aggregated data in poverty maps can mask areas that could be targeted if data were available at a finer detail. Recently, use of GIS and GPS in socio-economic household surveys opens the possibility of producing detailed maps for poverty targeting.

However, despite the now common use of GIS and GPS in household surveys there has been relatively little exploration of alternatives to mapping by averaging sample information to fixed administrative boundaries. Given the availability of fine scale spatial information, poverty targeting would benefit from more advanced understanding of the varying geographical relationships and scales of particular indicators of poverty. This is important for understanding the implications of the choice of a particular geographic scale in environmental assessment, specifically in socio-economic assessment.

Poverty could be represented by numerous spatial variables that might be expected to cluster spatially. In the case of the study from Sri Lanka that we use in this chapter, indicators of poverty from a household survey can be spatially represented because each household was georeferenced. Even if we assume (as many other authors have) that poor areas are found in clusters, we still need to consider whether all our indicators of poverty have the same geographical relationships, extension, or significance. These factors were necessarily neglected in the past before the advent of readily available spatial statistics and GIS tools, but they are crucial to consider before engaging in more complex analysis.

In this chapter we use data originally collected for analyzing synergies between water infrastructure and poverty alleviation in South West Sri Lanka. We used a subset of that dataset in an exploratory statistical context to study the cluster distribution, geographical scale and geographical relationships for each poverty variable and then another subset of the data to test the resulting poverty maps.

Specifically, this chapter presents results of a spatial analysis of the effect of varying scale in cluster detection of selected poverty indicators. The statistics include metrics for global and local spatial autocorrelation (Global G and Local Gi*) and GIS geo-processing using Voronoi Maps. Because these initial statistical tests suggest clustering of rich households, we include these rich clusters in our maps. We introduce a validation of clusters of low and high values, to estimate inclusion and exclusion errors in poor and rich areas. We also report on the method's characteristics, advantages and disadvantages, data requirements and potential applications in poverty targeting strategies at regional and local levels.

This chapter makes several methodological contributions. It provides a geoprocessing model to explore large amounts of data with limited background information to detect spatial clusters with multiple variables. It provides a method for identifying appropriate geographical scales and relationships based on the characteristics of the data rather than just third party assumptions. It illustrates a suite of exploratory spatial statistics analysis strong spatial statistics that lay the groundwork for performing more complex spatial statistics or econometric analysis to answer particular questions. It demonstrates a method for assessing errors of inclusion and exclusion for variables selected based on their spatial attributes. Finally, it shows the feasibility and potential advantages of using boundaries different than administrative ones.

3 OBJECTIVE

Explore and analyze spatial relationships and spatial distribution of poverty indicators at different spatial scales using geostatistical data from household surveys.

4 LITERATURE REVIEW

The following is a review of definitions, material and current methods used in poverty mapping. Emphasis has been put on demonstrating the need for a more flexible use of scale exploring spatial characteristics of socioeconomic indicators.

4.1 POVERTY MAPPING

Poverty mapping is a very useful tool for targeting poverty, and also a growing discipline that involves different fields such as econometrics, sociology, anthropology, geography and, more recently, spatial statistics and environmental sciences. There has been extensive research in poverty mapping. Bigman and Fofack (2000) state that this area has been in development since 1954. However, inclusion or attention to spatial issues in poverty mapping started in the 1990s with development of the computer science industry, diffusion of geographic information systems (GIS) and broader access to global positioning systems (GPS).

Several authors have already researched and compiled the wide and diverse literature on poverty mapping (Bigman and Fofack 2000, Davis 2003, Henninger and Snel 2002). These authors have proposed definitions of poverty mapping according to different objectives. For instance, Davis (2003) defines poverty mapping as "spatial analysis of poverty and food security, in visual and econometric terms". Henninger and Snel (2002) define poverty mapping as "the spatial representation and analysis of human well-being and poverty". Petrucci et al. (2003) give the following definition for poverty maps: "…important tools that provide information on the spatial distribution of poverty within a country. They are used to affect various kinds of decisions, ranging from poverty alleviation programs to emergency response and food aid." Despite the slight semantic differences between poverty mapping definitions, it seems that they mainly differ on the actual use of the tools (or maps) and the method selected to create them. Petrucci et al. (2003) highlight the lack of use of spatial statistics in current methods, proposing alternative procedures. Alternative methods may imply future redefinitions of poverty mapping.

In geographical terms, a poverty map is a thematic map that shows features related to human population location, classified or aggregated by a particular attribute or characteristic based on a definition or poverty line, a socioeconomic indicator, or an indicator of poverty. The goal of this geographical definition, for the objectives of this chapter, is to pay particular attention to important issues for creating useful poverty maps and that will be expanded later: scale, spatial aggregation of data, and poverty lines.

4.2 USES OF POVERTY MAPS

Targeting human populations with basic economic needs (nutrition, infrastructure service, education, etc.) is the most important use of poverty mapping. Several governments, international funding institutions (such as the World Bank, USAID, and the UN) require poverty maps in order to plan support programs, extend financial aid, or redefine development projects with the main objective of reducing poverty. Snel and Ballance (2002) list several applications, impacts and recommendations to enhance the impacts of poverty mapping. Some of these applications are listed below:

- Poverty alleviation/reduction
- Improve quality of life of the extreme poor
- Participative community planning
- Evaluate efficiency of poverty targeting
- Identify food insecure communes
- Analyze poverty and food insecurity
- Developing nutrition indicators
- Help contain a cholera outbreak
- Compare poverty and pollution
- Link poverty and health data
- Disease risk mapping

- Correct allocation of scholarships
- School lunch program
- Develop road strategies
- Risk and disaster management

One of the most important advantages of using poverty mapping is the possibility of accurately targeting funds for determined projects that would not be possible by using non-spatially referenced data alone.

Bigman and Fofack (2000) suggest that proper use of poverty maps can avoid or minimize errors of inclusion and exclusion (or type I and II errors respectively) resulting in more cost-effective programs. *Errors of inclusion* refer to including non-poor individuals or households in a poverty program, whereas *errors of exclusion* mean leaving out poor individuals or households. Selecting a proper methodology to create a poverty map will have an important impact on where and how many resources are allocated in a particular country, region, county, household or individual, and whether a program achieves poverty reduction.

An important element of poverty mapping is selecting a proper poverty line. Shim and Siegel (1995) define *poverty line* as "an income level that is considered minimaly sufficient to sustain a family in terms of food, housing, clothing, medical needs, and so on." Poverty lines need to be selected on a case by case basis. van den Berg et al. (2004) report that poverty definitions need to be compatible with the final goal for which they are needed. Also, the authors mention that poverty definitions generally depend on income and expenditure based measures. In that sense, income and expenditure measures are site specific, i.e. they are only useful to a particular area, neighborhood, region, country, etc.

4.3 CURRENT METHODS OF POVERTY MAPPING

Bigman and Deichmann (2000), Davis and Siano (2001), Davis (2003), and Petrucci et al. (2003) researched methods of poverty mapping. The common element of these methods is the requirement for socio-economic data for a particular country, region, census tracts or households. The data, or part of them could be geo-referenced[1] or not. The data could also be

1 Any type of data that has a set of X and Y coordinates that can be represented in a map and located on the ground.

a compilation of different datasets (census and survey), or represent different entities (population, infrastructure, natural resources, pollution, etc.). Researchers have to consider that any selection of datasets has to correspond to the same relative time to keep the results of the analysis at a desired level of accuracy. Their objectives may range from visualization to exploratory data analysis such as cluster analysis or point pattern analysis to some more complex data analysis involving spatial regressions and econometrics or a combination of them.

Two of the most important methods developed and used today were proposed by staff at the World Bank. The first one combines *household survey and population census data* (hereafter HSCD) (Demonbynes et al. 2002, Lanjouw 1998) and the second one is based on *household survey and area indicators* (hereafter HSAI) (Bigman and Fofack 2000). The HSCD method uses survey data to develop a prediction model of consumption or income. The variables used have to be found in the census data to extrapolate parameter estimates and derive poverty statistics (Demonbynes et al. 2002). As mentioned earlier, data from both the surveys and the census need to be from the same time period, because this method assumes that statistical inferences made on the household survey can also be made to the census data. This method offers procedures to check for compatibility of census and survey data, and also for estimation of errors. However, some issues are related to this method; two of them are the possibility of having wrong or missing data in the census and having a survey of insufficient sample size. On the other hand, it could be very difficult to get census data from some countries particularly if the data refer to a very detailed scale or include sensitive information. From a geographical point of view, the results of such a method are represented in minimum space units corresponding to census or county boundaries, which can mask the diversity of poverty in a particular area, hiding pockets of poverty and biasing the analysis.

HSIA uses average data related to smaller area units such as communities or small towns, instead of household level surveys (Bigman and Fofack 2000). One of the advantages of this method is that it may not require census data. However, the main innovation that

Bigman and Fofack proposed was to take into account different geographical information from the areas where the households are located, and not from the individual households. The result is a map that infers the probability of a household falling under a determined poverty region, defined by combined characteristics of the environment in which the household is located, i.e. a poverty risk map. This gives the researcher a lot of flexibility in the selection of thematic maps (weather patterns, land use, infrastructure, rivers, forest type, pollution presence, etc.) which will try to represent the conditions of that particular area. In that sense, this method takes advantage of GIS capabilities, which will be discussed later. Bigman and Deichmann (2000) suggest that aggregate data like these can be more accessible from more countries and more likely to be published than census or household surveys.

On the other hand, Minot and Baulch (2003) found that aggregated census data can lead to poverty rates underestimated below 50% and overestimated rates above 50% for data from Vietnam. They suggested that aggregated census data should be analyzed and interpreted carefully.

Petrucci et al (2003) combined the HSIA and the HSCD adding emphasis on spatial dependence control, with the objective of determining those variables that affect household poverty. They used data from censuses and households from Ecuador organized later in a GIS. The census data were combined with another dataset (INFOPLAN) to provide spatial reference to the level of county. The household survey was very extensive but was not geo-referenced; its only spatial reference was at the level of county and had information on type of living area. Based on these two attributes, they distributed the households randomly within counties to be able to conduct later spatial statistics analysis, which is necessary to infer causal relationships of poverty.

This analysis assumes that measured geographical variables may often hold some kind of spatial dependency (similar values are usually neighbors, i.e. elevation, temperature) and spatial heterogeneity (a phenomenon that usually occurs over a large area i.e. global warming). These two factors have reached increased attention in current (spatial) statistical analysis, as they are crucial to understand environmental, social, and economic events.

Figure 1 below summarizes the methodology of Petrucci et al. (2003). The first step consists in selecting and/or producing the variables that will be used to infer a level of poverty. The second step is where all these variables are analyzed for spatial dependency and presence of autocorrelation. The third step estimates the level of poverty with a spatial probit function and with better knowledge of the spatial characteristics of the variables in Step 1. The fourth and fifth steps perform consecutive validations of the predictions from Step 3. The authors also compared their results with Lanjouw's and Bigman's methods, noticing significant differences between the predictions even when the autocorrelation found was very small. These differences can produce different distributions of poverty among regions or smaller units and translate to different allocation of resources.

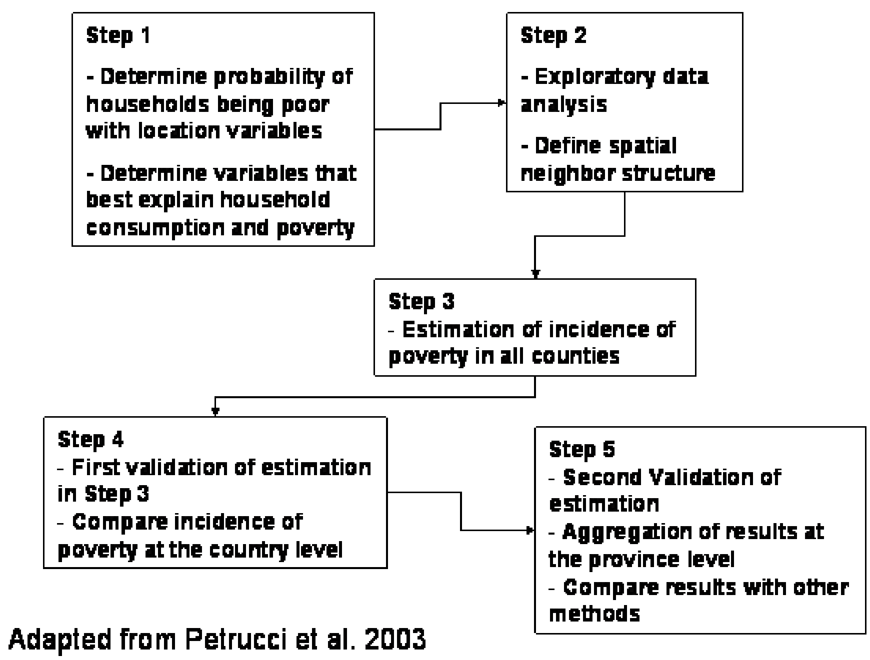


Figure 1. Poverty mapping method using spatial statistics

Considering the methods explained above, we can observe that most of them require consistent data from censuses or households and that it would be more appropriate to use with geo-referenced data. All make intensive use of econometrics and statistical analysis; however there is an increasing consideration of spatial issues in their use that will encourage development of better poverty mapping methods. GIS is being more intensively used, although in initial cases for visualization purposes. The inclusion of spatial statistics and/or spatial econometrics elements in poverty mapping methods, as well as wider access to geo-referenced environmental[2] data will trigger the use and development of more advanced analysis applications of GIS.

4.4 POVERTY ANALYSIS IN GIS

Zeiler (1999) describes GIS as a tool to organize, visualize, store, manage and analyze different kinds of information under a spatial component. Bigman and Fofack (2000) say that for different reasons, economists were reluctant to use GIS until recently. However, this situation has been changing with development of spatial statistics applications for GIS and spatial econometrics. A clear example of that is the development of GeoDa as a GIS tool for spatial econometrics (Anselin et al. 2006). Haining et al. (2000) suggest that GISs can be used not only to visualize spatial data in form of maps but also a tool to extract information from datasets. He also remarks that there is a need for developing data visualization methods as these are easily understandable by non-specialists rather than numeric or statistical formats. This would encourage a wider participation of users in spatial data interpretation. GIS in poverty mapping has been used firstly for visualization purposes, as most data (from censuses in particular) were not geo-referenced at that time and could be aggregated only from a small area unit equivalent to a county. This way, analysis is restricted to arbitrary boundaries that can hold diverse characteristics related to wealth. However, several geoprocessing operations can still be done (such as intersections, union, extraction, buffering, aggregation, etc.) if other geographic data were available (i.e. roads, rivers, weather patterns, household locations, etc.). However, we need to consider that this type of analysis would still

2 Understood here as ecological, social and economic.

carry a bias corresponding to a county level.

Today, wide availability of GPS, may help producing more geo-referenced surveys and increase the detail of analyses. Costs could increase as well, but these could be compared to the cost of resources misallocated due to errors of inclusion or exclusion in poverty maps, and the indirect effects on the target areas from those programs. A great advantage of having a geo-referenced household survey is to be able to analyze different relationships between households and conditions of the environment in which they live. Similarly, poor clusters or regions can be located within smaller units as a function of explanatory variables and not as a function of arbitrary administrative boundaries as counties[3]. In any case, counties, regions, or district boundaries can help as visual aids to inform in which jurisdictions different clusters of poverty can be found, without interfering with the analysis.

An aspect that needs further research is how well geo-referenced household information can predict spatial distribution of poverty. This implies previous knowledge of whether the variables or indicators used are spatially dependent for a particular study area. Spatial dependency could be assessed with spatial point pattern analysis methods such as Anselin's Moran's I test (Anselin 1995) or Getis-Ord's Global-G and Local Gi* tests (Ord and Getis 1995). These tests can be used to assess spatial dependency at the level of the region (Global G) or at a more detailed level (Moran's I, Getis-Ord Gi*)

4.5 SCALE ISSUES IN POVERTY MAPPING

Scale is a very important aspect not only in mapping but also in many other disciplines that deal with spatial distribution of spatial events and that have to base decisions upon them. Some authors (Henninger and Snel 2002) suggest that poor households occur in clusters, meaning that where there is a poor household it is very likely that there will be a poor neighbor, and that these clusters exist in specific places. Even though this is a widely used assumption, there is very little evidence regarding the spatial relationship between location and poverty, measured by any metric. However, Amarasinghe et al. (2005) suggest a more complete hypothesis that includes clustering of poor households as well as clustering of

3 Errors as an effect of the use of arbitrary boundaries are also being researched in other fields

non poor households. Several authors (Bigman and Fofack 2000, Henninger and Snel 2002, Petrucci et al. 2003, Bigman and Srinivasan 2002, Nelson 2001, Tole 2002) pointed out the need for using detailed datasets in order to gain more precision to target poverty areas. As mentioned before, the use of administrative boundaries to represent spatial units of poverty indicators from a survey or a census could mask the presence of poverty clusters in areas smaller that the chosen boundaries. This has several implications in the analysis of spatial data and has been denominated *Modifiable Areal Unit Problem* (MAUP) (Sheppard and McMaster, 2004). Figure 2 shows a schematic approach to precision when we choose to work at a particular scale. Notice that if we choose to average variables or indicators at the Census tract level (i.e. county boundary) we will miss information about poor clusters or poor households in our analysis.

The effect of scale in data analysis, and particularly of MAUP, has been addressed very frequently in landscape ecology where it is well known that similar analysis at different scales of aggregation can lead to different results (O'Neill et al. 1988, Turner et al. 1989). For instance, Turner et al. (1989) found that the magnitude of several attributes of landscape patterns changed when scale (i.e. size of grain in a grid) was changed. Some patterns would disappear with increased grain, although this depends also on their arrangement and shape. Patterns that are dispersed would disappear faster than clumped patterns. In that sense, the proportion and number of patterns would change with changed scale. This problem has been identified in poverty mapping as well (Bigman and Fofack 2000) and its implications are important not only to be able to locate patterns of poverty but to understand relationships between these patterns and their local environment. These considerations have to be taken into account when performing analysis with different datasets and different variables or indicators. In a practical sense, it is very important that all thematic datasets (especially when working with GIS) need to be at the same scale, or they need to be rescaled with known loss of precision. Similarly, studying the behavior of different geographical relationships at different scales becomes recommendable to better understand the overall landscape (Welsh et al 2004). The researcher should decide to control errors of rescaling data that could influence the results of a particular study. Ultimately, loss of precision should be managed according to the scale in which results are more relevant. However, the ideal situation where full control over spatial's accuracy is achieved is rare, as datasets are collected from different sources, with very little or no specification whatsoever regarding their preparation. Most commonly, authors may adopt certain adaptations to spatial data that carry a certain degree of uncertainty in the analysis. This may lead to focus on methods that could give us an idea of analytical error rather than methods that assume high data accuracy or high sampling intensity.

4.6 VARIABLES NATURE, SELECTION AND AGGREGATION

The nature and selection of variables and indicators depends largely on the objective of the targeting. We have to consider that poverty maps are not final products but a baseline reference for decision making. Shyamsundar (2002) presents a very extensive reference to select indicators according to different objectives. The author included several cases where particular indicators were chosen according to the relationship with poverty that was being researched. She/He mentions that a good indicator is unambiguous in terms of identifying improvements, sensitive to changing policy and circumstances, and is cost effective. She/He emphasizes the complex relationship between poverty and environment as a crucial factor to consider when selecting an indicator.

Perhaps the most important or used measure of wealth in poverty targeting is household income (Davis 2003, Bigman and Fofack 2000). However it is also one of the hardest measurements to get. Income data are usually available at a survey scale; however, it is suggested that in most cases information about income is biased by survey participants (Bigman and Fofack 2000).

There are of course other variables or indicators of poverty. Examples of other indicators provided in the literature are: household expenditure, access to safe drinking water, incidence of waterborne diseases, and aggregated indexes that involve several other single measurements (Snel and Balance 2002, Shyamsundar 2002). The number and type of variables depends on the objectives of poverty targeting. Census and surveys tend to gather very large amounts of information such as size and type of household. In order to deal with large amounts of information, Davis (2003) suggests using several multivariate models (such as principal components analysis, factor analysis) in order to reduce the dataset to a few non-correlated variables that could explain a particular aspect of poverty. Similarly, categorizing groups based on common characteristics can be done with cluster analysis and logistic regression (discriminant analysis).

All these methods are very useful to infer relationships between poverty distribution and environmental characteristics even if the datasets do not have a detailed geo-reference (despite that the use of geo-referenced indicators is becoming more frequent).

4.7 USE OF SPATIAL STATISTICS FOR EXPLORATORY ANALYSIS

There is an increasing trend to acknowledge the importance of spatial behavior of variables used in poverty mapping, particularly when we want to target dispersal of the poor. As mentioned before, variables may present spatial dependency or spatial heterogeneity which, if not considered, may bias the resulting poverty map by increasing inclusion and/or exclusion errors with its implications in misallocation of resources. This tendency may suggest that, in the future, most methods will include a preliminary step where the variables are checked for their spatial behavior. Getting familiar with this aspect will be very important for selecting a proper set of variables/indicators and a proper methodology. Several factors will increase the use of spatial statistics in poverty mapping:

- More extensive use of GIS software, GPS equipment
- Wider availability of geo-referenced datasets (specially household surveys)
- Wider availability of environmental data (satellite images, raster and vector information)
- Consensus on the use of high detail data
- Need to understanding complex relationships between environment and poverty
- Consensus on the importance of knowledge of spatial behavior of spatial data

In that sense cluster analysis techniques within spatial statistics could be used in poverty mapping. as these can help identify clusters or areas of high autocorrelation within a spatial dataset based on data nature (continuous or discrete) and location.

4.8 DETECTION OF SPATIAL CLUSTERS WITH CONTINUOUS DATA

To analyze continuous data, there are several spatial autocorrelation methods that can be used to find if spatial dataset contains areas that tend to have regions where values of similar magnitud are grouped. Statistical tests that provide information of spatial autocorrelation such as Global G are suggested by Getis and Ord (1992). This method returns a value (global z-score) to evaluate the spatial dependency level of a dataset, and is widely used in spatial exploratory analysis. The Global G provides information of whether high or low values in a dataset tend to cluster. However, this dataset provides only a unique value for the whole dataset and it does not provide a location of where those cluster exist (Ord and Getis 1995). So this test could be used as a preliminary step to determine if a spatial dataset tends to cluster or not.

Other analysis such as Local Indicators of Spatial Association (Anselin, 1995) are used to find more especific information regarding each value in dataset. For instance, the Moran's I test (Anselin, 1995), provides information of existence of outliers and spatial autocorrelation (clusters) in general. The drawback of this method for mapping poverty clusters is that it does not directly provide information on location of clusters of high or low values for an indicator. This is an important element since poverty maps are produced from census and surveys that provide data of wide ranges, e.g. covering high and low income areas, where it is important for us to differentiate clusters of high income from clusters of low income.

On the other hand, the Getis-Ord Gi* test (Getis and Ord 1992), provides information on clusters of high and low values within regions of a spatial dataset extension for each observation and seems to be very useful for working with extensive spatial datasets.

Both these methods has been used and adapted intensively in different areas such as epidemiology, crime assessment, and more recently in poverty analysis (see Ratcliffe and McCullagh 1999, Amarasinghe et al. 2005).

Different commercial and non-commercial software have included these methods among their GIS and spatial statistic tools. These methods are continuously being improved, and intensively used in exploratory analysis of outliers, clusters, and hot-spots.

4.9 DETECTION OF SPATIAL CLUSTERS WITH DISCRETE DATA

One of the methods to determine the existence of association among points in a dataset is spatial clustering (Okabe et al 1985); also referred to as spatial clumping, spatial association, spatial juxtaposition, or spatial affinity. This method has been used to analyze distribution of different geographical features, such as retail stores (Okabe et al, 1985) without the need of continous data but only their geographical location. The main idea of this method is that given a set of points on a plane, a circular area can be drawn having each point as the center of the circle with a radius *r* to represent the neighborhood of that point. When neighborhoods overlap each other, we can say that there is a cluster or clump. The number of overlapping neighborhoods will define the order of a clump, for instance, two overlapping neighborhoods will be a clump of order two.

This process can be applied to a single category or to a multiple category of points, for instance, Okabe et al (1985) applied this method to find whether particular types of stores - or categorical data - tended to clump in a given area. A more recent advance in the clumping theory is the Variable Clumping Method (VCM) (Okabe and Funamoto 2000). In this method, the radius of the circle for each point is variable (as opposed to fixed in the original method) and can define multiple levels of clumping. Even though this analysis could be interpreted as a way to assess clusters at different radius of clumping, or different scales, the authors emphasizes its use on finding “significant clumps at continuous clump radius”. A complementary research by Sadahiro (2003) compares four methods to assess the uncertainty in cluster detection. This last study takes into account the fact that GIS data is seldom accurate.

4.10 CHALLENGES OF USING GEO-REFERENCED HOUSEHOLD DATA

There are some factors that will become more evident as GPS and GIS technologies become more popular for collecting household data. Having more accurate data on household locations will increase the detail of the analysis and of the final products and allow the assessment of spatial and socio-economic relationships. Poverty regions can be determined based on distribution of poor households, and its relationships with environmental elements, natural resources or infrastructure can be studied as well. On the other hand, accuracy issues related to data collection and database construction will have to be taken care of to provide sound information within a known and acceptable degree of uncertainty. One of the most important advantages of having highly detailed household information for poverty mapping is the chance to study relationships between people and their environment independent of rigid administrative boundaries or at fixed scale of analysis. In addition, with use of global and local tests of spatial association, we have a new window of opportunities for exploring methods that can provide information at multiple scales.

5 METHODOLOGY

Data used for this research were provided by Pattanayak et al. (forthcoming). and include approximately 816 GPS points and surveys of households taken in the area of Negombo in south-west Sri-Lanka (Figure 2).

The original objective of the household survey was to find synergies between poverty alleviation and water supply policies (van den Berg et al. 2004). Geographic targeting serves as a tool to analyze these concepts in a spatial context. The sampling framework of the data collection involved interviewing households in "Grama Niladari" units (GN) (Amarasinghe 2005), which are equivalent to counties. Each survey was geo-referenced and assigned to its correspondent GN.

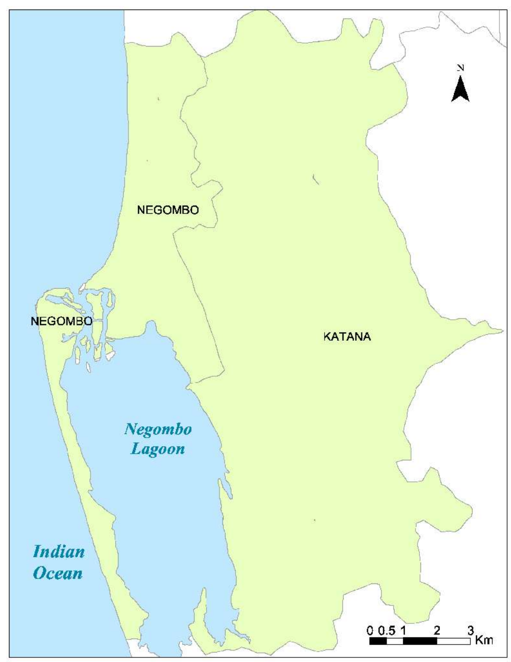


Figure 2: General location of study area.
Source: Pattanayak et al. (forthcoming)

Among many possible variables from the survey, we chose water consumption per adult equivalent (WATPAE) (Table 1). WATPAE is the measure of total consumption in water per household. A large value of this variable indicates a person that is well-off and vice-versa. The complete number of observations (816) was used in this analysis.

Table 1. Summary of statistics for variables used

	WATPAE
Minimum	0
Mean	9.52
Maximum	450
Std. Deviation	21.71

Observations: 816

5.1 EXPLORATORY ANALYSIS WITH SPATIAL STATISTICS

5.1.1 GETIS-ORD LOCAL GI AND MAPPING OF HOT-SPOTS*

To evaluate whether the dataset demonstrates spatial autocorrelation, i.e. if there were clusters of high or low values, we used a Getis-Ord G_i^* test. The Local G_i^* test (Ord and Getis 1995) measures existence of clusters of high or low values surrounding an observation. This test includes the value at *i* in the summation. The G_i^* returns a z-score is returned for each observation in the dataset. If z-score values are high, then high values of the parameter are clustered around this observation. If z-scores are low, observations with low values are clustered. The search distance for neighbors is chosen by the researcher. This test can be used to find clusters of high or low values and represent them in a choropleth map. The G_i^* formula is shown below:

$$G_i^*(d) = \frac{\sum_j w_{ij}(d)\, x_j - \bar{x} \sum_j w_{ij}(d)}{S \sqrt{\frac{N \sum_j w_{ij}^2(d) - \left(\sum_j w_{ij}(d)\right)^2}{N-1}}} \quad , \quad \textit{for all } j$$

$$\textit{where} \quad \bar{x} = \frac{\sum x_j}{N} \qquad S = \sqrt{\frac{\sum x_j^2}{N} - \bar{x}^2}$$

$w_{ij}(d)$ are distance weights

Two geographical relationships were used: inverse distance and fixed band distance. Inverse distance defines clusters as decreasing similarity with increased distance, whereas with Fixed Distance Band, two observations can be clustered regardless of distance. Operationally speaking, the weight $w_{ij}(d)$ is defined by a binary operator where if a neighbor falls within the search distance *(d)* then its value is $w_{ij}(d)$ equals 1, and 0 otherwise. This algorithm corresponds to the fixed band distance relationship. Other weights could be assigned by the researcher depending on assumptions about geographic relationships. The inverse distance relationship assigns a weight to each observation that decreases as distance from x_i increases within the search range (Mitchell 2005). This is done by calculating the inverse value of the distance between two neighbors.

The fixed distance band allows the user to freely extend the size of clusters of high or low values which can be particularly useful when different geographical relationships need to be tested.

Both fixed distance band and inverse distance geographical relationships used the "City Block" method of distance search which calculates a distance between points by adding the absolute values of the vertical and horizontal distances between them (without squaring them as in Euclidean distance). This is appropriate for distance calculations in an urban environment as it simulates the presence of obstacles such as buildings, houses, etc. (Hrvatin 1998).

For both inverse distance and fixed distance band methods, a z-score above 2.0 means that the dataset shows clusters of high values of the variable used at a significance of 0.05. A z-score above 1.0 means that the dataset shows clusters of high values of the variable used at a significance of 0.32. On the other hand a z-score of -2.0 represents high significance of clusters of low values. Depending on the variables used, poverty clusters would be represented by a highly negative z-scores in the case of WATPAE.

5.2 USING VORONOI MAPS AND GEOPROCESSING FOR CLUSTER MAPPING

In order to visualize the hot-spots for each variable at each of the distances used in the Local G_i^* test, a geo-processing model was developed with ArcGIS 9.1 spatial analysis tools and automated with Python. This process is summarized in Figure 3. Automating this method proved to be very convenient since testing for spatial clusters with several variables and distances is a very time consuming, repetitive and computationally intensive task that can produce large amounts of data. The point datasets with embedded z-scores returned by the Local G_i^* test were used to produce Voronoi maps[4]. This process uses the observations' locations (points) as centroids for drawing polygons around each of them. In a Voronoi map each polygon represents the maximum area that could be assigned to a point, where each boundary segment is equidistant between two neighboring points.

4 Also denominated Thiessen Polygons

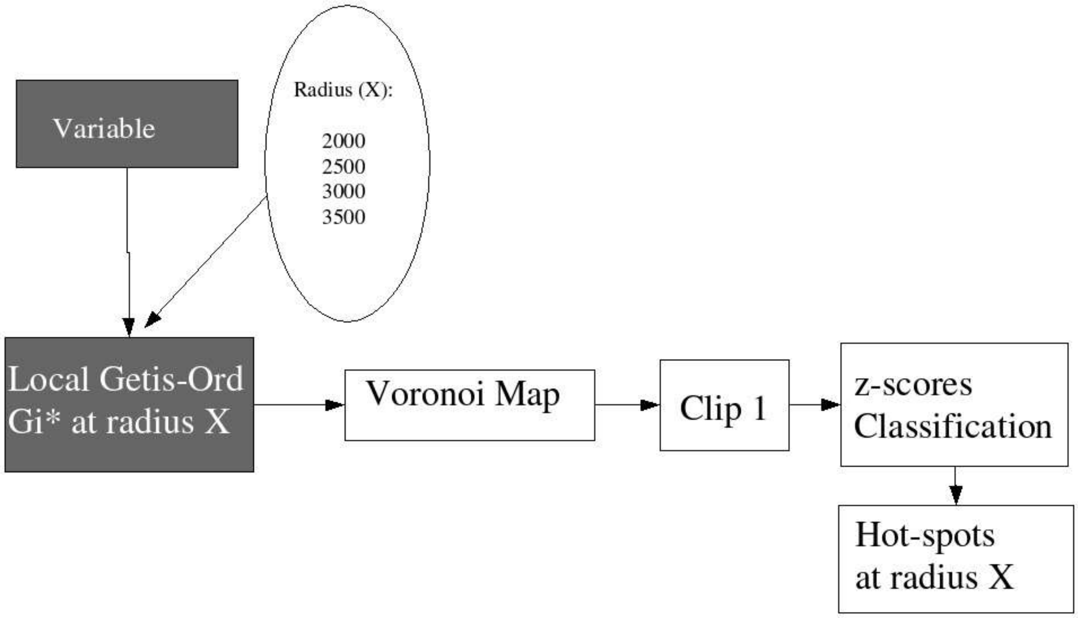


Figure 3. Geoprocessing and Tests for Spatial Correlation – Local G_i^*

The next step was to use the study area's boundary to clip each original Voronoi map to the study area's extension**.** For visualization purposes the z-scores were classified into categories to show clusters of high significance of high and low values.

5.3 NORMALIZED GN MAPS OF WATER CONSUMPTION

To compare Voronoi cluster maps with z-scores with water consumption values distributed by GN, it was necessary to normalize water consumption values within each GN. The method used for that was:

$$Normalized\ Water\ Consumption\ in\ Cluster_j = \frac{\bar{x}_{in\ cluster\ j} - \frac{\sum}{N}}{SD_{sample}}$$

$$where:$$

$$\bar{x}_{in\ cluster\ j} = mean\ water\ consumption\ of\ observations\ in\ cluste$$
$$X = water\ consumption\ observations\ in\ entire\ sample$$
$$N = sample\ size$$
$$SD = Sample\ standard\ deviation$$

The mean water consumption values per GN were calculated using a database management system using all the observations (points), as each of the points recorded their correspondent GN. This process created a new set of unique values per GN that was joined to the GN polygon shapefile for mapping purposes. Each of the maps was classified into four categories divided by natural breaks.

5.4 NORMALIZED VORONOI MAPS OF WATER CONSUMPTION

Another comparison method used was to normalize the water consumption values within each cluster z-scores classification from the Voronoi maps. The objective was to compare these maps with the normalized GN water consumption maps. Because the Fixed distance band method returned more spatially variable clusters than the Inverse distance method, only the clusters produced with the Fixed distance band were used for this analysis. There is an important computational difference between these two methods, as the Inverse distance algorithm tends to produce clusters of small size even when increasing the search distance. On the contrary, the Fixed distance band algorithm produces larger clusters with increased search distance. This latter characteristic was more appropriate for the objectives of this chapter.

The formula used was:

$$Normalized\ Water\ Consumption\ in\ Cluster_j = \frac{\bar{x}_{in\ cluster\ j} - \frac{\sum X}{N}}{SD_{sample}}$$

$$where:$$

$$\bar{x}_{in\ cluster\ j} = mean\ water\ consumption\ of\ observations\ in\ cluster\ j$$
$$X = water\ consumption\ observations\ in\ entire\ sample$$
$$N = sample\ size$$
$$SD = Sample\ standard\ deviation$$

Even though this method "borrows" the spatial component from the Voronoi z-scores maps, it is not a spatial statistic method in a strict technical sense. Instead, it is used as a way to find the variability across clusters and compared them to the normalized GN maps of water consumption. As a way to describe the variability within each Voronoi cluster, we obtained the standard deviation for each of them.

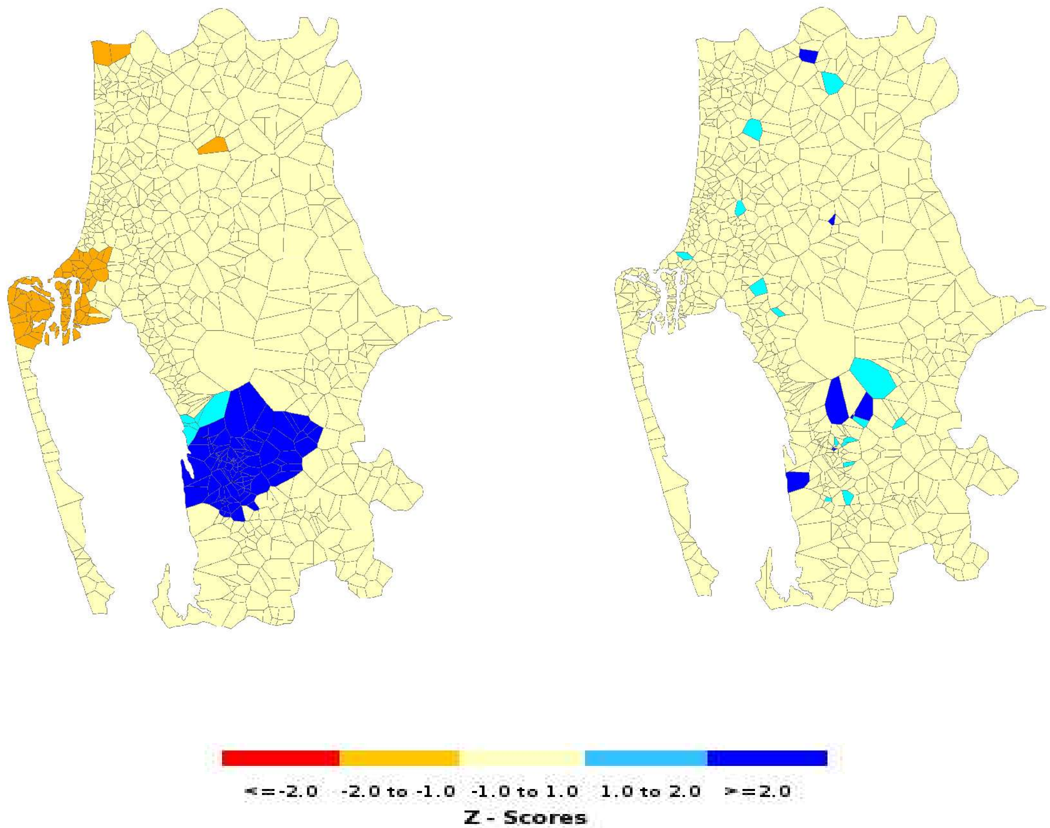
6 RESULTS

6.1 LOCAL GI* AND HOT SPOT MAPS

Based on the results of the previous step, WATPAE was used to produce cluster maps of water consumption. The distances selected for this test were based on the range of distances that would cover the whole study area more adequately. The radii were set to not exceed the East to West extension of the dataset (approx. 6 km). As a result, the distances for defining neighbors and hence clusters were from 2000 m to 3500 m

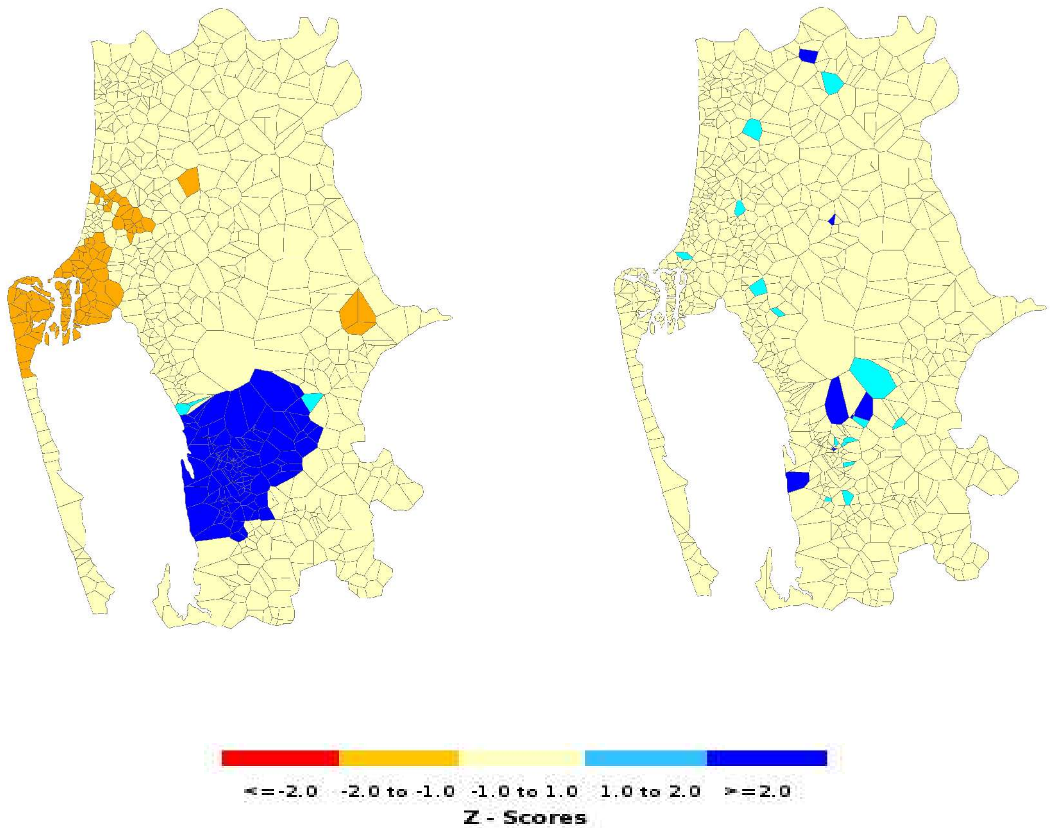
As mentioned in the methods section, a z-score above 2.0 means that the dataset shows clusters of high values with a significance of 0.05; z-scores below that mean show areas of non-significance. Figures 4 to 7 show distributions of z-scores with Voronoi maps using Fixed Distance Band and Inverse Distance geographic relationship for water consumption.

Both types of geographic relationships used produced spatial clusters, however, the clusters produced using a Fixed Distance Band dramatically increased of size with increased distance. The clusters produced using Inverse Distance did not change of size with increased distance. The main highly significant cluster is an area of high water consumption towards the South West of the study area. This cluster is present in all fixed distance band maps as a large single area, and as fragmented areas in the inverse distance maps. Other areas of low significance of low to high water consumption are also present but never reach significance with increasing distance.



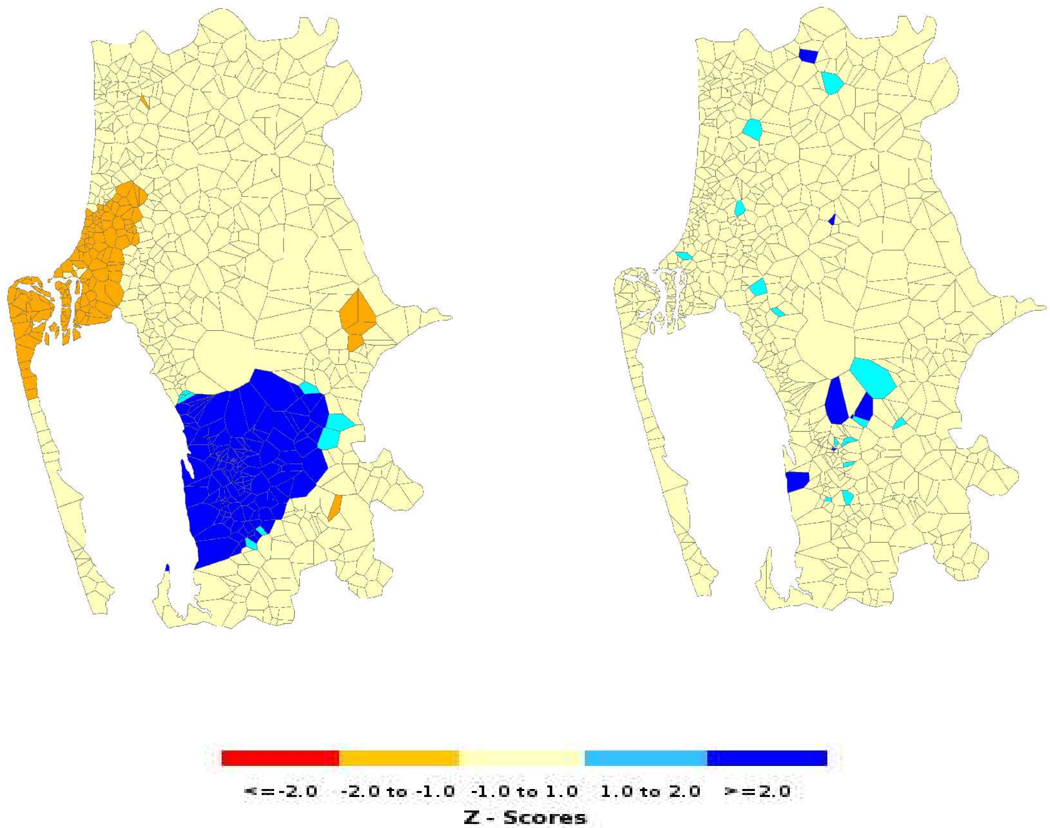
(a) Fixed Distance Band **(b) Inverse Distance**

Figure 4. Voronoi maps showing Z-scores for water consumption at 2000 m



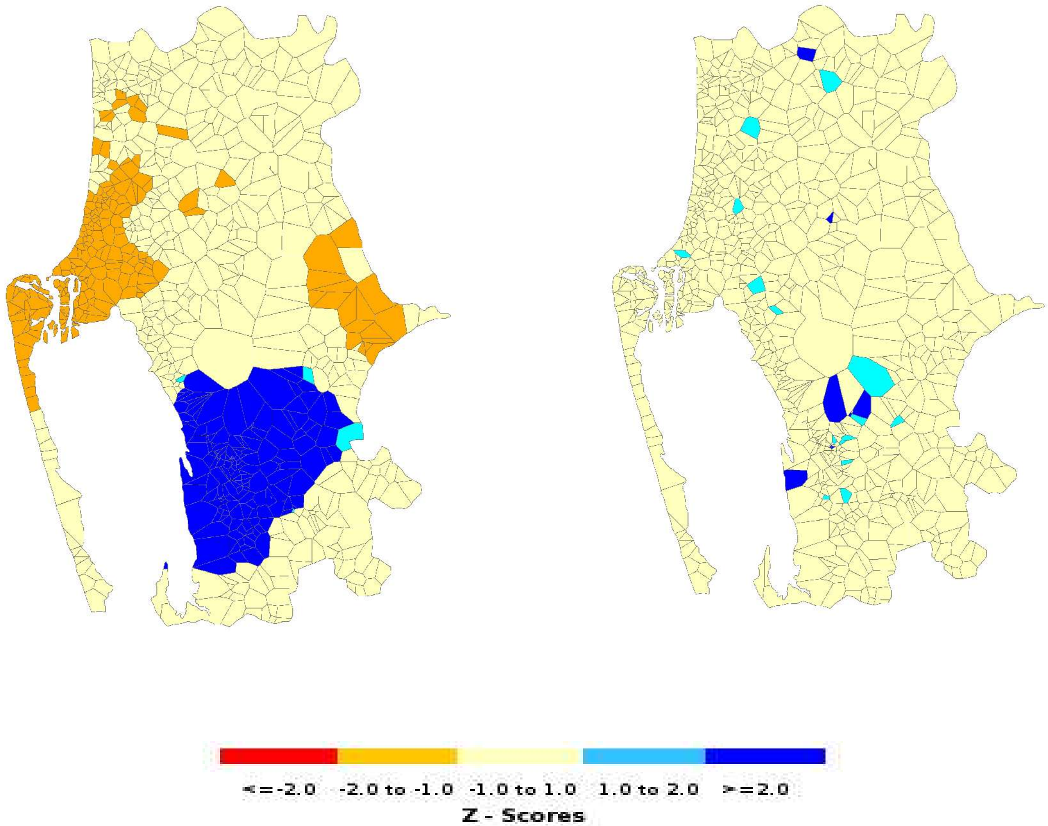
(a) Fixed Distance Band **(b) Inverse Distance**

Figure 5. Voronoi maps showing Z-scores for water consumption at 2500 m



(a) Fixed Distance Band **(b) Inverse Distance**

Figure 6. Voronoi maps showing Z-scores for water consumption at 3000 m



(a) Fixed Distance Band **(b) Inverse Distance**

Figure 7. Voronoi maps showing Z-scores for water consumption at 3500 m

The voronoi maps illustrate how clusters of high or low z-scores can expand as we increase the radius distance. Areas showing high or low values can become more intense with increased radius of search. In some cases small areas of high or low values can disappear, which may be due to the lack of neighbors with similar values. The interesting aspect of this method is the ability to observe the change of extension of geographic process based on socioeconomic variables as we increase the area of search. At the same time we are able to geographically locate statistically significant areas of interest that would not be perceived if we had used an administrative boundary in which case we would have had to average values to each administrative boundary. Additionally, the Voronoi maps are capable of showing survey data at a higher resolution that the GN maps as shown in Figure 8. The importance of this method and its practical implications for poverty targeting will be expanded in the discussion section.

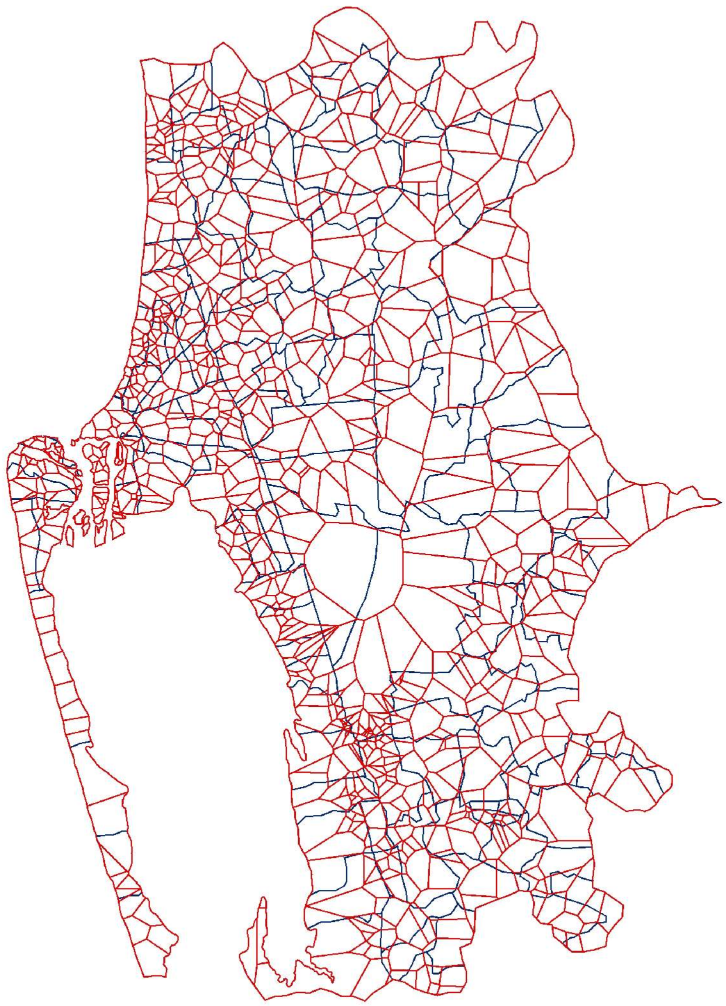
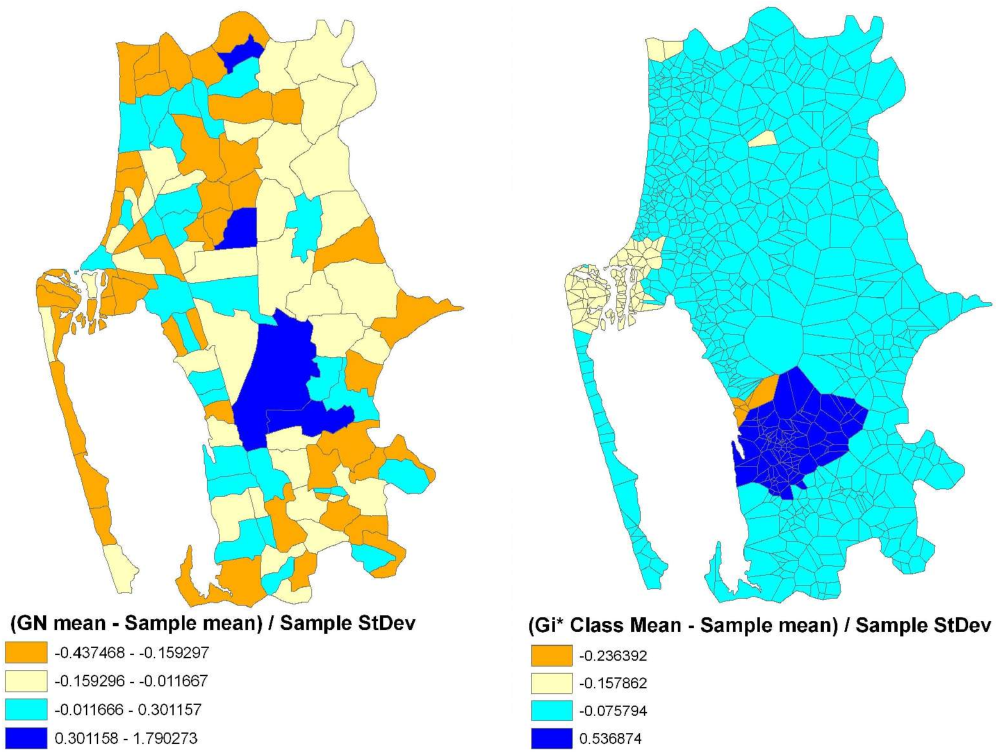


Figure 8. Comparison of GN map units with Voronoi polygons.

6.2 NORMALIZED GN MAPS VS. NORMALIZED VORONOI MAPS

This subsection compares GN maps using administrative boundaries with Voronoi maps. As mentioned earlier the fixed distance band method produces clusters composed by several polygons whereas the inverse distance produces clusters composed by a single or very few polygons. As the Voronoi maps using fixed distance band showed clusters of increasing sizes we chose only maps using this procedure for normalization and comparison with normalized GN maps. Figures 9 to 12 contrast the differences between a single map of water consumption normalized by GN against Voronoi maps of Water consumption values normalized by clusters.

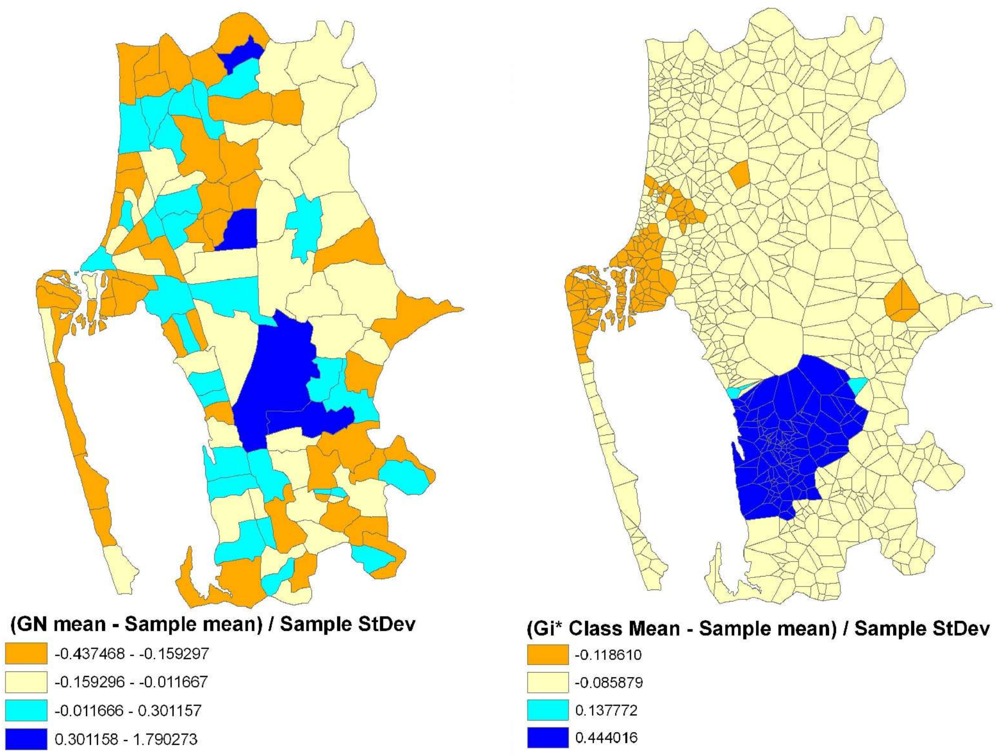
In Figure 9, the GN map show few clusters of high water consumption aligned towards the center of the study area and a few scattered clusters of low water consumption scattered across the study area. The Voronoi map at 2000 m shows a similar placement for the cluster of high water consumption, however it does not show large or numerous clusters of low water consumption.



(a) Normalized GN map **(b) Normalized Voronoi map (2000 m) fixed distance band**

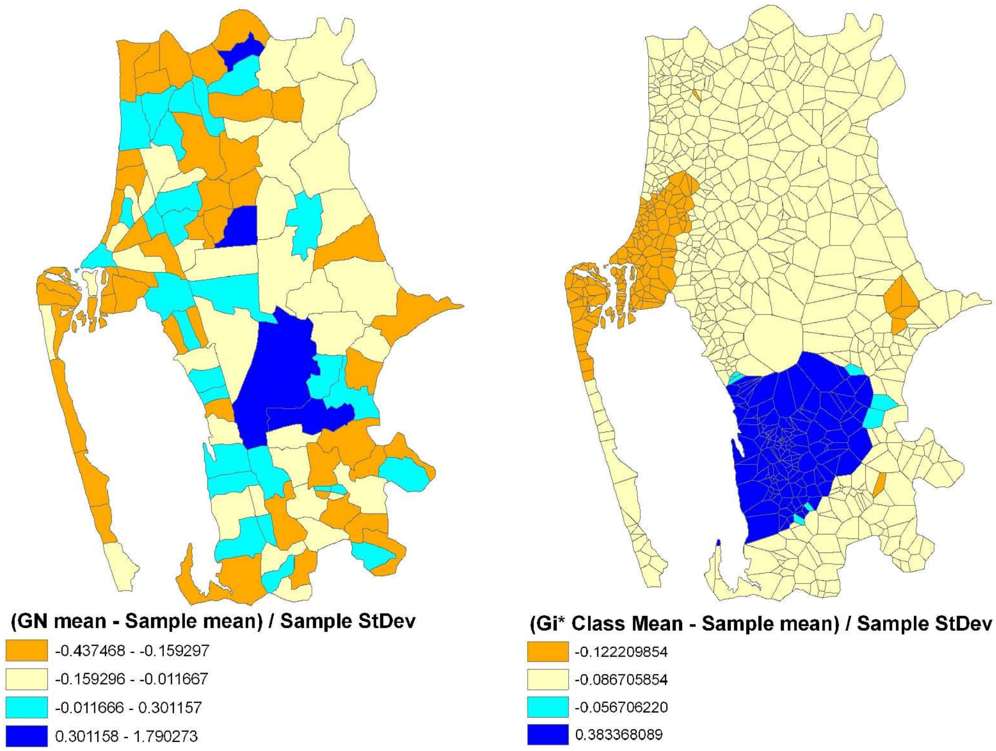
Figure 9. GN and Voronoi cluster maps of normalized water consumption at 2000 m.

Figure 10 compares the same normalized GN map with the normalized Voronoi map at 2500 m. The cluster of high consumption of water increases in size but not in general location. However, areas of low consumption are more notorious towards the western section of the study area. Also, the predominant light blue area observed in the Voronoi map of Figure 9 has become a lower consumption area when the search distance increased by 500 m. Similar effects occurred when the distance search is changed to 3000 and 3500 m as shown in Figures 11 and 12. The main observation to highlight is that the cluster of high consumption of water increases in area with increasing search distance. It is important to consider that according to the Gi* test only the high water consumption cluster in all Voronoi maps were statistically significant, whereas the rest of them were not.



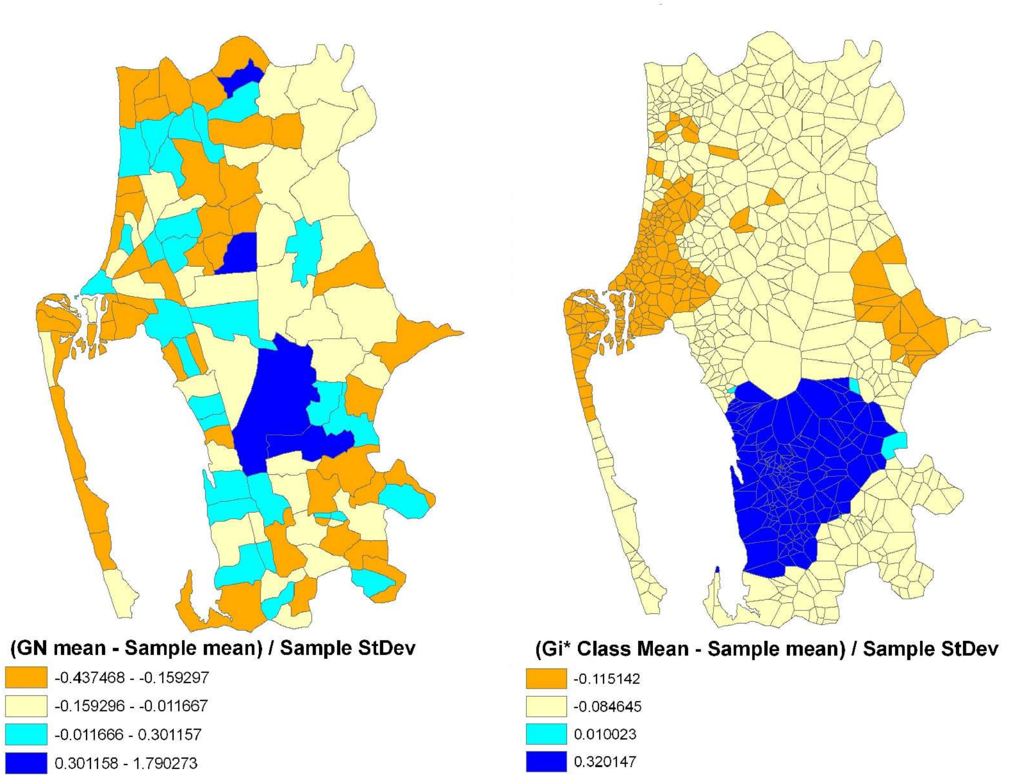
(a) Normalized GN map **(b) Normalized Voronoi map (2500 m) fixed distance band**

Figure 10. GN and Voronoi cluster maps of normalized water consumption at 2500 m



(a) Normalized GN map **(b) Normalized Voronoi map (3000 m) fixed distance band**

Figure 11. GN and Voronoi cluster maps of normalized water consumption at 3000 m



(a) Normalized GN map **(b) Normalized Voronoi map (3500 m) fixed distance band**

Figure 12. GN and Voronoi cluster maps of normalized water consumption at 3500 m

The variation of values within cluster is shown in Table 2. Table 2 shows the standard deviation of water consumption values within clusters. In the case of this household dataset, "blue" clusters' (A) standard deviation tends to decrease with increased search distance from 52.66 at 2000 m to 42.17 at 3500 m. In the case of "light blue" clusters (B) the standard deviation increases from 1.89 at 2000 m to 10.49 at 2500 m and then decreases to 4.99 at 3000 m to later slightly increase again to 6.41 at 3500 m. The standard deviation of the "yellow" (C) and "orange" (D) areas vary as well with increased search distance, although not as much as the "blue" and "light blue" clusters.

Table 2. Standard deviation of water consumption within clusters in Voronoi maps by search distance

Cluster Type	Search Distance (in meters)			
	2000	**2500**	**3000**	**3500**
A*	52.66	48.44	45.04	42.17
B	1.89	10.49	4.99	6.41
C	7.73	7.63	7.85	8.43
D	4.91	5.86	5.63	5.08
* Cluster of significance = 0.05				

7 DISCUSSION

7.1 LOCAL HOTSPOT ANALYSIS

The Getis-Ord analysis performed on water consumption gave some insights into location of clusters of particularly high values and of general distribution of water consumption. After analyzing the variable with a local test of association, the Getis-Ord Gi* test, we are able to identify hot-spots of high values, however, we were not able to identify hot spots of low values which was our main expectation.

The tendency of clustering of high values for water consumption (WATPAE) indicates that areas of high water consumption concentrate within the study area. This clustering behavior is surprising, as the expectation of this research was to locate poor areas with the assumption that poor pockets of neighborhoods of low water consumption would be found in spatial clusters or hot-spots. Although, the existence of high values of water consumption cluster significantly across the study area does not imply the non-existence of low water consumption areas, but that low consumption data is too scattered to be statistically significant. In other words, poor neighborhoods or poor sectors in our study are described by areas of low water consumption; however, the results suggest that these sectors do not tend to cluster as high values do and are instead spread out in the study area. Another possible interpretation of these results is that the area is generally poor in terms of water consumption, with few areas that are well off.

The specific application of the methodology is to provide an exploratory analysis of spatial data that facilitates identifying clusters of high or low values before applying a policy targeting mechanism or a more in depth analysis such as proposing a spatial econometric model or finding a spatial relationship between hotspots and other variables such as expenditure, urban infrastructure or other environmental characteristics. As several studies in poverty targeting have used the assumption that poor areas may be found in clusters, this methodology allows us to explore the validity of that assumption at varying spatial scales. This is possible by using different radii of search analysis in the Getis-Ord fixed distance band test. Bearing this in mind, research on poverty targeting would have to approach the feasibility of finding isolated critical poor areas with survey data without assuming that they could be clustered. A radius or more could be set by the researcher depending principally on the extension of the area and the density of the data. It is also important to avoid gaps of data within the study area because they may produce meaningless clusters in cases where search distances are large enough to include those gaps. This method could be used as a way to explore the geographical extension of a socioeconomic question, for instance the extension of high of water consumption in a study area and its relationship with high expenditures.

An advantage of using Voronoi maps compared to GN maps is that poverty hot-spots can be quantified according to the extension that they cover, depending on the search radius, by calculating the areas of the polygons. It is unclear though which could be the "right" combination of data density and search distance. From our observations in this study, smaller and larger ratios can be used to study a particular variable when high density of data is available. However, it is hard to point what the lower data density limit for any particular search radius could be. It would be important to evaluate given a search distance the most efficient range of data density that could be used that would not affect statistical significance.

On the other hand, it is important to consider that hot spots or areas of interest obtained using Getis-Ord cluster analysis with Voronoi maps suggest a possible location, but do not define a rigid boundary (e.g., a city or a county). If boundaries were primordial for a better comprehension of the information, they could be defined by using a qualitative categorization of pixel values. It will be important for the researcher to select the proper set of categories and to acknowledge that bias could be added in this way.

A more interesting use of this method is to define or investigate areas of poverty within thresholds of distance, for instance, using three different radii of search as 500-750-1000, and choosing 750 as our average area and using 500 and 1000 as lower and upper level boundaries. This could allow use of different scales of analysis under which the variables show a significant spatial behavior (clustering, autocorrelation, etc.) instead of restricting the analysis to only one rigid scale.

Different range of resolutions (i.e. 500-1200 m) could serve different research objectives. For instance, an NGO targeting poor neighborhoods could use a cluster map produced with a radius range of 300-500 m, whereas a municipality may prefer a 1000-1500m radius for a similar objective. In other words, by using varied types of resolution we adapt or focus the strategies of development policies to a more appropriate geographical scale. However, more research is needed to find a optimal data density range that could be used in these cases to select the proper search distance radius.

Next steps in this area could aim at analyzing the relationships between socio-economic variables in order to produce a risk or vulnerability map of water and general poverty that could be useful for policy makers and planners. On the other hand, part of this methodology has been automated but other important aspects need to be added to allow the researcher to run analyses in a timely manner, especially when including several variables, as this process is computationally demanding.

7.2 GEOGRAPHIC RELATIONSHIPS - WHEN AND WHY?

This chapter showed the principles and applications of a methodology based on building Voronoi maps from geostatistical data. Additionally, within this methodology two geographic relationships were used: inverse distance and fixed band distance.

The inverse distance relationship means that observations closer to one classified as poor are possibly poor and other observations further away are less likely to be poor. We found that Voronoi maps based on this assumption had hotspots of similar size, even with increasing radius of search. This suggests that if the relationship were true, then the clusters found would cover a limited small area. In that sense, assuming this relationship would be suitable for areas smaller than GNs, for the case of this study, or when observations represent units smaller than the administrative unit in which they are contained. However, a small survey sampling intensity could lead to generate small hotspots or, worse, fail to detect them. Additionally, the algorithm for calculating inverse distance may produce very small clusters when using large distances (ESRI Support Center, 2006). Consequently, small sample density and inability to generate large clusters could produce large errors of exclusion. These two factors need to be acknowledged by the researcher in order to interpret accurately results of hotspot analysis. The researcher could experiment either by increasing the sample density to collect and/or by including a large weight into the inverse distance algorithm.

The opposite scenario may occur when using a fixed distance band. As mentioned earlier this geographic relationship assumes that observations surrounding an observation classified as poor could be poor as well regardless of their distance to the central observation. This assumption could be useful, even when not true, if the sampling intensity is not high. Similarly, this relationship allows the researcher to select different ranges of radius, allowing analysis of these data at different scales or more precisely geographical extensions. Using a fixed distance band in our study allowed us to find poverty clusters of different sizes at varied search distances. The drawback of this method is that errors of inclusion could be large. However, we have not tested for variation of errors of inclusion or exclusion within hotspots with varying search distances. It is therefore important to consider applying a fixed distance method when a geographical relationship assumption is not required, is not known or when we require alternative geographical scales that cannot be represented by the local administrative boundaries available.

7.3 POVERTY CLUSTERS AND POLICY TARGETING

After becoming more familiar with the cluster methodologies used, we must research the applications of these techniques to policy targeting. Cluster analysis techniques help us to find where statistically significant clusters of high or low values occur. In this paper the cluster analysis used did not detect clusters of low values, which could have been quickly interpreted as poor neighborhoods. However, we can find low consumption values within the sample used that falls below the poverty level for water consumption. In spatial statistics' terms, poor households that consume very little water are not clustered, but are instead spread out in the study area. The idea of finding clusters was to facilitate the application of targeting mechanisms on the ground, as having small areas where to focus a targeting program is logistically more sound than having to target a much larger area. However, application of spatial cluster analysis in other variables or poverty indicators could report a different result and it needs to be explored as well.

8 CONCLUSIONS

In this paper we have introduced alternative methods to build hot-spots maps for poverty targeting based on Getis-Ord Local Gi* test and Voronoi Maps. A comparison with conventional lattice maps using administrative units known as GN demonstrated important differences between location and area of hotspots of high values and general detection of hot-spots.

In the case of Voronoi maps, smaller hot-spots are defined at smaller radius and larger hot-spots are found at larger radius when using a fixed distance band geographical relationship. However smaller hot-spots are found as well at larger radius of search, which cannot be done using GN units. On the other hand, using an inverse distance relationship found clusters of constant size even with increased search radius in Voronoi maps.

Even when using different inverse distance and fixed distance band as geographic relationships leads to different size of clusters, their application may be useful in cases where sample intensity or scale are important.

However, development of alternative validation methods that do not require extra datasets are recommended for economic reasons. Automation of the process from global and local test to validation are encouraged.

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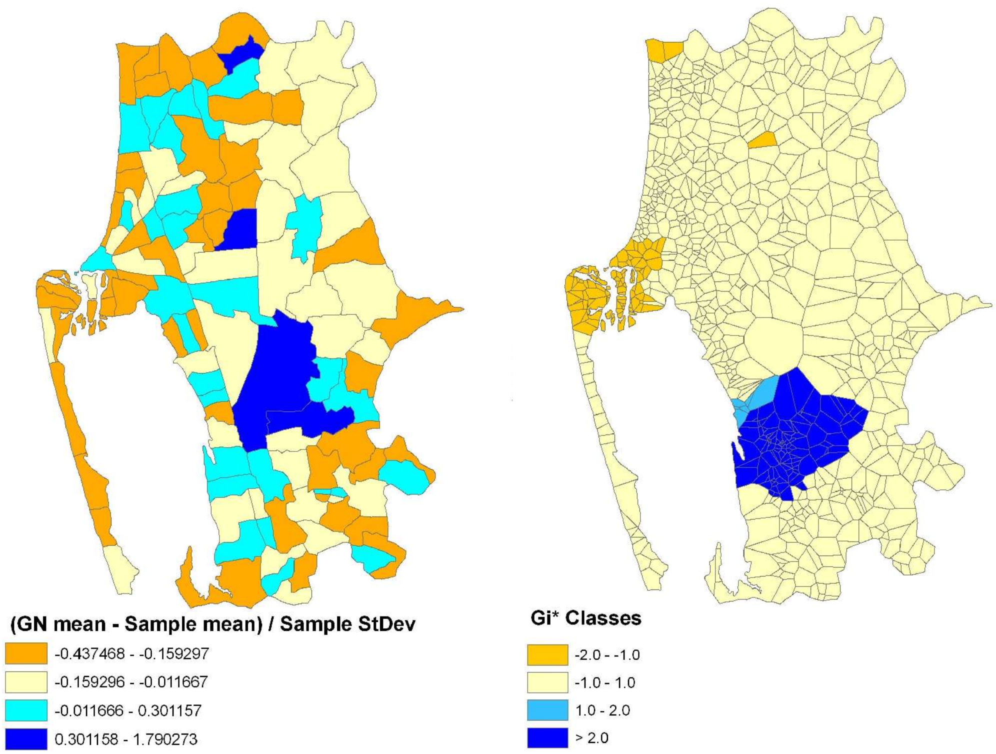
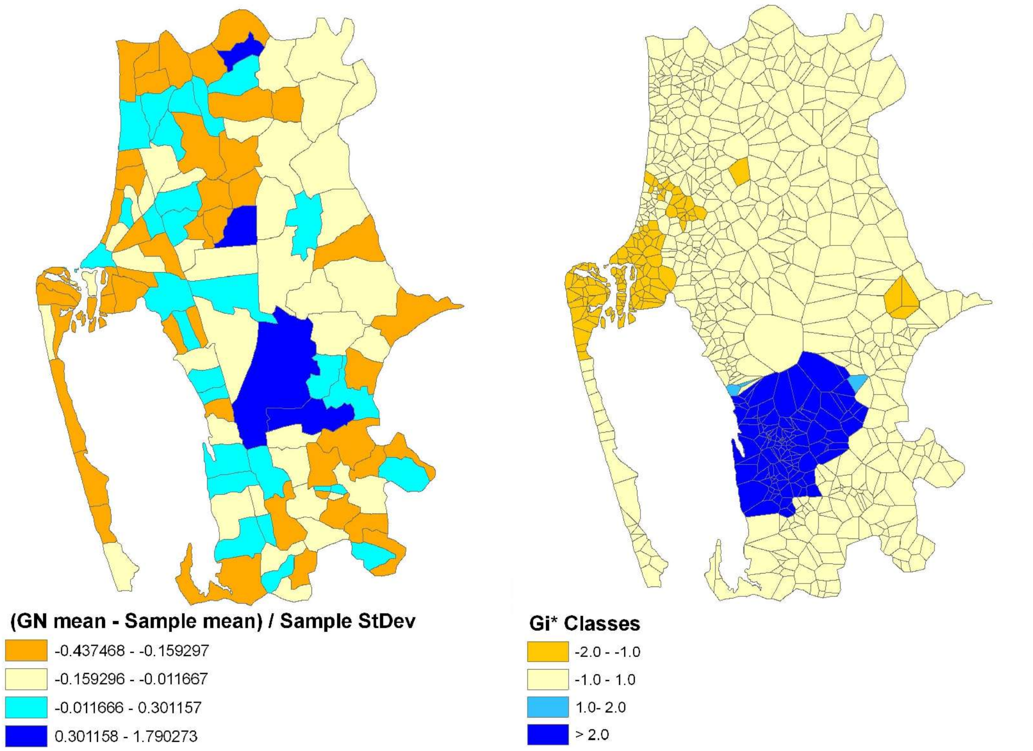
Appendices

Appendix 1: Normalized GN and Voronoi Cluster Maps based on Gi z-Scores*



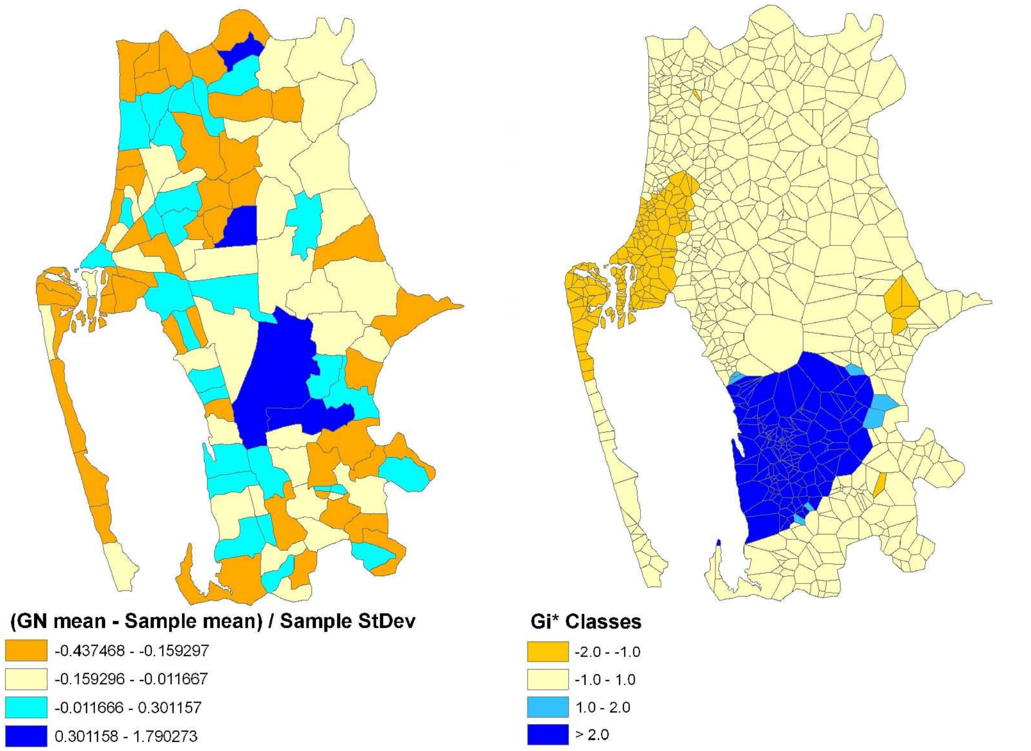
(a) Normalized GN map **(b) Voronoi map (2000 m) fixed distance band**

Figure 13. GN map (normalized) and Voronoi map based on z-scores of water consumption at 2000 m



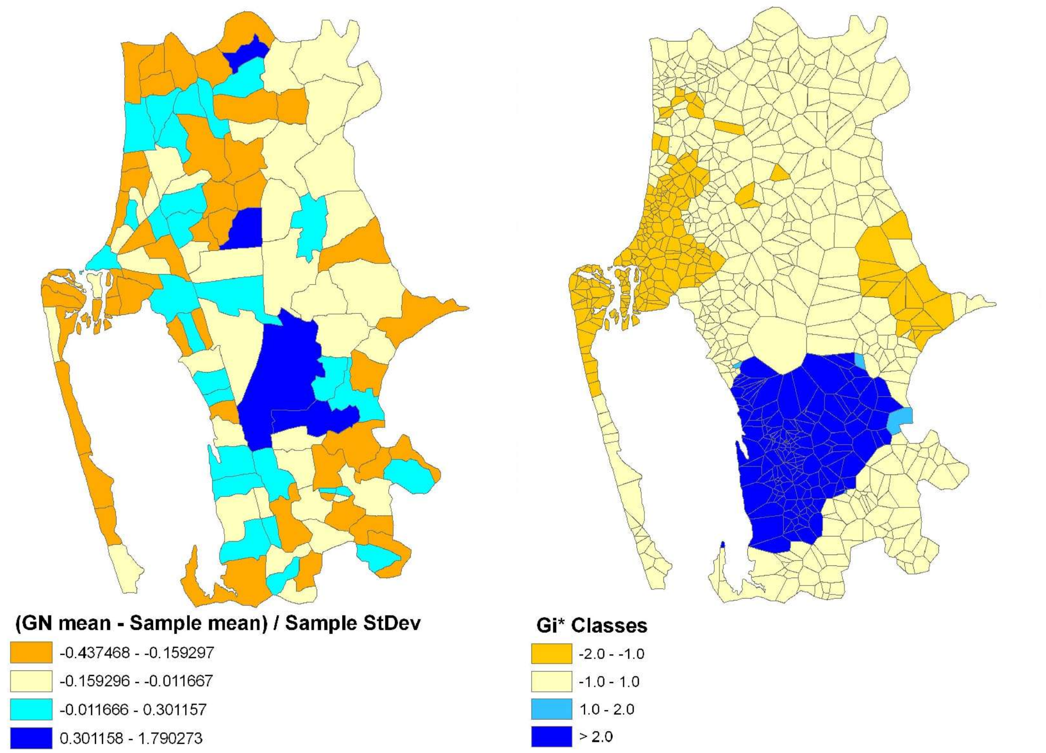
(a) Normalized GN map **(b) Voronoi map (2500 m) fixed distance band**

Figure 14. GN map (normalized) and Voronoi map based on z-scores of water consumption at 2500 m



(a) Normalized GN map **(b) Voronoi map (3000 m) fixed distance band**

Figure 15. GN map (normalized) and Voronoi map based on z-scores of water consumption at 3000 m



(a) Normalized GN map **(b) Voronoi map (3500 m) fixed distance band**

Figure 16. GN map (normalized) and Voronoi map based on z-scores of water consumption at 3500 m.

Appendix 2: Application of Voronoi Maps in a Poverty Targeting Context

Methods

A simple validation of the hot-spots/Voronoi maps developed in this research was performed by using a random subset of the original dataset reserved for this purpose. Using ArcGIS, these test observations were overlaid on the low and high value clusters. The metrics used for this validation were errors of exclusion and inclusion for poor and rich areas (or for low and high values hotspots).

Following the literature on poverty targeting, the generic formulation of the error of exclusion in poor areas (EEP) for each map was:

$$EEP = \frac{\textit{Number of poor observations}\ \text{from}\ \textit{testing sample outside of poor areas}}{\textit{Total number of poor observations}\ \text{in}\ \textit{testing sample}}$$

Similarly, the generic formulation of error of inclusion for poor areas (EIP) for each map was:

$$EIP = \frac{\textit{Number of not poor observations}\ \text{in}\ \textit{testing sample inside poor areas}}{\textit{Total number of observations}\ \text{in}\ \textit{poor areas}\ \text{in}\ \textit{testing sample}}$$

In order to identify the poor households, we defined poverty lines for water consumption and one for expenditures. For water one possible absolute standard is 1.2 m^3 of water per adult equivalent per month the minimum amount of water any person should have access to according to the UN (citation here) and 3365 rp/month of expenditures. However, all households in the testing sample had water consumption above this standard. Thus, we included relative poverty lines for water consumption and expenditure. These correspond to the first and third quartiles. The second measure corresponds to the first quartile of the total sample 3.7 m^3. The richness line was set at 10 m^3 per adult equivalent per month, which represents the value for the third quartile in the sample. In the case of expenditures per month per adult equivalent, the poverty line was established at 4000 rp/month and the richness line was set at 8065 rp/month (first and third quartile).

We also defined metrics for evaluating a possible policy of excluding rich areas, rather than targeting poor areas.

The generic formulation of the error of exclusion in rich areas (EER) for each map was:

$$EER = \frac{\textit{Number of rich observations}\ \text{in}\ \textit{testing sample out of rich areas}}{\textit{Total number of rich observations}\ \text{in}\ \textit{testing sample}}$$

Similarly, the generic formulation of error of inclusion for rich areas (EIR) for each map was:

$$EIR = \frac{\textit{Number of not rich observations}\ \text{in}\ \textit{testing sample inside rich areas}}{\textit{Total number of observations}\ \text{in}\ \textit{rich areas}\ \text{in}\ \textit{testing sample}}$$

Using geoprocessing methods, or a logical sequence of spatial data processing, the calculation of numerators and denominators for each formula was automated (Figures 2.5-2.8). This way the results for each parameter for each variable were calculated and a contingency table was built using the ratios from each calculation in percentage format. The comparison is performed based on the target of trying to minimize both the error of inclusion and exclusion in each of the mapping techniques used.

Geoprocessing Models for Application of Voronoi maps vs GN maps in a poverty targeting context

Figure 17 shows the geoprocessing model used to calculate the required parameters for the error of exclusion. This model is basically composed of two parallel processes. One is set to calculate the number of poor observed in the test sample according to a poverty line set by the user (denominator), and the second one is set to select poor areas for particular variables as defined by the significance level (Z-value from Gi* test). An intermediate process used the count of total poor in the sample and counts only those who do not fall within poor areas. This way it is easy to calculate the number or count of poor observed out of the poor areas. Both, the poverty line for any variable and the level of clustering can be selected in a menu (Figure 18).

A similar geoprocessing process is used to calculate the other metrics.

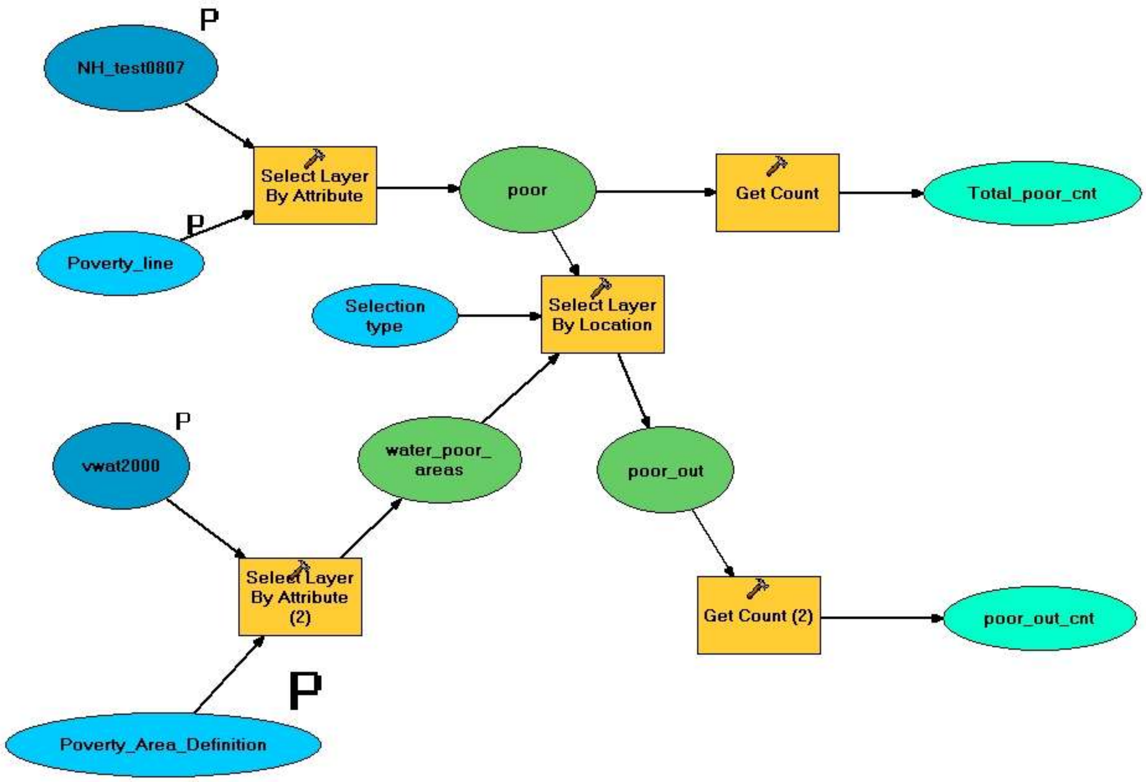


Figure 17. Geoprocessing model for Exclusion error

Similarly, a geoprocessing model for obtaining parameters for calculating the error of inclusion was built as well. Figure 19 shows the geoprocessing model used. In this case the model finds first poor areas as defined by significance level and not poor observed in the test sample. Later, it calculates the number of people not poor inside poor areas and the total number of people in poor areas. This geoprocessing model is also adapted to get the inclusion error for rich observations using the geoprocessing menu.

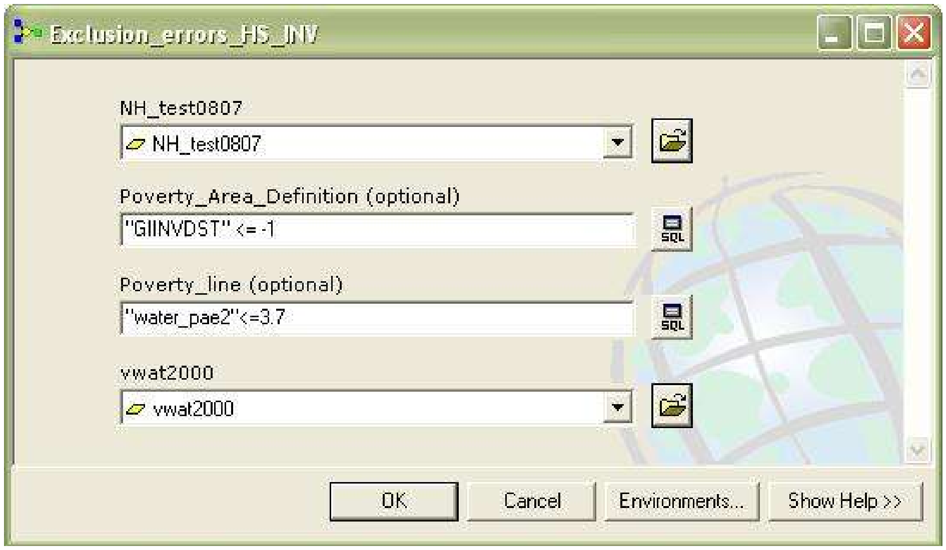


Figure 18. Geoprocessing model menu for exclusion error

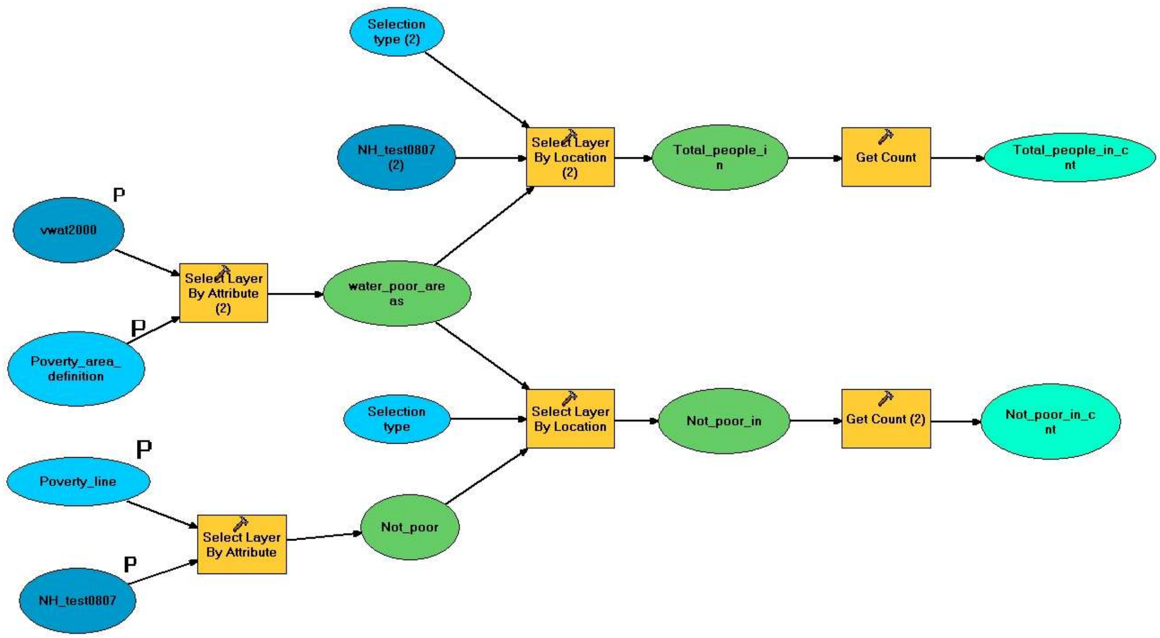


Figure 19. Geoprocessing model for calculating inclusion error

Figure 20. Geoprocessing menu for inclusion error

Results of Application of Hotspot Analysis and Comparison with GN Average Maps

Table 4 shows the errors of exclusion and inclusion for expenditures (EXPAED) and water consumption (WATPAE) for all the mapping methods described in this chapter.

In the case of expenditure, the EEP is higher in the GN average method (100%) than in the rest of the methods. The Voronoi maps method using fixed distance band has the smallest error (63%). The rest of the methods' errors vary between 81% and 85%.

The EIP for expenditures shows a wider range. In the case of GN maps it was undetermined as number of poor in poor hot spots was zero. Low EIP are shown by GN map with inverse distance band (18%) and for Voronoi maps with inverse distance (27%). Higher errors are shown by the methods using fixed distance band (70% for GN and 75% for Voronoi map). This is expected since the areas of low expenditure detected by this latter method are much larger than when using an inverse distance.

In the case of water expenditure, the EEP seems to be related to the lack of low consumption clusters since the error reaches 100% for the GN clustering methods using hotspot analysis and the Voronoi map using inverse distance. The GN hotspot map with fixed distance band reaches 83% of error and the GN average map shows only 1%. The EIP are mostly undetermined but in the GN average map (3%) and in the Voronoi fixed distance band (2%).

The EER for expenditure varied between 67% (Voronoi map with fixed distance band) and 93% (GN with fixed distance band). On the other hand, EIR for expenditure varied between 59% (GN average maps) and 77% (Voronoi maps with inverse distance).

Since all the mapping techniques used detected clusters of high expenditure areas, the calculations of these values seem to present fewer anomalies than those shown for poor areas.

Similar results are found for water expenditure in high consumption areas. EEP varied between 66% (Voronoi map, fixed distance band) and 95% (GN map fixed distance band).

Considering the previous results, none of these methods consistently shows lowest errors of inclusion or exclusion with either geographic relationship. This suggests that both low and high error percentages can occur by using any of these methods. However, it is also important to consider whether the previous methods used an adequate poverty line to be able to detect poor areas (assuming that they in fact exist within the study area). Similarly, the broad statistical significance used to map clusters may have led to high errors of inclusion.

Table 4. Errors of exclusion and inclusion for different poverty mapping methods

Error Reference	Variable	GN average	HH HS / Inv-CB	GN HS / Inv-CB	HH HS / FB-CB	GN HS / FB-CB
Poor - exclusion	EXPAED	100%	85%	85%	63%	81%
Poor - inclusion	EXPAED	und.	27%	18%	75%	70%
Poor - exclusion	WATPAE	1%	100%	100%	83%	100%
Poor - inclusion	WATPAE	3%	und.	und.	2%	und.
Rich - exclusion	EXPAED	77%	91%	89%	67%	93%
Rich - inclusion	EXPAED	59%	77%	60%	70%	71%
Rich - exclusion	WATPAE	68%	92%	92%	66%	95%
Rich - inclusion	WATPAE	69%	83%	64%	71%	90%

und: Undetermined as number of poor in poor hot-spots were = 0
GN: Units are GN, classified by poor and rich indexes
HH HS/Inv-CB: Units are HH with Voronoi maps, Gi* analysis for Hotspots using inverse distance and City block method
GN HS/Inv-CB: Units are GN, Gi* analysis for Hotspots using inverse distance and City block method
HH HS/FB-CB: Units are HH with Voronoi maps, Gi* analysis for Hotspots using fixed distance band and City block method
GN HS/FB-CB: Units are GN, Gi* analysis for Hotspots using fixed distance band and City block method
EXPAE: Monthly expenditure per adult equivalent, poor <= 3365 rp/m, rich >= 8065 rp/m
WATPAE: water consumption in m^3 pae per month. poor<=1.2 m3/month, rich>= 10m3/month
Poor hotspots are defined by z-score <=-1 for HH and GN maps
Rich hotspots are defined by z-score >= 1 for HH and GN maps

In order to test whether changing the poverty line would improve detection of poor clusters different poverty lines for expenditures and water expenditures were used (see Table 5). In that case poor observations for expenditure were set at 4000 rp/month and for water expenditure were set at 3.7 m^3/person per month. These values were the correspondent lower quartiles for the sample within the study area for each indicator. Since the richness lines did not present problems during their calculations, we will not work with alternative richness references in the rest of the chapter.

Using new poverty lines, we obtained the results shown in Table 5. Unfortunately, none of the methods chosen showed consistent low errors for poor clusters, although some variations are found. In this case it is easy to demonstrate that errors of inclusion and exclusion are sensitive not only to the method of aggregation used but also to the poverty (or richness) line used. Nevertheless, care should be taken when selecting a poverty line and a method since both should represent the geographic scale and the distribution of the data.

Table 5. Errors of exclusion and inclusion for different poverty mapping methods

Error Reference	Variable	GN average	HH HS/Inv-CB	GN HS/Inv-CB	HH HS/FB-CB	GN HS/FB-CB
Poor - exclusion	EXPAED	96%	88%	90%	0%	87%
Poor - inclusion	EXPAED	63%	70%	64%	69%	63%
Poor - exclusion	WATPAE	85%	100%	100%	78%	100%
Poor - inclusion	WATPAE	59%	und.	und.	69%	und.
Rich - exclusion	EXPAED	77%	91%	89%	67%	93%
Rich - inclusion	EXPAED	59%	77%	60%	70%	71%
Rich - exclusion	WATPAE	68%	92%	92%	66%	95%
Rich - inclusion	WATPAE	69%	83%	64%	71%	90%

und: undetermined as number of poor in poor hot-spots were = 0
GN: Units are GN, classified by poor and rich indexes
HH HS/Inv-CB: Units are HH with Voronoi Maps, Gi* analysis for Hotspots using inverse distance and City block method
GN HS/Inv-CB: Units are GN, Gi* analysis for Hotspots using inverse distance and City block method
HH HS/FB-CB: Units are HH with Voronoi Maps, Gi* analysis for Hotspots using fixed distance band and City block method
GN HS/FB-CB: Units are GN, Gi* analysis for Hotspots using fixed distance band and City block method
EXPAE: Monthly expenditure per adult equivalent, poor <= 4000, rich >=8065 rp/m
Watpae: water consumption in m^3 pae per month. poor<=3.7m3, rich>=10m
Poor hotspots are defined by z-score <=-1 for HH and GN maps
Rich hotspots are defined by z-score >= 1 for HH and GN maps

Both errors of exclusion and inclusion are consistently above 60%, which suggests that cluster areas are smaller on the ground and that this analysis needs to be run as well at smaller radius than 2000 m to get better validation results. Let's remember that this analysis considers only the scale of 2000 m (of search radius), as it reflected the midpoint of the significant scale range of the Global G test. Future analyses of clustering methods based on G_i^* need to consider the latter mentioned factor.

CHAPTER III - MULTI-SCALE ASSESSMENT OF POLICY EFFECTS IN FOREST COVER

Luis Eduardo Carrasco

1 ABSTRACT

The Payments for Environmental Services in Costa Rica (PSA) has brought a lot of attention during its first years of implementation. Under a protection contract, the PSA program pays forest land owners to conserve their lands to produce ecosystem services that could be used by everyone. This paper models the distribution of PSA protection contracts at subregional, household level, and countrywide scale in order to identify determinants of protection contract location during the years 1997 to 2000 and illustrate selected spatial analysis tools. The methods used include exploring relationships relevant to the PSA program at different scales and exploring potential spatial spillovers by (a) identifying multilevel relationships between deforestation and the PSA program, and location of PSA protection contracts using a grid of 2500 m^2 cells, (b) testing for spatial lag and spatial error in household and canton level models, and (c) modeling enforcement activity at the individual property level. At the subregional scale, we found evidence suggesting that distance to PSA fincas are negatively correlated to probability of deforestation, relationship increased by a multilevel effect of biodiversity conservation areas (GRUAS) even when controlling for effects of administrative units. At the household level, there is a moderate correlation between PSA protection contracts and visits by environmental agencies. There was no evidence suggesting countrywide convergence of PSA contracts or of spillovers.

2 INTRODUCTION

Payments for Environmental Services (PES) policies have brought attention since the late nineties. The implication of this policy to the ecosystem and to society are appealing not only to governments, institutions and policy makers. *Payments for Environmental Services* is adopted at local or country levels. The effects of these policies have been studied at a regional scale (Sanchez-Azofeifa et al. forthcoming) but only recently at local scale (Sills et al. forthcoming). Similarly, very little has been done to understand the role of spatial scale in examining policy-environment impacts. Therefore, it is important to know if beneficial feedback could be obtained by testing different scale-based approaches that could get information from local and regional levels.

Understanding spatial and temporal scale analysis is important to provide scale-relevant assessments and determine the effects of regional policies within the correct geographical extension. In this chapter we explore multiscale assessment methods for evaluating different aspects of Costa Rica's environmental services programs. We assess this program using three scale-based methods: regional, subregional, and multilevel. These analyses have been done with available data existing in geodatabases and with spatially explicit household survey data. The outputs of these analyses provides feedback on spatial and non-spatial relationships existing between participant agents in PES. In Costa Rica, the current program of environmental services is commonly referred as "Pagos por Servicios Ambientales" or PSA. This particular program has brought much attention to policy makers worldwide and to researchers from different disciplines (Pagiola et al. 2004).

3 OBJECTIVES

This paper targets individual questions regarding the PSA program. The main idea is to provide an example of the use of available spatial information and analysis for the monitoring or evaluation of regional policies. The primary objectives of this paper are to model the distribution of PSA protection contracts at subregional, household level, and countrywide scale in order to identify determinants of protection contract location during the years 1997 to 2000 and illustrate selected spatial analysis tools.

The secondary objectives include exploring relationships relevant to the PSA program at different scales and exploring potential spatial spillovers by (a) identifying multilevel relationships between deforestation and the PSA program, and location of PSA protection contracts using a grid of 2500 m^2 cells, (b) testing for spatial lag and spatial error in household and canton level models, and (c) modeling enforcement activity at the individual property level.

4 BACKGROUND

4.1 PSA DESCRIPTION

Payments for environmental services (PES) are mechanisms in which landowners who own forested areas are considered producers of environmental services and remunerated for participating in their production (Pagliola et al. 2004, 2005a). Specific purposes and application of PES vary by country. Pagliola et al. (2005a) observe that payments for ecosystem services (PES) program are being implemented in Latin American countries.

In the case of Costa Rica, the PSA program derived its structure and implementation from former government administered forest management and reforestation programs. The PSA is currently funded by a tax on gas and payments from users of ecosystem services who use these services, such as hydroelectric companies and water bottlers. FONAFIFO is the independent entity that manages the contracts and payments to private landowners of forestlands (Pagliola 2006). These mechanisms apply to rural forested or partially forested properties, in which the program pays landowners for maintaining their forest cover. This way, ecosystem services provided by forests can be used at a widespread level. Additionally, its goals and strategies are revised or changed after a given period of time, making the program operationally complex. Many lessons can be learned from the first years of implementation of the PSA in Costa Rica, which can help model similar policies in other parts of the world.

Several studies describe the PSA regarding purpose, participation requirements, progress, and current strategies for reaching these goals (Ortiz 2003, Pagliola et al. 2004, 2005a, 2005b and 2006, Sanchez-Azofeifa et al. forthcoming, Sills et al. forthcoming). The PSA's progress and current strategies have attracted several researchers into applying spatially explicit tools that include geographic information systems, econometrics, spatial statistics and others to assess whether the PSA is achieving its objectives and propose alternative targeting and payment strategies. These studies' results highlight important lessons about the program that could be incorporated in future stages of its implementation.

The PSA program is an example of an environmental policy that requires ongoing evaluation of environmental impacts. The general purpose of the PSA is to generate a continuous flow of diverse environmental services such as provision of water for urban, rural or hydroelectric consumption; mitigation of green house gases emissions; biodiversity and habitat protection; conservation and sustainable use, as well as other non-quantifiable benefits such as scenic beauty (Ortiz 2003). Hence, in order to account for these broadly defined positive impacts it is important to consider the development of a monitoring system that could quantify at least some of the most tangible impacts (such as forest cover, carbon sequestration, water quality, soil protection, green house gases emissions) which could be done based on preselected indicators. These indicators could be used for different purposes at the regional level to monitor the PSA program.

Researchers have mainly used forest cover change as a convenient proxy for different ecosystem services and to evaluate the program's success (Sanchez-Azofeifa et al. forthcoming, Sills et al. forthcoming). However, the impacts of the program may well go beyond ecosystem services (i.e biophysical impacts or environmental interactions). For instance, Pagliola et al. (2004) suggest that poverty reduction could also be a positive social impact of the program.

However, there are different scales at which positive outcomes of a national program could be expected and different scales in which these outcomes could be effectively measured. For instance, a country program could produce effects at a local level, at which these could be measured with precision but at prohibitive costs if we wanted to know the outcome for the whole country. This situation could make it a challenge to develop cost-effective monitoring strategies in the short term without sound planning and participation (Pagliola et al. 2004). Nevertheless, the "Costa Rica Atlas" (Costa Rica Atlas/ FONAFIFO/ FUNDECOR 2005) could potentially become the basis of a monitoring system for the PSA program. The atlas is a collection of spatial datasets that comprises a wide range of environmental themes (geology, watershed, ecologic zones, soil types, rivers), administrative units (districts, provinces, cantones, conservation areas, ecomarket zones), and social infrastructure and services (schools, hospitals, roads and highways, airports). The "Costa Rica Atlas" (CRA) is publicly available and has been used intensively in PSA research. The analysis of this spatial dataset with other ancillary information can help to draw lessons regarding the performance of the PSA program.

The program's strategies and goals are set at a regional scale or country level, however, the main program actions (payments) are carried out at the local scale or fincas levels (Figure 1). The outcome of the program, or ecosystem services are expected to be accounted for at the regional scale. While several studies have tried measurements of net forest increase at the country level (Pfaff et al. forthcoming, Sanchez-Azofeia et al forthcoming) it is difficult to detect forest cover change at the country level without using spatial data that has suffered some loss of resolution. Thus, we may not be able to effectively account for impacts at subregional (local) scales with such data. Therefore, to assess impacts of the PSA program as a consequence of the actions of landowners, using forest as a proxy, we need to use techniques that consider multiple spatial levels as connected entities at finer resolution.

A monitoring system could help producing relevant data and let us analyze the effects of the program at different scales, by collecting fine resolution data, as exemplified by Boucek and Moran (2004). Boucek and Moran (2004) make a call for awareness of scale relationships between coarse and fine scale remotely sensed data while taking care of precision in environmental studies. Applications of studies involving spatial analysis are described by Bradshaw and Muller 2004). The authors emphasize that policy and decision makers are increasingly relying on spatial data at different stages of public policy processes. Particularly, they mention that use and sophistication of spatial analysis have the potential to increase "public participation in decision-making" Bradshaw and Muller (2004, p. 318).

Ideally we need to consider the scale at which the PSA's main actions occur and the scale at which increase or decrease of a particular ecosystem service needs to be accounted for as connected processes. A more detailed or scale sensitive approach than the one described in Figure 1, would consider production of ecosystem services from the parcel level and aggregated to coarser scales. It is important to consider that some ecosystems services may be produced by different biophysical processes. For instance, ecosystem services may be produced by direct and indirect interactions or impacts. As the temporal dimension in this program is important for its continued evaluation, there could be interactions among different elements that could produce cumulative impacts as well. In that sense, an information systems platform will be useful if it is able to provide data at different spatial and temporal scales. However, the CRA only provides partial temporal information for forest cover at only one scale.

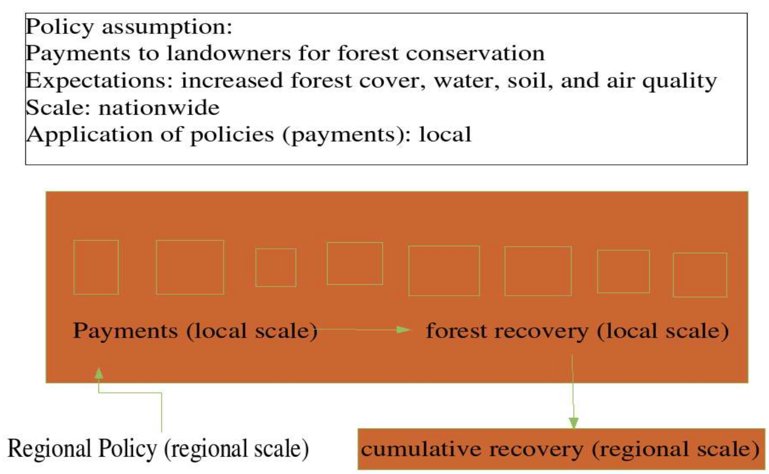


Figure 1. Scale of Action of PSA

4.2 PRIOR STUDIES OF THE PSA PROGRAM

Table 1 lists a summary of PSA studies' objectives, methods and proxies used to identify ecosystem services. This brief list of studies highlights the importance of spatial analysis, integrated with econometric and statistical techniques, for evaluating the PSA program. These studies pay special attention to household decision-making in order to evaluate the progress of the PSA in the social context. This is important the PSA is implemented at the household scale. However, there are other studies that evaluate the PSA from a coarser scale (Sanchez-Azofeifa forthcoming). In this latter case, the intention is to evaluate the nationwide impacts of the program by aggregating data collected with remote sensing techniques and analyzed with GIS. At a coarse scale, though, it is challenging to disaggregate the effects of the PSA from other programs such as forest management and reforestation.

Table 1. Summary of relevant research of PSA

Author(s)	Main objective(s)	Method(s) used	Spatial data used	Main results
Zbinden and Lee (2004)	Examines participation in the PSA and factors that motivate farmers, households and landowners	Survey and econometric analysis	None	Farm size, human capital and household economic factors influence participation in PSA program alternatives. Larger farmers and forest landowners disproportionately represented
Sills et al. (forthcoming)	Assess impact of PSA at household level	Household survey, Propensity matching scores, GIS	Land use and land cover data from 1996 and 2000. Survey data	Not a strong difference between forest increase between PSA and non-PSA fincas
Pfaff et al. (forthcoming)	Assess impact of PSA in deforestation rates	Propensity matching scores, GIS	Observed and projected deforestation rates from GIS	PSA program had little impact on deforestation rates. PSA program lacks targeting strategies
Sanchez-Azofeifa et al. (forthcoming)	Identify allocation of payments in different ecologic, conservation and administrative units and relative to deforestation threat	GIS, Remote sensing, Econometrics	Payments records, deforestation layers from 1997-2000 with 5km cells	PSA payments broadly distributed across units. 1997-2000 deforestation rate is not significantly different among PSA and non-PSA areas
Newburn et al. (2006)	Analyzed site selection process	Compared benefit-loss-cost targeting approaches with more conventional targeting ones	Literature review of conservation site selections	Suitable high vulnerability sites are more expensive than low vulnerability sites with low high quality
Pagliola et al. (2005b)	Effects of PSA in poverty reduction	Analysis of literature	Literature review	Identified important synergies between PSA and poverty reduction. Also identified negative impacts

One scale of assessment will be more appropriate than others depending on the questions to address. Fine scale studies with remote sensing data are expensive, but fine and very useful data can be collected at household levels as well, as suggested by Boucek and Moran (2004). Household data collection is limited mainly because of logistic issues (Sills et al. forthcoming) affecting final sample size. Therefore statistical power of any analysis that uses these data is diminished. Also, household data collection's cost is prohibitive at larger extensions, forcing data analysts to target subregions or relatively small areas. The resulting information is mainly applicable to a small area and few extrapolations to other areas could be recommended or considered accurate by consensus.

An alternative analytical method requires using a multilevel, hierarchical or multiscale assessment. In this method some variables are defined at fine scale and the rest of the variables are defined at a coarser scale, and both groups of variables are suspected to interact with each other. For instance, household characteristics such as income, family size, area of forest per parcel are defined at a fine resolution, whereas characteristics such as political boundaries and other man-made biophysical classifications are defined at a coarse resolution. In this case, an analysis sensitive to scales and their interactions can be used to detect relationships between individuals or their proxies and their coarse environment. Applications of this type of analysis are common in social science (Raudenbush et al. 1993) and getting more attention in ecology (Pan and Bilsborrow 2005).

An interesting background for applying multilevel analysis is suggested by Geist and Lambin (2002). The authors describe two main components of tropical deforestation: proximate causes and underlying drivers. Proximate causes are human activities or immediate action at the local level, such as agricultural expansion, that originate from intended land use and directly impact forest cover. Underlying driving forces are fundamental social processes, such as human population dynamics or agricultural policies, that underpin the proximate causes and either operate at the local or global level and indirectly affect forests.

Geist and Lambin (2002) suggest that there is no universal link between cause and effect of tropical deforestation, but by a combination of multiple factors: proximate and underlying in varying geographical and historical contexts: development of market economies, expansion of croplands. These factors are region specific. The authors acknowledge an interaction between global or regional factors and local factors that need to be identified on a case by case basis.

These concepts could be applied to Costa Rica's PSA program. For instance, what Geist and Lambin (2002) describe as proximate causes of deforestation are equivalent to first level variables, and what they describe as underlying drivers are equivalent to second level variables in a multilevel or hierarchical modeling context. Table 2 shows some hypothetical non-comprehensive elements that could be considered.

Table 2. Proximate and underlying causes of Deforestation in a Hierarchical Level Modeling Context

Proximate causes (First level variables)	Underlying drivers (Second level variables)
Distance to roads and highways Distance to sawmills (market) Forested areas ownership Property physical characteristics (elevation, slope, type of soils, etc.) Landowner socioeconomic characteristics (income, education, family size, etc.)	Landownership policies Market prices of wood Market prices of agricultural products Administrative regional and subregional policies (Cantones, Districts, Protected areas, etc)

In a broader sense, it is important to analyze relationships that could be detected at disparate scales as well as their connections. Reconciling this knowledge could help us to better understand the PSA program and propose sound methods for studying large range environmental policies and different ecologic, economic and social factors and dynamics.

Similarly, it is relevant to consider the importance of data collection planning and implementation during the existence of the program with the goal of monitoring the program's goals. Since the PSA program may have different goals from one period to another, it would be more useful for future program evaluators to count with accurate data gathered during the life of the program. This implies that several research questions need to be anticipated by program managers in cooperation with program evaluators. This process would help to devise program indicators and the type of data that needs to be collected and help establishing a monitoring system that could be implemented during the program's lifetime.

In the next section we explain three different spatial analysis approaches for assessing the performance of the PSA at country, regional, and household levels.

5 METHODOLOGY

This section describes three approaches used in this chapter to assess the PSA using different spatial data. The first approach is used to assess convergence of contracts within Cantones from 1997-2000 and possible presence of spillovers, which are indirect impacts of the program on households that are not involved in them. The second approach analyzes factors associated with deforestation at different spatial scales. The third approach assesses whether visits by environmental agencies to prospect fincas are affected by particular environmental factors.

5.1 MODELING DEFORESTATION AT 500X500 METERS

The objective of this analysis is to infer how the PSA program and environmental variables (such as elevation, slope, distance to roads, distance to highways) at the local scale, and administrative designations, among them biodiversity conservation areas (GRUAS), protection areas, at a larger scale affected or did not affect deforestation that occurred between 1997-2000. This analysis is performed at two levels using a hierarchical linear regression (HLM).

Wang (1997) suggests that HLM methods may have been developed simultaneously by different researchers under different names: multilevel linear models, multi-scale regression models, mixed effects models, repeated measures models. In all cases, the focus is analyzing the mixed effects of variables that represent different hierarchies (or scales) to the response variables. In theory, this reveals relationships that would not be seen in a simple OLS regression. Wong and Mason (1991) describe the components of a HLM as micro response, and micro and macro regressors, in which all the micro errors are assumed to be independent. At the macro or context levels, the macro errors or disturbances are assumed to be independent of the micro errors. They are also independent across contexts. This is particularly useful when the context refers to dispersed geographical locations. Even though social and health sciences are perhaps the main disciplines to apply HLM (Raudenbush 1993, Bigenheimer and Raudenbush 2004), it has been used as well in areas such as land use modeling (Pan and Bilsborrow 2005), and forestry (Monleon 2003).

HLM is used in this study to find effects of selected variables (distance to PSA protection contracts, distance to roads, elevation, slope) as proximate causes of deforestation and their interaction with underlying causes of deforestation as GRUAS. Primary roads in the study area are less common than secondary roads; therefore these two elements were treated independently along all the analyses in this chapter.

While performing such an analysis, it is also important to control for other environmental factors that could have a relationship with deforestation.

The raw data for this analysis consist in vector and raster data and are listed in Table 3:

Table 3 Data Sources and Output for HLM analysis

Data Source	Type	Transformation	Output Variable
PSA fincas from study area	Vector	Rasterization	Distance and density from each pixel to PSA contracts
Secondary Roads	Vector	Rasterization	Secondary roads density using kernel density function
Primary Roads	Vector	Rasterization	Primary roads density using kernel density function
Sawmills	Vector	Rasterization	Distance to sawmills
Administrative boundaries	Vector	Rasterization	Discrete raster with location of cantones
Land cover data from 1997-2000	Vector	Rasterization/ Reclassification	Deforested and non-deforested areas
Digital Elevation Model (28.5x28.5)	Raster	Slope and Elevation analysis	Slope percentage and Elevation

The resulting data were extracted using ArcGRID and imported into a database using

Oracle10gXE for preparation of data for HLM analysis. The data preparation involved calculating the means for all independent variables using the variable cantones as a grouping factor and assigning them to each observation. Later, each variable was centered to its group-mean by subtracting the original variable's value to the group mean. This procedure was done with all first level variables or micro regressors in CRAN-R statistical package[1].

The HLM analysis was performed in three steps using CRAN-R packages glm and glmmPQL. The glm function fits a generalized linear model while the glmmPQL fits a model using the penalized quasi-likelihood approximation to maximum likelihood (Thomson 2006). The first step is a generalized linear model for deforestation as a binary response using a logit link with the first level independent variables. The second step regresses the second level variables on deforestation. In the third step the significant variables for each process (from ~0.05 and below) are included in the HLM model.

The final sample size for each grid theme is of approximately 20000 cells, which could lead to high statistical significance simply because of the large sample size. However, significant relationships are interpreted in light of the policy context.

The first step is a generalized linear model logistic model of deforestation as a function of first level variables:

$$
\begin{aligned}
&Prob(Deforestation) = \beta_{0j} + \beta_{1j} DISTPSAPROT_{1j} + \beta_{2j} PSADUM_{2j} \\
&+ \beta_{3j} \mathrm{SLOPE\_PC}_{3j} + \beta_{4j} \mathrm{ELEV\_500}_{4j} + \beta_{5j} DHW_{5j} \\
&+ \beta_{6j} DROAD_{6j} + \beta_{7j} DENHW_{7j} + \beta_{8j} DENROAD_{8j} \\
&+ \beta_{9j} DSAWMILL_{9j} + \beta_{10j} GUACIMO_{10j} + \beta_{11j} POCOCI_{11j} + \tau_{ij}
\end{aligned}
$$

Where:

DEFOR: Deforestation = 1, Other (plantations, forest cover, non-forested areas) = 0

DISTPSAPROT: Distance to PSA finca

PSADUM: Dummy for PSA (PSA=1, NON PSA=0)

SLOPE_PC: Slope in percentage

1 Several software packages are able to run HLM models such as HLM, CRAN's nlme and glmmPQL, SAS PROC MIXED (Singer 1998), and others. However, de Leeuw and Kreft (1995) alert the researcher to be aware of problems arising from different software using different algorithms and interpretation of coefficients.

ELEV_500: Elevation in meters

DHW: Distance to highways

DROAD: Distance to roads

DENHW: Highways density

DENROADS: Road density

DSAWMILL: Distance to sawmills

GUACIMO: Dummy for canton

POCOCI: Dummy for canton

The second step is a generalized linear model of forest cover as a function of second level variables:

$$\begin{aligned}&Prob(Deforestation) = \beta_{0j} + \beta_{1j} GUACIMO_{1j} + \beta_{2j} POCOCI_{2j}\\&+ \beta_{3j} TORT_{3j} + \beta_{4j} CVC_{4j} + \beta_{5j} GRUA_{5j} + \beta_{6j} HUM_{6j}\\&+ \beta_{7j} PN_{7j} + \beta_{8j} RN_{8j} + \beta_{9j} RF_{9j} + \tau_{ij}\end{aligned}$$

Where:

Prob(Deforestation): Deforestation = 1, Other = 0

GUACIMO: Dummy for canton

POCOCI: Dummy for canton

TORT:Dummy for Tortuguero conservation area

CVC: Dummy for Cordillera Volcanica Central conservation area

GRUAS: Dummy for GRUAS

HUM: Dummy for Humedales type of protection area

PN: Dummy for National Park type of protection area

RN: Dummy for National Reserve type of protection area

RF: Dummy for Forest Reserve type of protection area

After estimating the initial glm models, we detrended the significant variables from step one by extracting their mean. These detrended variables are shown in Table 4.

Table 4. Source of Detrended Variables Used in HLM for modeling deforestation

Initial variables in GLM	Detrended variables used in HLM
DISTPSAPROT: Distance to PSA finca SLOPE_PC: Slope in percentage ELEV_500: Elevation in meters DROAD: Distance to roads DSAWMILL: Distance to sawmills	MNPSAPROT MNSLOPE MNELEV MNDROAD MNDSAWMILL

Later we included these centralized variables into a hierarchical linear model of forest cover:

$$Prob(Deforestation) = \beta_{0j} + \beta_{1j} MNPSAPROT_{1j} + \beta_{2j} MNSLOPE_{2j}$$
$$+ \beta_{3j} MNELEV_{3j} + \beta_{4j} MNDROAD_{4j} + \beta_{5j} MNDSAWMILL_{5j} + \tau_{ij}$$

With the second level effects:

$$\beta_{0j} = \gamma_{00} + \gamma_{01} GRUA + \mu_{0j}$$
$$\beta_{1j} = \gamma_{10} + \gamma_{01} GRUA + \mu_{1j}$$
$$\beta_{2j} = \gamma_{20} + \gamma_{01} GRUA + \mu_{2j}$$
$$\beta_{3j} = \gamma_{30} + \gamma_{01} GRUA + \mu_{3j}$$
$$\beta_{4j} = \gamma_{40} + \gamma_{01} GRUA + \mu_{4j}$$
$$\beta_{5j} = \gamma_{50} + \gamma_{01} GRUA + \mu_{5j}$$

Which results in:

$$Prob(Deforestation) = \gamma_{00} + \gamma_{01} GRUA + \mu_{0j} + (\gamma_{10} + \gamma_{01} GRUA + \mu_{1j}) * MNPSAPROT_{1j}$$
$$+ (\gamma_{20} + \gamma_{01} GRUA + \mu_{2j}) * MNSLOPE_{2j} + (\gamma_{30} + \gamma_{01} GRUA + \mu_{3j}) * MNELEV_{3j}$$
$$+ (\gamma_{40} + \gamma_{01} GRUA + \mu_{4j}) * MNDROAD_{4j} + (\gamma_{50} + \gamma_{01} GRUA + \mu_{5j}) * MNDSAWMILL_{5j} + \tau_{ij}$$

and after multiplying the first and second level variables we have that:

$$
\begin{aligned}
&Prob(Deforestation) = \gamma_{00} + \gamma_{01} GRUA + \mu_{0j} \\
&+ \gamma_{10} * MNPSAPROT_{1j} + \gamma_{01} GRUA * MNPSAPROT_{1j} + \mu_{1j} * MNPSAPROT_{1j} \\
&+ \gamma_{20} * MNSLOPE_{2j} + \gamma_{01} GRUA * MNSLOPE_{2j} + \mu_{2j} * MNSLOPE_{2j} \\
&+ \gamma_{30} * MNELEV_{3j} + \gamma_{01} GRUA * MNELEV_{3j} + \mu_{3j} * MNELEV_{3j} \\
&+ \gamma_{40} * MNDROAD_{4j} + \gamma_{01} GRUA * MNDROAD_{4j} + \mu_{4j} * MNDROAD_{4j} \\
&+ \gamma_{50} * MNDSAWMILL_{5j} + \gamma_{01} GRUA * MNDSAWMILL_{5j} + \mu_{5j} * MNDSAWMILL_{5j} \\
&+ \tau_{ij}
\end{aligned}
$$

Which could be divided in fixed effects:

$$
\begin{aligned}
&\gamma_{00} + \gamma_{10} * MNPSAPROT_{1j} + + \gamma_{20} * MNSLOPE_{2j} \\
&+ \gamma_{30} * MNELEV_{3j} + \gamma_{40} * MNDROAD_{4j} + \gamma_{50} * MNDSAWMILL_{5j}
\end{aligned}
$$

mixed effects:

$$
\begin{aligned}
&+ \gamma_{01} GRUA + \gamma_{01} GRUA * MNPSAPROT_{1j} + \gamma_{01} GRUA * MNSLOPE_{2j} \\
&+ \gamma_{01} GRUA * MNELEV_{3j} + \gamma_{01} GRUA * MNDROAD_{4j} + \gamma_{01} GRUA * MNDSAWMILL_{5j}
\end{aligned}
$$

random effects:

$$
\begin{aligned}
&+ \mu_{0j} + \mu_{1j} * MNPSAPROT_{1j} + \mu_{2j} * MNSLOPE_{2j} + \mu_{3j} * MNELEV_{3j} \\
&+ \mu_{4j} * MNDROAD_{4j} + \mu_{5j} * MNDSAWMILL_{5j}
\end{aligned}
$$

and the error: $+\tau_{ij}$

The elements of the HLM model are shown in Figure 2

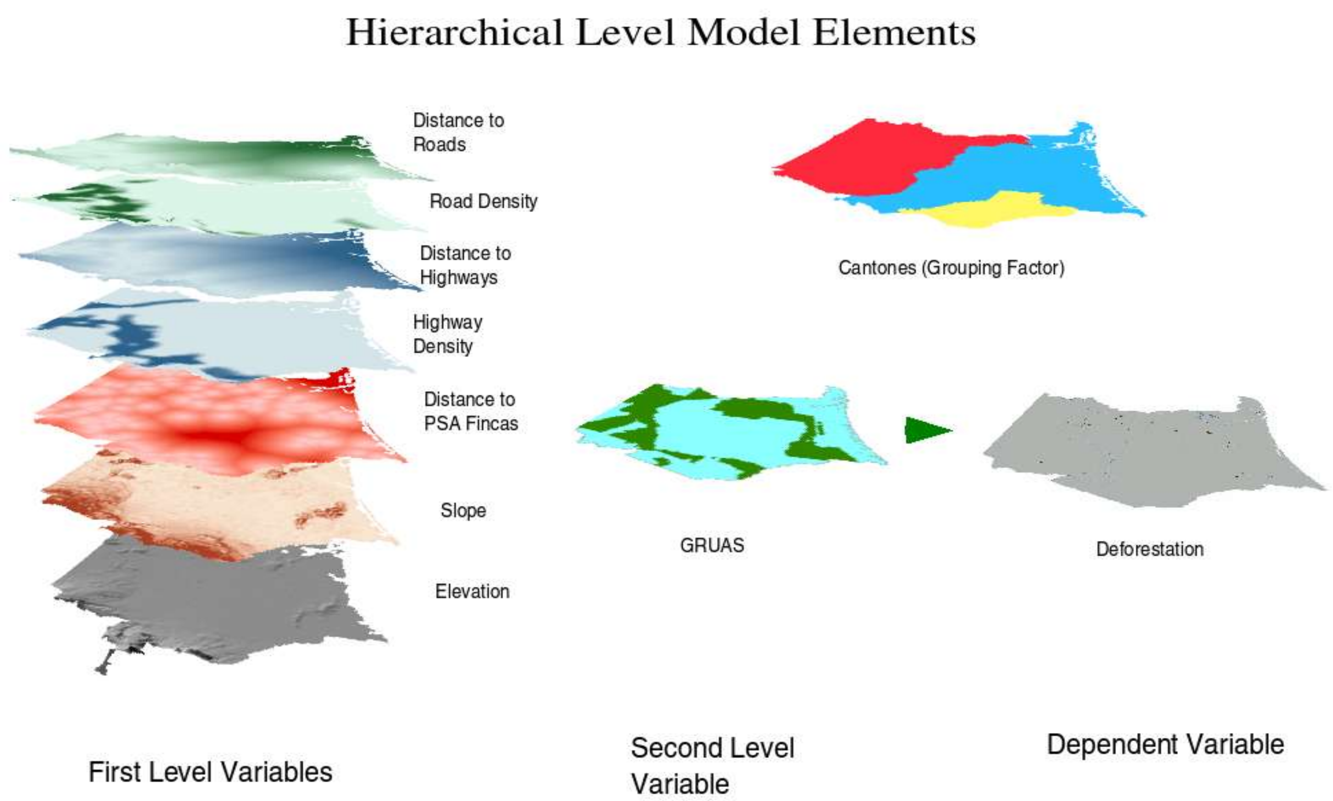


Figure 2: Hierarchical Level Model elements for study area

5.2 MODELING LOCATION OF PSA CONTRACTS

A similar approach to the assessment of deforestation was used to assess the probability of a PSA protection contract. The following logistic model was used:

$$
\begin{aligned}
&Prob(PSA)=\beta_{0j}+\beta_{1j}PSA1999DIST_{1j}+\beta_{2j}PSA1998DIST_{2j} \\
&+\beta_{1j}PSA1997DIST_{1j}+\beta_{2j}DEFOR_{2j} \\
&+\beta_{3j}\mathrm{SLOPE\_PC}_{3j}+\beta_{4j}\mathrm{ELEV\_500}_{4j}+\beta_{5j}DHW_{5j} \\
&+\beta_{6j}DROAD_{6j}+\beta_{7j}DENHW_{7j}+\beta_{8j}DENROAD_{8j} \\
&+\beta_{9j}DSAWMILL_{9j}+\beta_{10j}GUACIMO_{10j}+\beta_{11j}POCOCI_{11j}+\tau_{ij}
\end{aligned}
$$

Where:

PSA: PSA protection contract = 1, Non-PSA contract = 0

PSA199xDIST: Distance to PSA protection contract in year "x"

SLOPE_PC: Slope %

ELEV_500: Elevation in meters

DHW: Distance to highways

DROAD: Distance to roads

DENHW: Highways density

DENROADS: Road density

DSAWMILL: Distance to sawmills

GUACIMO: Dummy for canton

POCOCI: Dummy for canton

Also, candidates for second level variables were used in a second logistic model

$$
\begin{aligned}
&Prob(PSA)=\beta_{0j}+\beta_{1j}GUACIMO_{1j}+\beta_{2j}POCOCI_{2j} \\
&+\beta_{3j}TORT_{3j}+\beta_{4j}CVC_{4j}+\beta_{5j}GRUA_{5j}+\beta_{6j}HUM_{6j} \\
&+\beta_{7j}PN_{7j}+\beta_{8j}RN_{8j}+\beta_{9j}RF_{9j}+\tau_{ij}
\end{aligned}
$$

Where:

Prob(PSA): Probability of PSA protection contract = 1, Non-PSA contract = 0

GUACIMO: Dummy for canton

POCOCI: Dummy for canton

TORT: Dummy for Tortuguero conservation area

CVC: Dummy for Cordillera Volcanica Central conservation area

GRUAS: Dummy for GRUAS

HUM: Dummy for Humedales type of protection area

PN: Dummy for National Park type of protection area

RN: Dummy for National Reserve type of protection area

RF: Dummy for Forest Reserve type of protection area

After running the initial GLM models, we included the significant variables in a HLM model using the following detrended variables (Table 5) from the GLM:

Table 5. Source of Detrended Variables Used in HLM for location of PSA contracts

Initial variables in GLM	Detrended variables used in HLM
SLOPE_PC: Slope in percentage	MNSLOPE
ELEV_500: Elevation in meters	MNELEV
DROAD: Distance to roads	MNDROAD
DSAWMILL: Distance to sawmills	MNDSAWMILL
PSA1997DIST	MNPSA97
PSA1998DIST	MNPSA98
PSA1999DIST	MNPSA99

$$Prob(PSA) = \beta_{0j} + \beta_{1j} MNSLOPE_{1j} + \beta_{2j} MNELEV_{2j}$$
$$+ \beta_{3j} MNDROAD_{3j} + \beta_{4j} MNDSAWMILL_{4j}$$
$$+ \beta_{5j} MNPSA99_{5j} + \beta_{6j} MNPSA98_{6j} + \beta_{7j} MNPSA97_{7j} + \tau_{ij}$$

With the second level effects:

$$\beta_{0j} = \gamma_{00} + \gamma_{01} GRUA + \mu_{0j}$$
$$\beta_{1j} = \gamma_{10} + \gamma_{01} GRUA + \mu_{1j}$$
$$\beta_{2j} = \gamma_{20} + \gamma_{01} GRUA + \mu_{2j}$$
$$\beta_{3j} = \gamma_{30} + \gamma_{01} GRUA + \mu_{3j}$$
$$\beta_{4j} = \gamma_{40} + \gamma_{01} GRUA + \mu_{4j}$$
$$\beta_{5j} = \gamma_{50} + \gamma_{01} GRUA + \mu_{5j}$$
$$\beta_{6j} = \gamma_{60} + \gamma_{01} GRUA + \mu_{6j}$$
$$\beta_{7j} = \gamma_{70} + \gamma_{01} GRUA + \mu_{7j}$$

Which results in:

$$Prob(PSA)=\gamma_{00}+\gamma_{01}GRUA+\mu_{0j}+(\gamma_{10}+\gamma_{01}GRUA+\mu_{1j})*MNSLOPE_{1j}$$
$$+(\gamma_{20}+\gamma_{01}GRUA+\mu_{2j})*MNELEV_{2j}+(\gamma_{30}+\gamma_{01}GRUA+\mu_{3j})*MNDROAD_{3j}$$
$$+(\gamma_{40}+\gamma_{01}GRUA+\mu_{4j})*MNDSAWMILL_{4j}+(\gamma_{50}+\gamma_{01}GRUA+\mu_{5j})*MNPSA99_{5j}$$
$$+(\gamma_{60}+\gamma_{01}GRUA+\mu_{6j})*MNPSA98_{6j}+(\gamma_{70}+\gamma_{01}GRUA+\mu_{7j})*MNPSA97_{7j}+\tau_{ij}$$

$$Prob(PSA)=\gamma_{00}+\gamma_{01}GRUA+\mu_{0j}$$
$$+\gamma_{10}*MNSLOPE_{1j}+\gamma_{01}GRUA*MNSLOPE_{1j}+\mu_{1j}*MNSLOPE_{1j}$$
$$+\gamma_{20}*MNELEV_{2j}+\gamma_{01}GRUA*MNELEV_{2j}+\mu_{2j}*MNELEV_{2j}$$
$$+\gamma_{30}*MNDROAD_{3j}+\gamma_{01}GRUA*MNDROAD_{3j}+\mu_{3j}*MNDROAD_{3j}$$
$$+\gamma_{40}*MNDSAWMILL_{4j}+\gamma_{01}GRUA*MNDSAWMILL_{4j}+\mu_{4j}*MNDSAWMILL_{4j}$$
$$+\gamma_{50}*MNPSA99_{5j}+\gamma_{01}GRUA*MNPSA99_{5j}+\mu_{5j}*MNPSA99_{5j}$$
$$+\gamma_{60}*MNPSA98_{6j}+\gamma_{01}GRUA*MNPSA98_{6j}+\mu_{6j}*MNPSA98_{6j}$$
$$+\gamma_{70}*MNPSA97_{7j}+\gamma_{01}GRUA*MNPSA97_{7j}+\mu_{7j}*MNPSA97_{7j}$$
$$+\tau_{ij}$$

Which could be divided in fixed effects:

$$\gamma_{00}+\gamma_{10}*MNSLOPE_{1j}+\gamma_{20}*MNELEV_{2j}$$
$$+\gamma_{30}*MNDROAD_{3j}+\gamma_{40}*MNDSAWMILL_{4j}+\gamma_{50}*MNPSA99_{5j}$$
$$+\gamma_{60}*MNPSA98_{6j}+\gamma_{70}*MNPSA97_{7j}$$

mixed effects:

$$+\gamma_{01}GRUA+\gamma_{01}GRUA*MNSLOPE_{1j}+\gamma_{01}GRUA*MNELEV_{2j}$$
$$+\gamma_{01}GRUA*MNDROAD_{3j}+\gamma_{01}GRUA*MNDSAWMILL_{4j}+\gamma_{01}GRUA*MNPSA99_{5j}$$
$$+\gamma_{01}GRUA*MNPSA98_{6j}+\gamma_{01}GRUA*MNPSA97_{7j}$$

random effects:

$$+\mu_{0j}+\mu_{1j}*MNSLOPE_{1j}+\mu_{2j}*MNELEV_{2j}+\mu_{3j}*MNDROAD_{3j}$$
$$+\mu_{4j}*MNDSAWMILL_{4j}+\mu_{5j}*MNPSA99_{5j}+\mu_{6j}*MNPSA98_{6j}$$
$$+\mu_{7j}*MNPSA97_{7j}$$

and the error: $+\tau_{ij}$

5.3 STRATEGY FOR CONTRACTING LANDOWNERS

This approach helped to assess if environmental factors at the household level affect the number of visits from forestry offices that landowners receive to promote PSA participation. Strategically speaking, visiting landowners to encourage participation in the program could produce positive neighbor effects or spillovers resulting in increased contracts with landowners that are and are not visited. In the latter case, contracting encouragement would occur as an indirect effect from visited landowners information dispersion.

The data used were collected from a field household survey performed in Costa Rica during 2006. The survey was targeted toward landowners in the PSA program and landowners out of the program. The data were imported into a database using OracleXE10g. Only the variables listed were extracted and incomplete records were eliminated from the sample. The data were spatially referenced and imported into ArcGIS. The statistical analysis was performed in GeoDA.

The model has a simple linear form:

$$\begin{aligned} &\textit{Visits by Environmental Agencies} = \beta_0 + \beta_1 HA + \beta_2 BNH \\ &+ \beta_3 BNL + \beta_4 \text{DISTANCE\_E} + \beta_5 \text{DISTANCE TO PSA} \\ &+ \beta_6 \text{POOR\_SOIL} + \beta_7 \text{LARGE\_SLOPE} + \beta_8 \text{TYPE\_OF\_CONTRACT} \\ &+ \beta_9 \text{DISTANCE\_TO\_PSA} + \beta_{10} \text{DISTANCE\_TO\_ROADS} \\ &+ \beta_{11} \text{DISTANCE\_TO\_HIGHWAYS} + \beta_{12} \text{DISTANCE\_TO\_SAWMILLS} + \epsilon_i \end{aligned}$$

Where:

HA: Size of finca in hectares

BNH: Old forest in hectares

BNL: Young forest in hectares

DISTANCE_E: Distance to environmental agencies in meters

DISTANCE TO PSA: Distance to nearest PSA protection finca, where PSA fincas are extracted from FUNDECOR/FONAFIFO's dataset

POOR_SOIL: Percentage of finca with poor soil

LARGE_SLOPE: Percentage of PSA finca with large slope

Type of contract: PSA = 1, nonPSA = 0

DREDCAM: Distance to roads

DCARR: Distance to highways

The statistical model used is an OLS model with correction for spatial dependency if there is evidence of spatial lag or spatial error. Consideration is given to significant variables and the sign of their coefficients to understand whether their relationship with visits to fincas is positive or negative.

5.4 PROBABILITY OF PSA CONTRACTS, PROXIMITY AND LOCAL TARGETING

A second model was run in order to assess whether probability of PSA contracts is related to environmental variables followed this logistic form:

$$\begin{aligned} Type\ of\ Contract &= \beta_{0j} + \beta_{1j}\,\mathrm{VISITS\_ENV}_{1j} + \beta_{2j}\,DREDCAM_{2j} \\ &+ \beta_{3j}\,DCARR_{3j} + \beta_{4j}\,DSAWMILL_{4j} + \beta_{5j}\,DPSAPROT_{5j} + \tau_{ij} \end{aligned}$$

Where:

Type of contracts was 1 for PSA and 0 for non-PSA,

VISITS_ENV = Visits by extension agents,

DREDCAM = Distance to roads,

DCARR = Distance to highways,

DSAWMILL = Distance to sawmills,

DPSAPROT = Distance to PSA contracts

5.5 REGIONAL CONVERGENCE AND SPILLOVERS OF PSA CONTRACTS AT THE COUNTRY LEVEL

This method is used to analyze the distribution of PSA contracts across cantones in 2000 as a function of the initial distribution of the program in 1997, as well as the distribution of other conservation programs such as Management and Reforestation.

The goal is to identify which policy(ies) has been more influential in the spatial distribution of PSA contracts between 1997 and 2000. Additionally, the analysis will test whether effects are caused by neighbor effects, which in this context are interpreted as spatial spillovers.

There are three possible patterns. One is convergence, which means that cantones with few contract initially "catch-up" by gaining contracts more quickly than cantones that originally had many contracts. Other possibilities are divergence or no relationship to original contracts. Convergence could be due to differences in administrative procedures and/or a combination of operational factors such as differences in rural extension. In that case, landowners might be interested right away in signing up for the program, but their contracts may be delayed by administrative procedures. A convergence model could test whether cantones are "catching up" with respect to increase of PSA contracts. However, this model would also be sensitive spatial dependencies such as spatial lag or spatial error (Anselin 1988). Neighbor effects could influence the rate at which PSA con are added in contiguous areas. Cantones that are next to others with many contracts may be more likely to gain contracts as well. This is also known in regional geography as spillovers (Rey and Montouri 1999). This method is used here as a descriptive model of the relationships between land contracts in different forest conservation policies.

Regional convergence is a process by which regions considered to be less developed by a particular indicator than other regions exhibit a larger rate of growth or recovery (or beta-convergence) than others that are more developed. In theory, if all regions keep growing, at some point they will tend to equalize (Rey 1999, Lundberg 2006). This process has been largely studied and applied in regional geography and used to study causes of economic development of countries and regions. For instance Rey (1999), Lundberg (2006), Ertur et al. (2006) and Carrington (2003) applied these methods to study income and growth rates in the USA, Sweden and Europe respectively.

Spatial analysis has been influential in the development of economic geography or regional economics and econometrics since the late 1980s (Anselin 1988, Florax and van der Vlist 2003). Literature on regional convergence often cites methods to assess spatial lag and spatial error. These latter methods are used to assess whether the growth of regions is due to the growth of neighboring regions, also known as spillovers or transfer (Rey 1999). Rey (1999), Lundberg (2006), and Ertur et al. (2006) demonstrate the importance of studying spatial interactions for understanding spillovers between zones that exhibit economic growth and their neighbors. van Stel and Nieuwenhuijsen (2004) provide a complementary definition for spillovers in the context of competition in which enterprises (regions) improve the performance of other, without the latter investing in this improvement. Spatial statistics or spatial econometrics has been applied to study knowledge spillovers (van Stel et al. 2004), investment on telecommunications infrastructure (Yilmaz et al 2002), regional investment (Sun et al. 2002), and ecological issues (Storch et al 2005, Rand et al. 2006).

In the context of this study regional convergence methods can help address questions such as: are all districts in Costa Rica converging in percentage of PSA contracts? Similarly spillover methods can help address questions such as: do neighboring geographical units in Costa Rica tend to have a higher percentage of PSA contracts than other areas with isolated contract areas?

The model used is adapted from Rey's (1999) analysis of beta convergence of US states GSP between 1929 to 1994. According to Rey (1999) the outcome and explanatory what of "beta convergence" variables has the general linear form:

$$\ln(\mathrm{Y}) = \beta_0 + \beta_1 \ln(X) + \epsilon_i$$

Where Y is the response rate of a particular observation at the objective year and X is the initial value for the same observation at year 0. β_0 is the intercept of the linear regression, β_1 is the slope coefficient and ϵ_i is the error.

This simple OLS form is adapted to relate the percent of area under PSA contract per canton in 2000 as a convergence function of the area under PSA contract per canton in 1997, controlling for other programs (management and reforestation) that were already in place at the time when the PSA program's implementation began:

$$\ln(\text{PSA\_2000}) = \beta_0 + \beta_1 \ln(\text{PSA\_1997}) + \beta_2 \ln(\text{MAN\_1997}) + \beta_3 \ln(\text{REF\_1997}) + \epsilon_i$$

Where:

That means, the variables used were the natural logs of:

- Hectares of PSA protection contracts in 2000 as a percent of total hectares in canton (PSA_2000)
- Hectares of PSA protection contracts in 1997 as a percent of total hectares in canton (PSA_1997)
- Hectares of PSA reforestation contracts in 1997 as a percent of total hectares in canton (REF_1997)
- Hectares of PSA protection contracts in 1997 as a percent of total hectares in canton (MAN_1997)

Many of the observations missed a date attribute. Because this is most likely to be the case for contracts signed early in the program before the record-keeping system was well-established they were assumed to be of 1997.

We are also interested in assessing evidence of spatial errors. Which we can find when the spatial error variable $(I - \zeta W)$ is significant. Thus we apply the following form:

$$\ln(\text{PSA\_2000}) = \beta_0 + \beta_1 \ln(\text{PSA\_1997}) + \beta_2 \ln(\text{MAN\_1997}) + \beta_3 \ln(\text{REF\_1997}) + (I - \zeta W)^{-1} \mu_i$$

where:

I = Moran's I scalar

ζ = scalar spatial error coefficient

W = weight matrix defined by Euclidean distance between canton centroids

Similarly, in the case of a positive correlation, we are interested in finding whether an increase of the dependent variable is due not only to its linear relationship with the independent variables but if it is due to spatial lag. Therefore, a spatial lag term $(I - \rho \mathrm{W})$ is added to the original OLS formula:

$$(I-\rho\,\mathrm{W})\ln(\mathrm{PSA\_2000})=\beta_0+\beta_1\ln(\mathrm{PSA\_1997})$$
$$+\beta_2\ln(\mathrm{MAN\_1997})+\beta_3\ln(\mathrm{REF\_1997})+\epsilon_{ij}$$

where:

I = Moran's I scalar

W = weight matrix defined by Euclidean distance between canton centroids

ρ = scalar autoregressive parameter

In which case if the spatial lag variable results in significant means then there is evidence of spillovers. Sanchez-Azofeifa (forthcoming) performed a linear regression using grid units to find if PSA policies had positive effects on deforestation within the whole country, finding no support for that hypothesis. However, other policy proxies were not used by the author.

The spatial data used for this study were obtained from FONAFIFO (2006) and prepared in ArcGIS. The analysis is performed in GeoDA (Anselin et al. 2006). The policy data comes from FONAFIFO's fincas polygon file. with attributes indicating whether the fincas were under management, protection (PSA), or reforestation contracts. Several observations or contracts have a null attribute for the calendar year field. Given that situation, these were assumed to be from 1997 for each of these variables. In other words, the errors of data handling were distributed among the variables used (protection or PSA, management and reforestation) and is expected to be similar. Despite that areas under protection were shown to have current or past PSA contracts, only areas that were not under protection were considered for the analysis.

To predict spatial clusters of second degree neighbors, or neighbor's neighbors relative to a central polygon a contiguity based weights method was prepared using a "Queen" method with level 2 (Anselin 2005). Highly significant positive coefficients for any of the independent variables would suggest that either PSA programs, or reforestation or management programs in 1997 directly influenced PSA contracting until year 2000.

The statistical procedure for this approach followed the chart shown in Figure 3, where the initial operation is an ordinary least squares (OLS) regression with subsequent tests for spatial lag and errors as required. Spatial lag and spatial error models follow the OLS regression in case of significance of linear model lag and linear model error respectively as clearly shown in Figure 3.

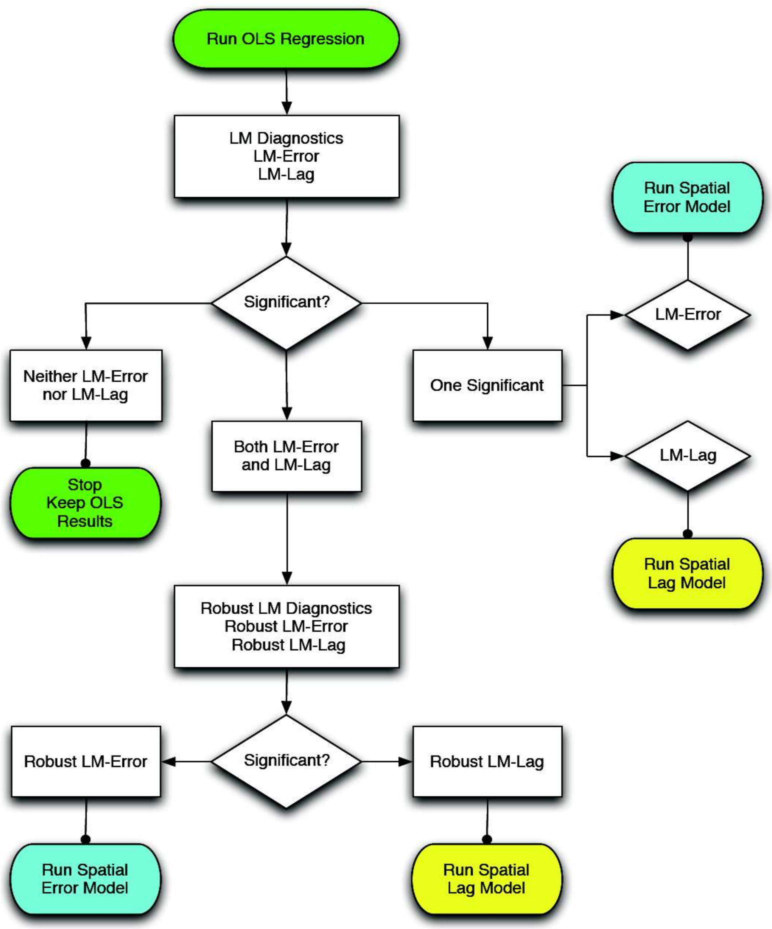


Figure 3. Decision process for analysis of spatial data in linear regression.

Source: Anselin (2005)

The beta convergence index is obtained by using the following formula:

$$\theta = \ln(b_1 + 1) / -k$$

In which θ theta is the convergence index, b_1 is the coefficient of PSA1997 and k is the number of years in the period 1997-2000. Regional convergence is suggested when θ is negative and the beta coefficient b_1 is significant (Rey, 1999).

6 RESULTS

Figure 4 shows area of new PSA contracts as a percentage of total area of canton (administrative unit) from 1997 to 2000. In 1997, the percentage of areas under new contract reached a maximum of approximately 9% with most areas having 2%. In 1998, maximum percentage of areas under contract lowers to 5%, while most areas reach a maximum of 2%. Overall there are less new contracts in 1998 than the year before. In 1999, a few cantones that did not have contracts earlier seem to reach a maximum of 8 to 17%, while most of the country kept a rate of 2% as in 1997-98. In 2000, the rate of areas under contract seems to have decreased with respect to previous years, reaching a 4% rate in only three cantones and 2% in the rest of active cantones.

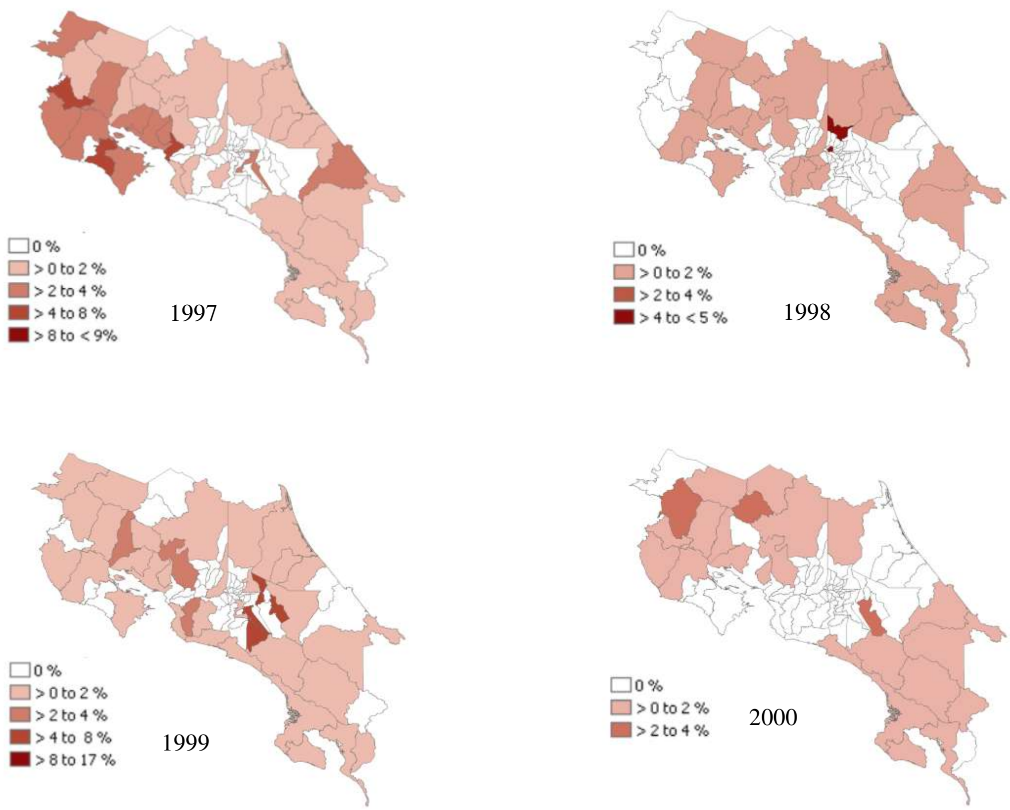


Figure 4. Percentage of Area per Canton under PSA contracts from 1997 to 2000

6.1 HIERARCHICAL LINEAR MODEL FOR PROBABILITY OF DEFORESTATION

This subsection shows the results of the GLM regressions with first and second level variables and the output of the HLM analysis. Table 6 shows a summary of basic statistics for the variables used.

Table 6. Continuous variables used in HLM

Statistic	Elevation (m)	Slope Percentage (%)	Distance to PSA contract (m)	Distance to Road (m)	Distance to Highway (m)	Density of Roads
Min.	0	0	0	0	0	0
1st_Qu.	28	0.461	1118	2000	2693	0
Median	48	0.934	2062	6801	9000	0
Mean	169.9	2.991	3146	11075	13145	0.14231
3rd_Qu.	128	2.801	3905	17007	21983	0.04349
Max.	2430	57.613	29753	50480	46098	3.62604
Statistic	**Density of Highway**	**Distance to Sawmill (m)**	**Distance to 1999 PSA contract (m)**	**Distance to 1998 PSA contract (m)**	**Distance to 1997 PSA contract (m)**	
Min.	0	0	0	0	0	
1st_Qu.	0	8382	3536	5590	5025	
Median	0	13647	5852	9192	9000	
Mean	0.06926	15783	6817	10303	9675	
3rd_Qu.	0.00071	21213	9014	13509	13537	
Max.	1.15098	55218	35511	32596	35627	

Table 7 shows the results of the GLM first level variables including cantones, which, even though are not first level variables, were used as grouping factors for first level variables in the HLM analysis. Table 7 shows the high significance of distance to PSA (-3.294e-04, p-value 9.81e-07), elevation (-3.083e-03, p-value 0.00743), distance to highways (-3.780e-05, p-value 0.02987), and distance to sawmills (4.834e-05, p-value 0.00864). These results show that increasing distance to PSA fincas, increasing elevation, and distance to highways are negatively associated with deforestation probability. However, increasing distance to sawmills is related to increasing deforestation probability. The dummy variables for the cantones Guacimo and Pococi result in non-significant p-values.

Table 7. GLM Deforestation model for first level variables

Variable	Estimate ($x10^3$)	Std. Error	p-value	
(Intercept)	-4550.000	0.275	<2E-16	**
DISTPSAPROT	-0.329	0.000	0.000	**
PSADUM	-58.060	0.297	0.845	
SLOPE_PC	42.070	0.044	0.336	
ELEV_500	-3.083	0.001	0.007	**
DHW	-0.038	0.000	0.030	*
DROAD	0.014	0.000	0.292	
DENHW	-1221.000	1.054	0.247	
DENROAD	-379.200	0.545	0.486	
DSAWMILL	0.048	0.000	0.009	**
GUACIMO	-977.700	0.742	0.187	
POCOCI	308.600	0.276	0.263	

Signif. codes: 0.001 '**', 0.01 '*', 0.05 '.'

Null deviance: 1427.1 on 20084 degrees of freedom

Residual deviance: 1343.9 on 20073 degrees of freedom

Table 8 shows the result of the GLM regression using second level variables. In this case the canton Guacimo (-2.74, p-value 0.000543) has negative association with deforestation probability. The variable GRUAS shows positive association with probability of deforestation and high significance (0.782, p-value 9.04e-05).

Table 8. GLM Deforestation model for second level variables

Variable	Estimate	Std. Error	p-value
(Intercept)	-35.755	1568.967	0.982
GUACIMO	-2.744	0.793	0.000543 ***
POCOCI	-0.562	0.332	0.090443 .
TORT	14.808	627.851	0.981
CVC	13.946	627.851	0.982
GRUAS	0.782	0.200	9.04e-05 ***
HUM	16.464	1437.867	0.991
PN	0.668	1516.319	1.000
RN	16.294	1437.867	0.991
RF	16.141	1437.867	0.991

Signif. codes: 0.001 '**', 0.01 '*', 0.05 '.'

Table 9 shows the results of the HLM model using only the significant variables from previous GLM models. The model shows direct relationship between probability of deforestation and mean distance to roads (0.000104, p-value 0.0448) but the effects of GRUAS (-0.0000, p-value 0.0074) make this relationship negative. Similarly, Table 9 shows a mixed effect of GRUAS with distance to PSA (-0.000341 p-value 0.0029) negatively correlated to probability of deforestation, and a mixed effect of GRUAS with distance to sawmills (0.000 p-value 0.0009) directly correlated to probability of deforestation. A test for robustness is shown in Appendix 2 for the validity of these results in which the resulting multilevel relationships are distance to PSA, and distance to sawmills, eliminating distance to roads.

Table 9. Hierarchical Linear Model of deforestation of first and second level variables

Variable	Estimate ($x10^3$)	Std. Error	p-value
(Intercept)	-5971.662	0.195	0.000
MNPSAPROT	-0.180	0.000	0.102
GRUAS	-152.768	0.303	0.615
MNSLOPE	53.294	0.053	0.319
MNELEV	-1.471	0.001	0.259
MNDROAD	0.104	0.000	0.045
MNDHW	-0.028	0.000	0.317
MNDSMIL	-0.076	0.000	0.136
MNPSAPROT:GRUAS	-0.341	0.000	0.003
GRUAS:MNSLOPE	-11.693	0.076	0.878
GRUAS:MNELEV	-1.201	0.002	0.560
GRUAS:MNDROAD	-0.079	0.000	0.007
GRUAS:MNDHW	0.028	0.000	0.449
GRUAS:MNDSMIL	0.128	0.000	0.001

Number of Observations: 20085
Number of Groups: 3
Signif. codes: 0.001 '**', 0.01 '*', 0.05 '.'

Figure 5 shows plots for the fitted relationships between deforestation probability and distance to PSA, and distance to sawmills using HLM. Figure 6 shows that most deforestation occurs in Sarapiqui and Pococi. Deforested areas, according to the dataset used, overlap some GRUAS areas. Deforestation is also away from southern and western PSA contracts.

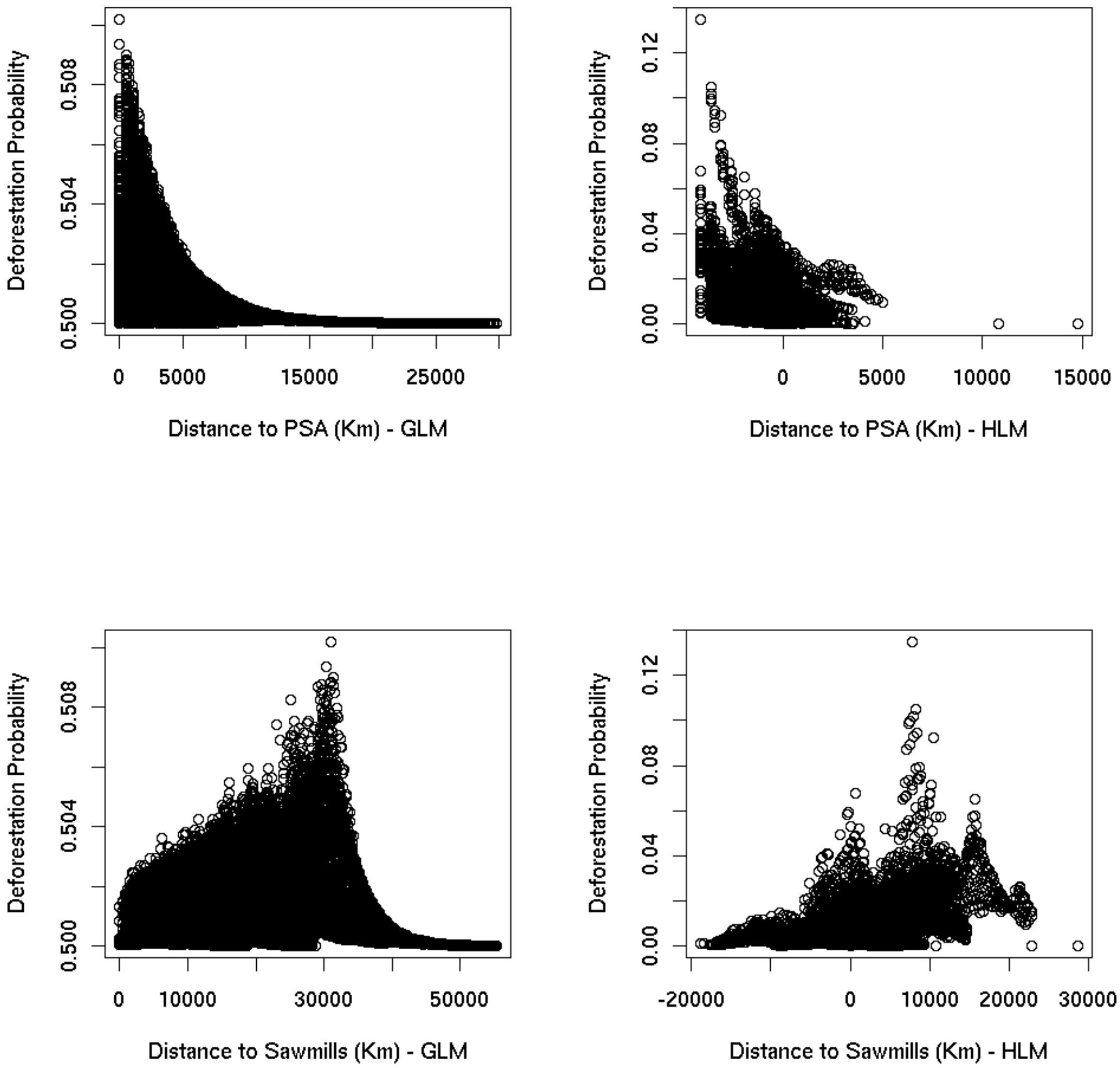


Figure 5: Significant relationships of environmental variables and deforestation probability using GLM and HLM.

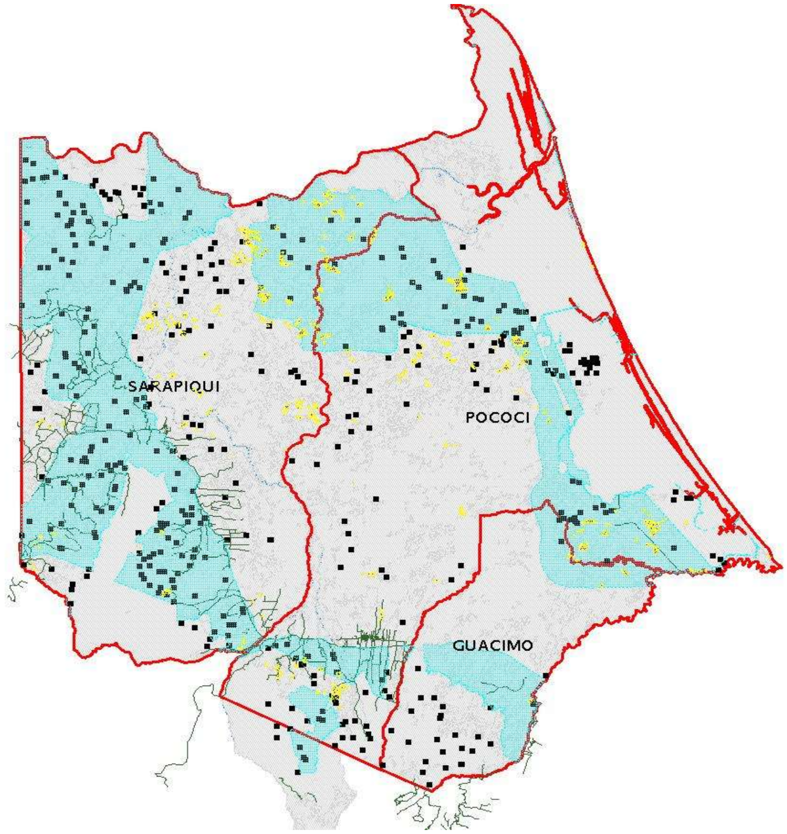


Figure 6: Distribution of deforestation between 1997-2000 in study area.

Legend: deforestation (yellow), cantones (red), roads (green), Gruas (cyan), and PSA contracts (square dots).

6.2 HIERARCHICAL LINEAR MODEL FOR PROBABILITY OF PSA CONTRACTS

This test was used to assess relationships between different variables and Probability of PSA contracts. Distance to PSA 1998 was negatively related to probability of PSA contracts (-1.694e-04, p-value 0.0193) in the first level GLM test (see Table 10). The second GLM test shows that GRUAS has a direct relationship with probability of PSA (1.73774, p-value 0.00537) (see Table 15). The HLM test confirms the relationship between probability of PSA and GRUAS. On the other hand the HLM test also shows the mixed effect of GRUAS and mean distance to PSA in year 1999 (0.0003, p-value 0.0392) (see Table 12).

Table 10. GLM PSA Contracts model for first level variables

Variable	Coefficient	Std.Error	p-value
(Intercept)	-491.200	0.982	0.000 **
PSA1999DIST	-0.000	0.000	0.963
PSA1998DIST	-0.017	0.000	0.019*
PSA1997DIST	-0.004	0.000	0.480
DEFOR	-1239.000	943.100	0.990
SLOPE_PC	5.813	0.056	0.299
ELEV_500	-0.170	0.001	0.234
DHW	-0.011	0.000	0.122
DROAD	0.000	0.000	0.948
DENHW	-50.190	1.643	0.760
DENROAD	-19.190	0.867	0.825
DSAWMILL	0.008	0.000	0.188
GUACIMO	-69.730	1.290	0.589
POCOCI	-92.490	0.798	0.246

Signif. codes: 0.001 '**', 0.01 '*', 0.05 '.'
Null deviance: 330.23 on 20084 degrees of freedom
Residual deviance: 300.75 on 20071 degrees of freedom

Table 11. GLM PSA Contracts model for second level variables

Variable	Estimate	Std. Error	p-value
(Intercept)	-7.756	1.726	0.000***
GUACIMO	0.685	1.386	0.621
POCOCI	-0.230	0.860	0.789
TORT	-15.610	821.386	0.985
CVC	1.430	0.981	0.145
GRUAS	1.738	0.624	0.005**
HUM	-1.171	1.074	0.276
PN	0.362	1.329	0.785
RN	15.266	821.386	0.985
RF	0.068	1.354	0.960

Signif. codes: 0.001 '**', 0.01 '*', 0.05 '.'
Null deviance: 330.23 on 20084 degrees of freedom
Residual deviance: 291.67 on 20075 degrees of freedom

Table 12. Hierarchical Linear Model Statistics for PSA Contracts using first and second level variables

Variable	Estimate ($x10^3$)	Std. Error	t-value	p-value
(Intercept)	-8851.221	0.894	-9.905	0.000
MNSLOPE	115.361	0.052	2.215	0.027
GRUAS	1635.197	0.552	2.964	0.003
MNELEV	-0.884	0.002	-0.463	0.644
MNDROAD	-0.038	0.000	-0.460	0.645
MNDSMIL	0.057	0.000	0.777	0.437
MNPSA99	-0.086	0.000	-0.573	0.566
MNPSA98	-0.097	0.000	-1.106	0.269
MNPSA97	0.103	0.000	0.889	0.374
MNSLOPE:GRUAS	-124.120	0.100	-1.240	0.215
GRUAS:MNELEV	3.007	0.002	1.232	0.218
GRUAS:MNDROAD	0.055	0.000	0.602	0.547
GRUAS:MNDSMIL	-0.055	0.000	-0.609	0.543
GRUAS:MNPSA99	0.323	0.002	2.062	0.039
GRUAS:MNPSA98	-0.097	0.000	-0.864	0.388
GRUAS:MNPSA97	0.099	0.000	1.055	0.292

Number of Observations: 20085
Number of Groups: 3
Signif. codes: 0.001 '**', 0.01 '*', 0.05 '.'

6.3 VISITS TO LANDOWNERS AND STRATEGY OF TARGETING PSA CONTRACTS

Table 13 shows the results of the OLS estimation results for model of environmental agency visits to landowners. The model resulted with a moderate R^2 of 0.30. According to this model, visits to landowners are explained by Type of contract (11.74, p-value of 0.003). There is no statistical evidence of spatial errors or spatial lag in this model, so no further spatial models were fit (Table 14).

Table 13. Ordinary Least Square model of visits from extension agents

Variable	Coefficient	Std. Error	p-value
CONSTANT	0.628	3.059	0.838
HA	0.002	0.011	0.853
BNH	-0.004	0.013	0.729
BNL	0.032	0.043	0.456
DISTANCE_E	0.054	0.078	0.496
POOR_SOIL	0.040	0.037	0.279
LARGE_SLOP	-0.032	0.035	0.363
TYPE	11.743	3.899	0.003
DNonPSA	0.002	0.001	0.257
DPSA	-0.000	0.000	0.743

R-squared: 0.301 Akaike info criterion : 1017.04

F-statistic: 5.829 S.E. of regression : 10.992

Table 14. Complementary tests for OLS model of visits from extension agents

DIAGNOSTICS FOR HETEROSKEDASTICITY			
TEST	DF	VALUE	PROB
Breusch-Pagan test	9	184.794	0.000
DIAGNOSTICS FOR SPATIAL DEPENDENCE			
TEST	MI/DF	VALUE	PROB
Moran's I (error)	-0.038	-1.124	0.261
Lagrange Multiplier (lag)	1	1.793	0.181
Lagrange Multiplier (error)	1	1.816	0.178

6.4 PROBABILITY OF PSA CONTRACTS, PROXIMITY AND LOCAL TARGETING

Table 6 shows the results of the logistic regression (using a generalized linear model) for probability of PSA based on survey and GIS variables. Two variables show direct relationship with probability of PSA: visits by extension agents (2.046e-01, p-value 0.0001) and distance to sawmills (1.237e-04, p-value 0.08005) although this last one with low significance value. Increased distance to PSA has a correlation with decreased probability of PSA contracts (-1.904e-03, p-value 0.000369). Figure 7 shows the plots of the most significant variables: number of visits and distance to PSA fincas versus probability of PSA.

Table 15. GLM for probability of PSA contracts

Variable	Estimate ($x10^3$)	Std. Error	p-value
(Intercept)	-1,317.000	0.977	0.178
VISITS_ENV	204.600	0.053	0.000**
DREDCAM	0.297	0.000	0.106
DCARR	-0.064	0.000	0.364
DSAWMILL	0.124	0.000	0.080.
DPSAPROT	-1.904	0.000	0.000**

Signif. codes: < 0.001 '**', 0.01 '*', 0.05 '.',
Null deviance: 154.691 on 131 degrees of freedom
Residual deviance: 63.734 on 126 degrees of freedom

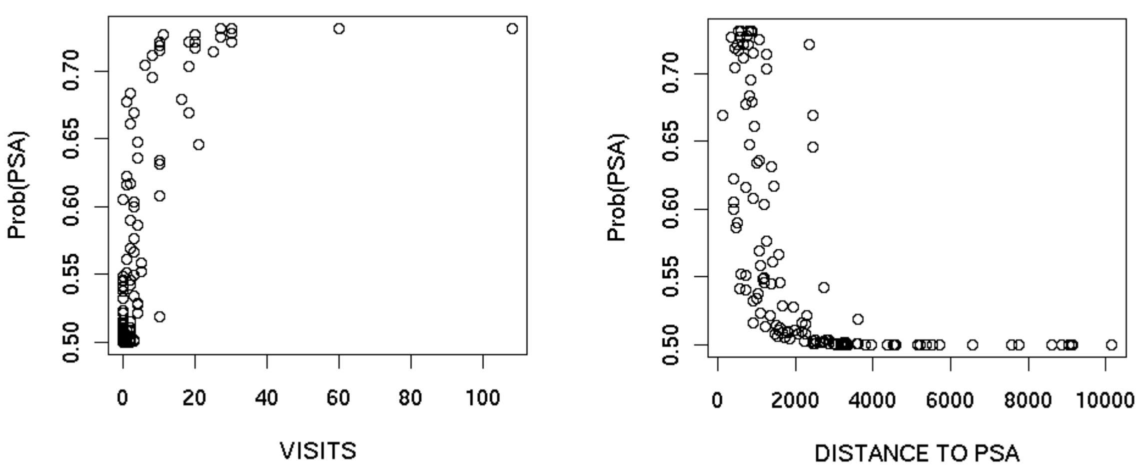


Figure 7. Significant relationships from test of probability of PSA

6.5 CONVERGENCE AND SPILLOVERS

Table 16 shown below shows no correlation ($R^2 = 0.058$) of the linear model used to explain percentage of PSA canton area under contract in 2000 as a function of percentage of canton area under PSA contracts in 1997, percent of areas under reforestation regimes in 1997, and percentage of area under management in 1997. However, there is a rather low significance at 10% between rates of percentage of area under PSA contracts in 2000 and percentage of areas under management in 1997. The beta coefficient in this correlation is positive and non-significant, which does not give enough evidence for convergence of areas under PSA contract from 1997-2000 among Cantones.

Table 16. Summary of Ordinary Least Square estimation and Convergence test

Period	R^2	Akaike Information Criterion	b (p-value)	Convergence rate (sigma)
2000	0.058	127.089	0.034 (0.631)	- 0.011 (-1.1%)
				sigma is ln(beta+1)/-k
Variable	Coefficient	Std.Error	t-Statistic	p-value
CONSTANT	0.646	0.125	-5.169	0.000
LNPSA1997	0.034	0.070	0.483	0.631
LNREF1997	0.030	0.077	0.378	0.706
LNMAN1997	0.219	0.134	1.627	0.108

Table 17 shows results of tests of spatial errors and spatial lag, which support the OLS model as having the best fit. Since the Lagrange Multiplier tests are non-significant, no other models were pursued in this assessment.

Table 17. Diagnostics for Spatial Dependence in Convergence test

TEST	MI/DF	VALUE	PROB
Moran's I (error)	0.02	0.770	0.441
Lagrange Multiplier (lag)	1	0.847	0.357
Lagrange Multiplier (error)	1	0.155	0.694

Overall the accuracy of this analysis may have been compromised due to lack of control on error for each variable and time frame because many of the independent observations that were missing a date attribute were assumed to belong to the year 1997.

7 DISCUSSION

Three different spatial approaches were used to assess the Costa Rica PSA Program performance from 1997 to 2000 using publicly available GIS data and spatially explicit household survey data. Three scales of analysis or resolutions were used: subregional, household level, and country wide. It was expected that these combinations of scales could help explain different environmental dynamics of the PSA program and helps us have a larger picture of the program.

7.1 MULTILEVEL RELATIONSHIPS IN DEFORESTATION

The multilevel approach used to assess relationships among environmental variables and deforestation between 1997-2000 was based in existing GIS data for NE Costa Rica. This analysis used PSA protection contracts as a single indicator of all PSA contracts between 1997-2000. It is very possible that information about deforestation contained in isolated cells in the original raster data was lost during raster cells aggregation. Thus, the deforestation dataset used in the analysis shows only a few patches of deforestation scattered along low elevation areas, areas away from roads and towards wetland areas.

The GLM analysis of first level variables shows several important relationships. The significantly negative relationship between distance to PSA contracts and deforestation probability during 1997-2000 suggests that as we move away from PSA fincas there are fewer deforested areas, or that deforestation has occurred near PSA fincas. However, deforestation has occurred near some PSA fincas, but it is found in certain sectors of the study area, and it is more notorious on the north eastern side, mostly away from the mountains. This could be because it is easier to extract forest in areas of low slope. The existence of PSA contracts in a cell does not have any effect on deforestation in the same cell.

The inverse relationship between elevation and probability of deforestation suggests to some extent that as we move higher in elevation there would be less chance for deforestation. This hypothesis could perhaps be related to the fact that higher higher elevations (associated to higher slopes) are deterrent for logging and also with higher opportunity costs from changing land use in areas of higher elevation, since transporting logs to sawmills from these areas could be very expensive. Even though this relationship seems to be independent from type of slope, it is very likely that slope aggregated at a low resolution 500m x 500m cells was not a very useful variable in this analysis for prediction purposes.

There is a negative relationship between distance to highways and deforestation probability, suggesting that deforestation is likely to occur near highways. However, there is no relationship between deforestation and distance to (secondary) roads. The direct relationship between distance to sawmills and probability of deforestation suggests that the farther we move from sawmills the higher the probability of deforestation, which seems counterintuitive. However, according to the data used, in this study area deforestation has occurred only in areas east of the mountain areas and mostly towards the north and it is not spread out uniformly, so this finding may be suggesting a spatial distribution or indicating that most cells are far from the few sawmills in the area.

In the second level GLM we observed that the relationship between deforestation and individual cantones in the study area described the spatial distribution of deforested areas across cantones. The significant negative relationship between Guacimo and deforestation can be observed in Figure 5, where we can see very few patches of deforestation or none in this canton. The rest of the cantones seem to have the larger patches of deforestation. The positive relationship of deforestation and GRUAS (priority areas for conservation based on macro vegetation) suggests that deforestation has a higher chance to occur in these areas than elsewhere during the period 1997-2000.

The HLM model for probability of deforestation confirms only one relationship found in the GLM analysis of first level variables: distance to PSA versus probability of deforestation. In other words, as we move farther from PSA fincas there are fewer chances of finding deforested areas. This effect is even stronger in GRUAS zones, as indicated by the negative coefficient on the interaction term between GRUAS and distance to nearest PSA contracts. On the other hand, distance to highway in the HLM analysis is no longer significant, but distance to roads becomes significant and positive - that is, the further from roads, the more likely deforestation. This effect is stronger outside of GRUAS zones (because it is moderated by small negative coefficient on interaction term). This results may be characterizing the spatial distribution of roads and deforestation. Roads, the same as highways, are clustered towards the southwestern section of the study area, opposite of where most deforestation patches are located. Curiously, GRUAS without roads show more deforestation patches than GRUAS with roads in the dataset. This may imply that in the latter areas forest protection enforcement is more feasible where in GRUAS areas, and in general in other areas where road infrastructure is lacking. The HLM model also shows multilevel effects between GRUAS and distance to PSA fincas, and GRUAS and distance to sawmills to probability of deforestation, suggesting that deforestation is located further from sawmills only in GRUAS zones. This finding suggests on one hand that PSA contracts were being targeted near deforestation areas within GRUAS. On the other hand, the HLM suggests deforestation is more likely to occur away from sawmills within GRUAS as well. All of these relationships were found after controlling for effects of cantones variability and testing for robustness in a similar model by extracting slope and roads to validate HLM deforestation model.

7.2 MULTILEVEL RELATIONSHIPS IN THE PSA PROGRAM

The second HLM model for probability of location of PSA contracts suggested that increasing distances to PSA contracts in 1999 are related with increasing chances of PSA contracts areas. This model is consistent with expected targeting of PSA contracts - there are more contracts on steep slopes and in GRUAS zones. However, it is important to consider that this model is subject to collinearity effects because the large amount of zero values for several variables in the dataset used in this model.

7.3 VISITS TO LANDOWNERS AND STRATEGY OF TARGETING PSA CONTRACTS USING A GENERAL LINEAR MODEL

The relationship between visits by extension agents and landowners under PSA contract suggests that environmental visits are targeted to current PSA contracts as a way to keep landowners in the program rather than to gather new ones. Landowner's or parcel's characteristics do not seem to have any relevance in visits to landowners by extension agents. There is no evidence of enforcement spillovers, in that distance to nearest parcel does not have any effect. However, the GLM analysis suggested that probability of PSA contracts has an inverse relationship with distance to PSA contracts, and a direct relationship to number of visits by extension agents and increasing distance to sawmills (although with a weak significance). It is important to acknowledge that the variable visits by extension agents is endogenous and can lead to significance because of reverse causality.

7.4 CONVERGENCE AND SPILLOVERS

FONAFIFO's records on the PSA program have missing year of contract for d a considerable amount of inaccuracies related to year of contract. I assumed that contracts without a year recorded were from 1997. This assumption could have a large impact on the analysis of convergence and spillovers of PSA contracts during the first period of the PSA program (1997-2000). Thus, I focus the discussion on the methodology and appropriate interpretation of the results rather than claiming that the results accurately characterize the PSA program's progress.

This approach used a convergence model based in OLS to link the percent of area under PSA contract in 2000 as a linear function of percent of area under contract of PSA in its earliest year (1997) as well as to reforestation and management programs. Special attention is given to the beta-convergence for the log of PSA_1997 since it can provide information regarding convergence of percent of contract area using the CR cantones as geographic units. The convergence rate (negative but non significant) did not provide support for convergence of PSA contracts; that is there is no evidence of a pattern of cantones "catching up" over these first years of the program. On the other hand, the lack of spatial lag suggests that there have not been spillovers across cantones, One interpretation of these results is that PSA contracts during 1997-2000 have occurred mainly in targeted areas across the country.

The percent of PSA areas under protection contract weakly related to percent of areas under management in 1997 could be interpreted as if the PSA protection contracts percentages had been influenced solely by the existing land inventory under forest management. This could mean that land under forest management contracts shifted to PSA contracts. Although, this may not be administratively feasible or legal, a landowner would consider moving from a contract in which he carries some operational cost (forest management) to another in which these costs are minimized (protection contract). For example, a landowner in 1997 under a management program has to invest time and resources to carry his practice. Then he learns about the PSA program in which, if he qualifies by size of parcel and forest cover, he would not have to invest more resources to be compensated by the program. Perhaps this would not work in all cases, i.e. some landowners could produce larger profits on their own than other landowners who would opt to shift of program. If this practice is admissible, then some landowners may be able to have both management areas and be allowed to keep other forested areas that they are not managing as protection areas and still be paid for it, which under the principles of the program could make sense.

7.5 IMPLICATIONS FOR PROGRAM STRATEGY

After evaluating the evolution of the program at a regional and subregional scale and with spatial components we need to ask how these findings could provide an important feedback for achieving the program goals. However, PSA programs seem to be spread out along the subregion studied and the statistical relationships presented here should be taken into account carefully. It is important to understand how this subregional scenario compares to other areas in the country before generalizing or extrapolating these findings to the rest of the nation, which is not the intention of this chapter. First, the PSA program's implementation has been focused mainly in GRUAS, which contain a large part of deforestation patches that occurred between 1997 and 2000. Initially deforestation and elevation were negatively correlated (albeit with low significance) and perhaps this explains in part that deforestation has occurred in low elevation areas where cost of wood extraction is higher than in higher elevation areas. This would hypothetically center the attention of the PSA Program to low areas and less to higher elevation areas. However, there is no strong support for this hypothesis since PSA areas, unlike deforestation, are spread out in both low and high areas. It is important to consider that there are at least two bases for targeting PSA contracts: (a) opportunity cost/ threat of deforestation, and (b) conservation value/production of ecosystem services, which can explain PSA contracts located within GRUAS but far from deforestation patches. This perhaps reflects an economic behavior suggested by Pfaff and Sanchez-Azofeifa (2003) by which landowners with a low opportunity cost for their lands, as those in high elevations, would conserve their forests regardless of being in the program or not. This also brings the question of whether zonification of payments needs to be done according to opportunity cost. and how this element can enhance or not the protection of ecosystem services which is the current main goal of the program.

However, the goals of the PSA program are reviewed every year, and so are the criteria for qualifying for a contract. The next generation of programs will attempt to serve as a poverty reduction mechanism (Ortiz 2006, personal communication), as anticipated by Pagliola (2004). In that sense, contracts may be focused in areas where landowners have a low opportunity cost for land use change.

7.6 AVENUES FOR IMPROVEMENT

In this study we showed the use of spatial analysis at different scales (regional, subregional, and household level). Each analysis suggested results that are relevant to each particular scale; the finer the scale, the more localized the application of these results. Even though one may be tempted to generalize results, particularly at the household level, as a way to infer about human decision making or human-policy dynamics in this particular area or worse at the national level, it would not be recommended because the results of this assessment also show a spatial interaction of environmental variables that may be applicable only to the area selected for subregional analysis.

Even though our findings made sense from a spatial point of view, we should carefully consider if our approaches make sense from a temporal point of view. In this case traditional cross sectional analysis may be very good to assess current policy practices. However, spatial and temporal analysis could be very helpful in providing feedback about the program's performance. Furthermore, we could consider the diversity of the country as an element to include in planning a monitoring system where a determined set of questions could be answered at the regional level and other questions could be addressed at subregional levels according to the environmental dynamics of each area.

The HLM model of deforestation had some weaknesses. In order to model correctly deforestation it is important to consider that deforestation could have occurred mainly areas that were forested in 1997, which could include PSA and non PSA areas. In this model, we did not include a variable that could control this difference by including forest cover in 1997 as a covariate. Future models could consider including a more explicit independent variable that could represent only the targeted PSA areas.

8 CONCLUSIONS AND RECOMMENDATIONS

This paper used three different approaches to assess the Costa Rica "Pagos por Servicios Ambientales" from 1997 to 2000 using publicly available geographic information systems data and spatially explicit household survey data. Three scales of analysis or resolutions were used: subregional, household level, and countrywide. The main aspect considered here was only the intermediate goal of decreasing deforestation by analyzing the distribution of PSA contracts and the distribution of deforestation.

On the study area used, the Northeastern area of Costa Rica, we found that PSA contracts are more likely in priority conservation zones and on elevated areas, which could indicate targeting to high priority areas, or volunteering due to high opportunity costs. In conservation priority zones (GRUAS) new contracts are less likely close to old PSA contracts, indicating no evidence of spillovers. Similarly, probability of deforestation decreases with distance to nearest PSA contract. However, we cannot assume targeting or unobserved spatial heterogeneity since the HLM model used did not control for other forested areas.

At the household level, visits by extension agents are higher on properties with PSA contracts but are unrelated to distance to nearest PSA contract, providing no evidence of enforcement spillovers. Similarly, PSA contracts are more likely further to sawmills and closer to other contracts, which suggests some evidence of information spillovers.

The results of the regional assessment approach at the canton level suggested that there is not enough evidence for convergence of PSA contracts during 1997-2000. At the same time, there are no effects of spillovers along the country that could suggest a spatial expansion in PSA contracting. However, distribution of PSA contracts in 2000 is related to the distribution of forest management plans in 1997, but not to other prior contract types.

It is recommended that more planning is focused in establishing a sound monitoring system for longterm evaluation of the program based on current and future goals, scale and time frame of program goals, indicators of program achievements and consistent spatial and longitudinal data collection.

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Appendices

Appendix 1: Summary of Statistics for variables used

```
    X_CRD             Y_CRD           CANTON_500        DEFOR
 Min.   :518869   Min.   :224859   Min.   :1.000   Min.   :0.000000
 1st_Qu.:539369   1st_Qu.:253859   1st_Qu.:2.000   1st_Qu.:0.000000
 Median :558369   Median :268859   Median :2.000   Median :0.000000
 Mean   :557130   Mean   :269601   Mean   :2.307   Mean   :0.005775
 3rd_Qu.:573869   3rd_Qu.:286359   3rd_Qu.:3.000   3rd_Qu.:0.000000
 Max.   :607369   Max.   :323859   Max.   :3.000   Max.   :1.000000
    PSADUM            LULCRC           ELEV_500         SLOPE_PC
 Min.   :0.00000   Min.   :0.0000   Min.   :   0.0   Min.   : 0.000
 1st_Qu.:0.00000   1st_Qu.:0.0000   1st_Qu.:  28.0   1st_Qu.: 0.461
 Median :0.00000   Median :1.0000   Median :  48.0   Median : 0.934
 Mean   :0.08588   Mean   :0.5379   Mean   : 169.9   Mean   : 2.991
 3rd_Qu.:0.00000   3rd_Qu.:1.0000   3rd_Qu.: 128.0   3rd_Qu.: 2.801
 Max.   :1.00000   Max.   :1.0000   Max.   :2430.0   Max.   :57.613
  DISTPSAPROT        DROAD            DHW             DENROAD
 Min.   :    0   Min.   :    0   Min.   :    0   Min.   :0.00000
 1st_Qu.: 1118   1st_Qu.: 2000   1st_Qu.: 2693   1st_Qu.:0.00000
 Median : 2062   Median : 6801   Median : 9000   Median :0.00000
 Mean   : 3146   Mean   :11075   Mean   :13145   Mean   :0.14231
 3rd_Qu.: 3905   3rd_Qu.:17007   3rd_Qu.:21983   3rd_Qu.:0.04349
 Max.   :29753   Max.   :50480   Max.   :46098   Max.   :3.62604
    DENHW              CONSERV          GRUAS             PROT
 Min.   :0.000000   Min.   :0.000   Min.   :0.0000   Min.   :1.000
 1st_Qu.:0.000000   1st_Qu.:1.000   1st_Qu.:0.0000   1st_Qu.:1.000
 Median :0.000000   Median :1.000   Median :0.0000   Median :1.000
 Mean   :0.069265   Mean   :1.266   Mean   :0.3444   Mean   :1.704
 3rd_Qu.:0.000707   3rd_Qu.:2.000   3rd_Qu.:1.0000   3rd_Qu.:2.000
 Max.   :1.150981   Max.   :2.000   Max.   :1.0000   Max.   :5.000
   DSAWMILL         PSA2000            PSA1999DIST     PSA1998DIST
 Min.   :    0   Min.   :0.000000   Min.   :    0   Min.   :    0
 1st_Qu.: 8382   1st_Qu.:0.000000   1st_Qu.: 3536   1st_Qu.: 5590
 Median :13647   Median :0.000000   Median : 5852   Median : 9192
 Mean   :15783   Mean   :0.001046   Mean   : 6817   Mean   :10303
 3rd_Qu.:21213   3rd_Qu.:0.000000   3rd_Qu.: 9014   3rd_Qu.:13509
 Max.   :55218   Max.   :1.000000   Max.   :35511   Max.   :32596
  PSA1997DIST       MEANLULC          MEANDPSA       MEANSLOPE
 Min.   :    0   Min.   :0.3700   Min.   :1945   Min.   :2.110
 1st_Qu.: 5025   1st_Qu.:0.5400   1st_Qu.:1945   1st_Qu.:2.110
 Median : 9000   Median :0.5400   Median :3643   Median :3.120
 Mean   : 9675   Mean   :0.5389   Mean   :3146   Mean   :2.991
 3rd_Qu.:13537   3rd_Qu.:0.5800   3rd_Qu.:4116   3rd_Qu.:3.120
 Max.   :35627   Max.   :0.5800   Max.   :4116   Max.   :6.060
   MEANELEV       MEANDENROAD       MEANDENHW         MEANDHW
 Min.   :108.8   Min.   :0.0400   Min.   :0.0300   Min.   : 5605
 1st_Qu.:108.8   1st_Qu.:0.0900   1st_Qu.:0.0300   1st_Qu.: 5605
 Median :182.5   Median :0.0900   Median :0.0600   Median : 6740
 Mean   :169.9   Mean   :0.1433   Mean   :0.0672   Mean   :13145
 3rd_Qu.:182.5   3rd_Qu.:0.2300   3rd_Qu.:0.1100   3rd_Qu.:21606
 Max.   :369.9   Max.   :0.2300   Max.   :0.1100   Max.   :21606
```

```
  MEANDROAD      MEANSMIL        MEAN99          MEAN98          MEAN97
Min.   : 5777 Min.   :10154  Min.   :5349   Min.   : 8167   Min.   : 8341
1st_Qu.: 6082 1st_Qu.:13233  1st_Qu.:5349   1st_Qu.: 8167   1st_Qu.: 9496
Median : 6082 Median :13233  Median :5441   Median :11014   Median : 9496
Mean   :11075 Mean   :15783  Mean   :6817   Mean   :10303   Mean   : 9675
3rd_Qu.:16942 3rd_Qu.:19505  3rd_Qu.:8497   3rd_Qu.:11014   3rd_Qu.:10170
Max.   :16942 Max.   :19505  Max.   :8497   Max.   :15264   Max.   :10170
```

Appendix 2: General Linear Model and Hierarchical Linear Model for deforestation

```
VARIABLES NAMES:
DEFOR: DEFORESTATION BETWEEN 1997-2000 (DEFORESTATION = 1, OTHER = 0)
DISTPSAPROT: DISTANCE TO PSA FINCA
SLOPE_PC: SLOPE %
ELEV_500: ELEVATION IN METERS
DHW: DISTANCE TO HIGHWAYS
DROAD: DISTANCE TO ROADS
DENHW: HIGHWAYS DENSITY
DENROADS: ROAD DENSITY
CANTON_500: CANTONES

summary(data3.glm.logit.d)
Call:
glm(formula = DEFOR ~ DISTPSAPROT + PSADUM + SLOPE_PC + ELEV_500 +
    DHW + DROAD + DENHW + DENROAD + DSAWMILL + GUACIMO + POCOCI,
    family = binomial(link = logit), data = data3)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-0.28857  -0.12960  -0.09626  -0.05864   3.72791

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept) -4.550e+00  2.749e-01 -16.551  < 2e-16 ***
DISTPSAPROT -3.294e-04  6.728e-05  -4.895 9.81e-07 ***
PSADUM      -5.806e-02  2.965e-01  -0.196  0.84476
SLOPE_PC     4.207e-02  4.372e-02   0.962  0.33595
ELEV_500    -3.083e-03  1.152e-03  -2.677  0.00743 **
DHW         -3.780e-05  1.740e-05  -2.172  0.02987 *
DROAD        1.358e-05  1.289e-05   1.053  0.29218
DENHW       -1.221e+00  1.054e+00  -1.158  0.24666
DENROAD     -3.792e-01  5.447e-01  -0.696  0.48628
DSAWMILL     4.834e-05  1.841e-05   2.626  0.00864 **
GUACIMO     -9.777e-01  7.415e-01  -1.319  0.18733
POCOCI       3.086e-01  2.759e-01   1.119  0.26331
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 1427.1  on 20084  degrees of freedom
Residual deviance: 1343.9  on 20073  degrees of freedom
AIC: 1367.9

Number of Fisher Scoring iterations: 9

summary(data3A.glm.logit.d)

Call:
glm(formula = DEFOR ~ GUACIMO + POCOCI + TORT + CVC + GRUAS +
    HUM + PN + RN + RF, family = binomial(link = logit), data = data3A)
```

```
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.2029  -0.1132  -0.1040  -0.0381   3.5910

Coefficients:
             Estimate Std. Error  z value Pr(>|z|)
(Intercept)  -35.7553  1568.9671   -0.023 0.981819
GUACIMO       -2.7437     0.7932   -3.459 0.000543 ***
POCOCI        -0.5624     0.3322   -1.693 0.090443 .
TORT          14.8075   627.8509    0.024 0.981184
CVC           13.9462   627.8509    0.022 0.982278
GRUAS           0.7818     0.1997    3.915 9.04e-05 ***
HUM           16.4637  1437.8668    0.011 0.990864
PN             0.6679  1516.3191 0.000440 0.999649
RN            16.2936  1437.8669    0.011 0.990959
RF            16.1406  1437.8670    0.011 0.991044
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 1427.1  on 20084  degrees of freedom
Residual deviance: 1330.3  on 20075  degrees of freedom
AIC: 1350.3

Number of Fisher Scoring iterations: 20

> summary(data4.glmmPQL.1)
Linear mixed-effects model fit by maximum likelihood
 Data: data4
     AIC      BIC logLik
  172408 172676.8 -86170

Random effects:
 Formula: ~MNPSAPROT + MNSLOPE + MNELEV + MNDROAD + MNDSMIL | CANTON
 Structure: General positive-definite, Log-Cholesky parametrization
            StdDev       Corr
(Intercept) 1.138081e-01 (Intr) MNPSAP MNSLOP MNELEV MNDROA
MNPSAPROT   1.445552e-04  1.000
MNSLOPE     3.191528e-02  0.997  0.997
MNELEV      1.264572e-03 -1.000 -1.000 -0.998
MNDROAD     7.213250e-05  1.000  1.000  0.998 -1.000
MNDSMIL     6.393064e-05 -1.000 -1.000 -0.998  1.000 -1.000
Residual    9.411985e-01

Variance function:
 Structure: fixed weights
 Formula: ~invwt
Fixed effects: DEFOR ~ MNPSAPROT * GRUAS + MNSLOPE * GRUAS + MNELEV *
GRUAS + MNDROAD * GRUAS + MNDSMIL * GRUAS
                  Value   Std.Error  DF      t-value p-value
(Intercept)    -5.979824 0.19302449 20071 -30.979613  0.0000
MNPSAPROT      -0.000170 0.00011112 20071  -1.530046  0.1260
GRUAS           -0.168324 0.29953690 20071  -0.561947  0.5742
MNSLOPE         0.054342 0.05356328 20071   1.014532  0.3103
MNELEV         -0.001310 0.00129806 20071  -1.009489  0.3128
```

```
MNDROAD          0.000094 0.00005035 20071   1.873930  0.0610
MNDSMIL         -0.000092 0.00004611 20071  -2.002752  0.0452
MNPSAPROT:GRUAS -0.000355 0.00011332 20071  -3.128965  0.0018
GRUAS:MNSLOPE   -0.011819 0.07559304 20071  -0.156349  0.8758
GRUAS:MNELEV    -0.001513 0.00191521 20071  -0.789746  0.4297
GRUAS:MNDROAD   -0.000070 0.00002740 20071  -2.560141  0.0105
GRUAS:MNDSMIL    0.000144 0.00003416 20071   4.207673  0.0000
 Correlation:
               (Intr) MNPSAPROT GRUAS   MNSLOP MNELEV MNDROA MNDSMI
MNPSAPROT:
MNPSAPROT       0.445
GRUAS          -0.385 -0.090
MNSLOPE         0.056  0.285     0.033
MNELEV         -0.104 -0.344    -0.032 -0.815
MNDROAD         0.130  0.614     0.067  0.302 -0.337
MNDSMIL        -0.038 -0.676    -0.096 -0.340  0.393 -0.911
MNPSAPROT:GRUAS -0.067 -0.393     0.550 -0.022 -0.049  0.034  0.074
GRUAS:MNSLOPE    0.025 -0.016    -0.169 -0.620  0.443  0.013  0.025  0.033
GRUAS:MNELEV    -0.045 -0.064     0.399  0.412 -0.473 -0.136  0.077  0.118
GRUAS:MNDROAD    0.202  0.036    -0.174 -0.007 -0.214 -0.447  0.347 -0.148
GRUAS:MNDSMIL   -0.227  0.091     0.039  0.070  0.068  0.237 -0.397 -0.085
               GRUAS:MNS GRUAS:MNE GRUAS:MNDR
MNPSAPROT
GRUAS
MNSLOPE
MNELEV
MNDROAD
MNDSMIL
MNPSAPROT:GRUAS
GRUAS:MNSLOPE
GRUAS:MNELEV    -0.689
GRUAS:MNDROAD   -0.027    0.188
GRUAS:MNDSMIL    0.029   -0.009   -0.633

Standardized Within-Group Residuals:
        Min          Q1         Med          Q3         Max
-0.42137723 -0.08586935 -0.06254750 -0.04268789 39.91483121

Number of Observations: 20085
Number of Groups: 3


HLM MODEL USED IN RESULTS

> data4.glmmPQL.1a<-glmmPQL(DEFOR ~
MNPSAPROT*GRUAS+MNSLOPE*GRUAS+MNELEV*GRUAS+MNDROAD*GRUAS+MNDHW*GRUAS+MNDSM
IL*GRUAS, random= ~ MNPSAPROT+MNSLOPE+MNELEV+MNDROAD+MNDHW+MNDSMIL|
CANTON,family = binomial(link=logit), data = data4)

> summary(data4.glmmPQL.1a)
Linear mixed-effects model fit by maximum likelihood
 Data: data4
       AIC      BIC    logLik
  172109.7 172449.7 -86011.83

Random effects:
```

```
 Formula: ~MNPSAPROT + MNSLOPE + MNELEV + MNDROAD + MNDHW + MNDSMIL |
CANTON
 Structure: General positive-definite, Log-Cholesky parametrization
            StdDev       Corr
(Intercept) 1.266080e-01 (Intr) MNPSAP MNSLOP MNELEV MNDROA MNDHW
MNPSAPROT   1.402619e-04  0.999
MNSLOPE     2.961518e-02  0.999  0.998
MNELEV      1.077674e-03 -1.000 -0.999 -1.000
MNDROAD     7.276508e-05  0.999  1.000  0.998 -0.999
MNDHW       7.816794e-10 -0.999 -1.000 -0.998  0.999 -1.000
MNDSMIL     6.671964e-05 -0.999 -1.000 -0.998  0.999 -1.000  1.000
Residual    9.361460e-01

Variance function:
 Structure: fixed weights
 Formula: ~invwt
Fixed effects: DEFOR ~ MNPSAPROT * GRUAS + MNSLOPE * GRUAS + MNELEV *
GRUAS + MNDROAD *      GRUAS + MNDHW * GRUAS + MNDSMIL * GRUAS
                   Value  Std.Error    DF    t-value p-value
(Intercept)    -5.971662 0.19487974 20069 -30.642807  0.0000
MNPSAPROT      -0.000180 0.00010993 20069  -1.634389  0.1022
GRUAS           -0.152768 0.30339811 20069  -0.503524  0.6146
MNSLOPE         0.053294 0.05349557 20069   0.996223  0.3192
MNELEV         -0.001471 0.00130274 20069  -1.129031  0.2589
MNDROAD         0.000104 0.00005170 20069   2.006752  0.0448
MNDHW          -0.000028 0.00002806 20069  -1.001503  0.3166
MNDSMIL        -0.000076 0.00005081 20069  -1.490270  0.1362
MNPSAPROT:GRUAS -0.000341 0.00011456 20069  -2.976000  0.0029
GRUAS:MNSLOPE   -0.011693 0.07593384 20069  -0.153985  0.8776
GRUAS:MNELEV    -0.001201 0.00206122 20069  -0.582779  0.5600
GRUAS:MNDROAD   -0.000079 0.00002967 20069  -2.676808  0.0074
GRUAS:MNDHW      0.000028 0.00003754 20069   0.757315  0.4489
GRUAS:MNDSMIL    0.000128 0.00003871 20069   3.310453  0.0009
 Correlation:
               (Intr) MNPSAPROT GRUAS   MNSLOP MNELEV MNDROA MNDHW  MNDSMI
MNPSAPROT       0.468
GRUAS          -0.387 -0.095
MNSLOPE         0.060  0.264     0.037
MNELEV         -0.083 -0.253    -0.054 -0.802
MNDROAD         0.140  0.582     0.081  0.273 -0.290
MNDHW           0.092  0.082    -0.087 -0.030  0.242 -0.172
MNDSMIL        -0.106 -0.666    -0.059 -0.288  0.214 -0.797 -0.333
MNPSAPROT:GRUAS -0.073 -0.406     0.554 -0.022 -0.073  0.044 -0.086  0.103
GRUAS:MNSLOPE    0.026 -0.016    -0.174 -0.629  0.464  0.015  0.030  0.009
GRUAS:MNELEV    -0.057 -0.076     0.430  0.404 -0.504 -0.108 -0.165  0.133
GRUAS:MNDROAD    0.225  0.055    -0.215 -0.008 -0.131 -0.468  0.339  0.199
GRUAS:MNDHW     -0.065 -0.062     0.169  0.022 -0.182  0.125 -0.749  0.253
GRUAS:MNDSMIL   -0.168  0.128    -0.027  0.050  0.169  0.151  0.406 -0.470
               MNPSAPROT: GRUAS:MNS GRUAS:MNE GRUAS:MNDR GRUAS:MNDH
MNPSAPROT
GRUAS
MNSLOPE
MNELEV
MNDROAD
MNDHW
MNDSMIL
```

```
MNPSAPROT:GRUAS
GRUAS:MNSLOPE    0.030
GRUAS:MNELEV     0.158     -0.662
GRUAS:MNDROAD   -0.174     -0.018    0.078
GRUAS:MNDHW      0.149     -0.036    0.318   -0.343
GRUAS:MNDSMIL   -0.145      0.042   -0.144   -0.375    -0.439

Standardized Within-Group Residuals:
        Min          Q1         Med          Q3         Max
-0.42174019 -0.08648276 -0.06301937 -0.04222975 39.49179853

Number of Observations: 20085
Number of Groups: 3
```

ROBUSTNESS TEST: EXTRACTING SLOPE AND ROADS TO VALIDATE HLM DEFORESTATION MODEL

```
> # 5a. FIRST HLM MODEL WITH BINARY RESPONSE - VALIDATION MODEL
> data4.glmmPQL.2<-glmmPQL(DEFOR ~
MNPSAPROT*GRUAS+MNSLOPE*GRUAS+MNDSMIL*GRUAS, random= ~
MNPSAPROT+MNSLOPE+MNDSMIL|CANTON,family = binomial(link=logit), data =
data4)

> summary(data4.glmmPQL.2)
Linear mixed-effects model fit by maximum likelihood
 Data: data4
       AIC      BIC    logLik
  166675.5 166825.8 -83318.76

Random effects:
 Formula: ~MNPSAPROT + MNSLOPE + MNDSMIL | CANTON
 Structure: General positive-definite, Log-Cholesky parametrization
            StdDev       Corr
(Intercept) 3.112178e-01 (Intr) MNPSAP MNSLOP
MNPSAPROT   1.375773e-04  0.999
MNSLOPE     6.198298e-02 -0.999 -1.000
MNDSMIL     1.087143e-06  0.910  0.902 -0.904
Residual    9.160039e-01

Variance function:
 Structure: fixed weights
 Formula: ~invwt
Fixed effects: DEFOR ~ MNPSAPROT * GRUAS + MNSLOPE * GRUAS + MNDSMIL *
GRUAS
                    Value  Std.Error    DF    t-value p-value
(Intercept)     -5.801588 0.24605855 20075 -23.578081  0.0000
MNPSAPROT       -0.000179 0.00010773 20075  -1.660544  0.0968
GRUAS            -0.006242 0.25368080 20075  -0.024606  0.9804
MNSLOPE         -0.055307 0.04654251 20075  -1.188313  0.2347
MNDSMIL         -0.000016 0.00001809 20075  -0.896599  0.3699
MNPSAPROT:GRUAS -0.000323 0.00010696 20075  -3.023573  0.0025
GRUAS:MNSLOPE   -0.029672 0.05509831 20075  -0.538535  0.5902
GRUAS:MNDSMIL    0.000103 0.00002550 20075   4.031564  0.0001
 Correlation:
                (Intr) MNPSAPROT GRUAS   MNSLOP MNDSMI MNPSAPROT: GRUAS:MNS
MNPSAPROT        0.711
```

```
GRUAS           -0.322 -0.097
MNSLOPE        -0.455 -0.410    -0.054
MNDSMIL         0.213 -0.137    -0.152 -0.068
MNPSAPROT:GRUAS -0.068 -0.399     0.562 -0.120  0.191
GRUAS:MNSLOPE   -0.087 -0.135     0.239 -0.342  0.033  0.231
GRUAS:MNDSMIL   -0.125  0.119    -0.139  0.034 -0.706 -0.212      0.090

Standardized Within-Group Residuals:
        Min          Q1         Med          Q3         Max
-0.30800205 -0.08866242 -0.07458808 -0.05332494 31.11467872

Number of Observations: 20085
Number of Groups: 3


PSA2000 = f(everything else)

> # 6. RUNS A LINEAR MODEL BINOMIAL FAMILY (GLM) LINK LOGIT: PSA2000 =
EVERYTHING ELSE
>
> data3a.glm.logit.d<-glm(PSA2000 ~
PSA1999DIST+PSA1998DIST+PSA1997DIST+DEFOR+SLOPE_PC+ELEV_500+DHW+DROAD+DENH
W+DENROAD+DSAWMILL+GRUAS+GUACIMO+POCOCI, family = binomial(link=logit),
data = data3)
> summary(data3a.glm.logit.d)

Call:
glm(formula = PSA2000 ~ PSA1999DIST + PSA1998DIST + PSA1997DIST +
    DEFOR + SLOPE_PC + ELEV_500 + DHW + DROAD + DENHW + DENROAD +
    DSAWMILL + GUACIMO + POCOCI, family = binomial(link = logit),
    data = data3)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-0.16377  -0.05362  -0.03236  -0.01284   4.12503

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept) -4.912e+00  9.817e-01  -5.003 5.63e-07 ***
PSA1999DIST -4.397e-06  9.407e-05  -0.047   0.9627
PSA1998DIST -1.694e-04  7.243e-05  -2.339   0.0193 *
PSA1997DIST -3.735e-05  5.291e-05  -0.706   0.4803
DEFOR       -1.239e+01  9.431e+02  -0.013   0.9895
SLOPE_PC     5.813e-02  5.598e-02   1.038   0.2991
ELEV_500    -1.703e-03  1.431e-03  -1.190   0.2341
DHW         -1.075e-04  6.957e-05  -1.546   0.1222
DROAD        3.979e-06  6.129e-05   0.065   0.9482
DENHW       -5.019e-01  1.643e+00  -0.305   0.7600
DENROAD     -1.919e-01  8.668e-01  -0.221   0.8248
DSAWMILL     7.649e-05  5.810e-05   1.317   0.1880
GUACIMO     -6.973e-01  1.290e+00  -0.540   0.5890
POCOCI      -9.249e-01  7.976e-01  -1.160   0.2462
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)
```

```
    Null deviance: 330.23  on 20084  degrees of freedom
Residual deviance: 300.75  on 20071  degrees of freedom
AIC: 328.75

Number of Fisher Scoring iterations: 18

> data3A.glm.logit.e<-glm(PSA2000 ~
GUACIMO+POCOCI+TORT+CVC+GRUAS+HUM+PN+RN+RF, family = binomial(link=logit),
data = data3A)
> summary(data3A.glm.logit.e)

Call:
glm(formula = PSA2000 ~ GUACIMO + POCOCI + TORT + CVC + GRUAS +
    HUM + PN + RN + RF, family = binomial(link = logit), data = data3A)

Deviance Residuals:
       Min          1Q      Median          3Q         Max
-1.704e-01  -5.873e-02  -2.464e-02  -9.360e-06   3.872e+00

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept)  -7.75565    1.72613  -4.493 7.02e-06 ***
GUACIMO       0.68477    1.38648   0.494  0.62138
POCOCI       -0.22970    0.85981  -0.267  0.78936
TORT        -15.60980  821.38593  -0.019  0.98484
CVC           1.43047    0.98081   1.458  0.14471
GRUAS          1.73774    0.62424   2.784  0.00537 **
HUM          -1.17059    1.07360  -1.090  0.27556
PN            0.36235    1.32911   0.273  0.78514
RN           15.26577  821.38603   0.019  0.98517
RF            0.06798    1.35400   0.050  0.95996
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 330.23  on 20084  degrees of freedom
Residual deviance: 291.67  on 20075  degrees of freedom
AIC: 311.67

Number of Fisher Scoring iterations: 22


> # 7. SECOND MODEL WITH BINARY RESPONSE
>
> data5.glmmPQL.1<-glmmPQL(PSA2K ~
MNSLOPE*GRUAS+MNELEV*GRUAS+MNDROAD*GRUAS+MNDSMIL*GRUAS+MNPSA99*GRUAS+MNPSA
98*GRUAS+MNPSA97*GRUAS, random= ~
MNSLOPE+MNELEV+MNDROAD+MNDSMIL+MNPSA99+MNPSA98+MNPSA97|CANTON,family =
binomial(link=logit), data = data5)

> summary(data5.glmmPQL.1)
Linear mixed-effects model fit by maximum likelihood
 Data: data5
       AIC      BIC    logLik
```

```
  210912.3 211331.4 -105403.2

Random effects:
 Formula: ~MNSLOPE + MNELEV + MNDROAD + MNDSMIL + MNPSA99 + MNPSA98 +
MNPSA97 | CANTON
 Structure: General positive-definite, Log-Cholesky parametrization
            StdDev       Corr
(Intercept) 1.183114e+00 (Intr) MNSLOP MNELEV MNDROA MNDSMI MNPSA99 MNPSA98
MNSLOPE     2.002140e-02  1.000
MNELEV      2.443702e-03 -1.000 -1.000
MNDROAD     6.017274e-05 -1.000 -1.000  1.000
MNDSMIL     2.033220e-05  1.000  1.000 -1.000 -1.000
MNPSA99     1.406175e-04 -1.000 -1.000  1.000  1.000 -1.000
MNPSA98     1.718306e-08  1.000  0.999 -1.000 -1.000  1.000 -1.000
MNPSA97     1.483936e-04 -1.000 -1.000  1.000  1.000 -1.000  1.000  -1.000
Residual    7.902736e-01

Variance function:
 Structure: fixed weights
 Formula: ~invwt
Fixed effects: PSA2K ~ MNSLOPE * GRUAS + MNELEV * GRUAS + MNDROAD * GRUAS
+ MNDSMIL *      GRUAS + MNPSA99 * GRUAS + MNPSA98 * GRUAS + MNPSA97 *
GRUAS
                 Value Std.Error    DF   t-value p-value
(Intercept)  -8.851221 0.8936008 20067 -9.905118  0.0000
MNSLOPE       0.115361 0.0520863 20067  2.214799  0.0268
GRUAS          1.635197 0.5516345 20067  2.964275  0.0030
MNELEV       -0.000884 0.0019107 20067 -0.462777  0.6435
MNDROAD      -0.000038 0.0000835 20067 -0.460147  0.6454
MNDSMIL       0.000057 0.0000729 20067  0.776840  0.4373
MNPSA99      -0.000086 0.0001492 20067 -0.573369  0.5664
MNPSA98      -0.000097 0.0000872 20067 -1.106403  0.2686
MNPSA97       0.000103 0.0001161 20067  0.888507  0.3743
MNSLOPE:GRUAS -0.124120 0.1000577 20067 -1.240488  0.2148
GRUAS:MNELEV   0.003007 0.0024404 20067  1.232391  0.2178
GRUAS:MNDROAD  0.000055 0.0000911 20067  0.601625  0.5474
GRUAS:MNDSMIL -0.000055 0.0000895 20067 -0.609089  0.5425
GRUAS:MNPSA99  0.000323 0.0001568 20067  2.061915  0.0392
GRUAS:MNPSA98 -0.000097 0.0001121 20067 -0.864019  0.3876
GRUAS:MNPSA97  0.000099 0.0000936 20067  1.054664  0.2916
 Correlation:
             (Intr) MNSLOPE GRUAS   MNELEV MNDROA MNDSMI MNPSA99 MNPSA98
MNPSA97
MNSLOPE       0.020
GRUAS         -0.446  0.038
MNELEV       -0.536 -0.565  -0.023
MNDROAD      -0.215  0.039  -0.282  0.435
MNDSMIL       0.011 -0.108   0.267 -0.327 -0.651
MNPSA99      -0.345 -0.046  -0.148  0.226  0.031 -0.029
MNPSA98       0.145  0.075  -0.250  0.318  0.211 -0.310 -0.254
MNPSA97      -0.741 -0.020   0.127  0.596  0.196 -0.086  0.412   0.030
MNSLOPE:GRUAS  0.097 -0.510  -0.065  0.210 -0.076  0.083 -0.040  -0.039
-0.087
GRUAS:MNELEV  -0.136  0.412   0.160 -0.365 -0.048  0.119  0.149  -0.244
0.036
GRUAS:MNDROAD -0.179 -0.051   0.288 -0.120 -0.724  0.499  0.183  -0.194
```

```
0.156
GRUAS:MNDSMIL  0.134  0.087  -0.265  0.168  0.463 -0.772 -0.045   0.256
-0.052
GRUAS:MNPSA99 -0.161  0.017   0.161  0.154  0.239 -0.087 -0.651   0.252
0.058
GRUAS:MNPSA98 -0.080 -0.072   0.358 -0.257 -0.162  0.263  0.210  -0.768
-0.037
GRUAS:MNPSA97  0.051 -0.022  -0.070 -0.086  0.229 -0.100  0.017  -0.022
-0.444
             MNSLOPE: GRUAS:MNE GRUAS:MNDR GRUAS:MNDS GRUAS:MNPSA99
GRUAS:MNPSA98
MNSLOPE
GRUAS
MNELEV
MNDROAD
MNDSMIL
MNPSA99
MNPSA98
MNPSA97
MNSLOPE:GRUAS
GRUAS:MNELEV  -0.592
GRUAS:MNDROAD  0.081    0.287
GRUAS:MNDSMIL -0.127   -0.315   -0.697
GRUAS:MNPSA99  0.035   -0.016   -0.190    -0.034
GRUAS:MNPSA98 -0.004    0.213    0.105    -0.133    -0.372
GRUAS:MNPSA97  0.109    0.168   -0.217     0.028     0.044       -0.029

Standardized Within-Group Residuals:
        Min          Q1         Med          Q3         Max
-0.27784493 -0.04501080 -0.01998147 -0.01229406 61.74942314

Number of Observations: 20085
Number of Groups: 3

Inserting DHW and taking ELEV out

> data5.glmmPQL.1<-glmmPQL(PSA2K ~
MNSLOPE*GRUAS+MNDROAD*GRUAS+MNDHW*GRUAS+MNDSMIL*GRUAS+MNPSA99*GRUAS+MNPSA9
8*GRUAS+MNPSA97*GRUAS, random= ~
MNSLOPE+MNDROAD+MNDHW+MNDSMIL+MNPSA99+MNPSA98+MNPSA97|CANTON,family =
binomial(link=logit), data = data5)

> summary(data5.glmmPQL.1)
Linear mixed-effects model fit by maximum likelihood
 Data: data5
       AIC      BIC    logLik
  211011.7 211430.8 -105452.9

Random effects:
 Formula: ~MNSLOPE + MNDROAD + MNDHW + MNDSMIL + MNPSA99 + MNPSA98 +
MNPSA97 | CANTON
 Structure: General positive-definite, Log-Cholesky parametrization
            StdDev       Corr
(Intercept) 9.427617e-01 (Intr) MNSLOP MNDROA MNDHW  MNDSMI MNPSA99 MNPSA98
MNSLOPE     3.700329e-02 -1.000
MNDROAD     4.178332e-05 -1.000  1.000
```

```
MNDHW       2.536905e-05  1.000 -1.000 -1.000
MNDSMIL     1.750480e-07  1.000 -1.000 -1.000  1.000
MNPSA99     1.253959e-04 -1.000  1.000  1.000 -1.000 -1.000
MNPSA98     7.296239e-07  0.789 -0.784 -0.788  0.789  0.788 -0.791
MNPSA97     3.933337e-05 -1.000  1.000  1.000 -1.000 -1.000  1.000  -0.787
Residual    8.146481e-01

Variance function:
 Structure: fixed weights
 Formula: ~invwt
Fixed effects: PSA2K ~ MNSLOPE * GRUAS + MNDROAD * GRUAS + MNDHW * GRUAS +
MNDSMIL *      GRUAS + MNPSA99 * GRUAS + MNPSA98 * GRUAS + MNPSA97 * GRUAS
                 Value Std.Error    DF    t-value p-value
(Intercept)  -8.678191 0.7897811 20067 -10.988097  0.0000
MNSLOPE       0.069187 0.0479329 20067   1.443405  0.1489
GRUAS         1.634850 0.5792572 20067   2.822321  0.0048
MNDROAD      -0.000054 0.0000995 20067  -0.542675  0.5874
MNDHW         0.000002 0.0000866 20067   0.027785  0.9778
MNDSMIL       0.000025 0.0000851 20067   0.294540  0.7683
MNPSA99      -0.000054 0.0001578 20067  -0.343011  0.7316
MNPSA98      -0.000105 0.0000871 20067  -1.208377  0.2269
MNPSA97       0.000039 0.0000775 20067   0.499620  0.6173
MNSLOPE:GRUAS -0.040355 0.0829509 20067  -0.486492  0.6266
GRUAS:MNDROAD  0.000078 0.0001094 20067   0.714497  0.4749
GRUAS:MNDHW   -0.000108 0.0001038 20067  -1.040448  0.2981
GRUAS:MNDSMIL  0.000017 0.0001000 20067   0.171815  0.8636
GRUAS:MNPSA99  0.000286 0.0001674 20067   1.708192  0.0876
GRUAS:MNPSA98 -0.000066 0.0001149 20067  -0.570961  0.5680
GRUAS:MNPSA97  0.000058 0.0000987 20067   0.583928  0.5593
 Correlation:
             (Intr) MNSLOPE GRUAS   MNDROA MNDHW  MNDSMI MNPSA99 MNPSA98
MNPSA97
MNSLOPE      -0.386
GRUAS         -0.530  0.057
MNDROAD       0.040  0.105  -0.348
MNDHW         0.125  0.230   0.074 -0.557
MNDSMIL      -0.149 -0.457   0.223 -0.171 -0.527
MNPSA99      -0.286  0.013  -0.144  0.035 -0.246  0.178
MNPSA98       0.252  0.471  -0.238 -0.006  0.174 -0.268 -0.324
MNPSA97      -0.402  0.399   0.261 -0.251 -0.009  0.148  0.108  -0.006
MNSLOPE:GRUAS -0.026 -0.442   0.021  0.024 -0.208  0.252  0.147  -0.312
-0.151
GRUAS:MNDROAD -0.256  0.025   0.289 -0.841  0.443  0.138  0.099  -0.031
0.296
GRUAS:MNDHW    0.063 -0.280  -0.006  0.418 -0.785  0.463  0.113  -0.109
-0.036
GRUAS:MNDSMIL  0.138  0.384  -0.205  0.144  0.452 -0.847 -0.156   0.233
-0.126
GRUAS:MNPSA99 -0.113  0.199   0.119  0.112  0.114 -0.165 -0.689   0.255
0.031
GRUAS:MNPSA98 -0.155 -0.374   0.332  0.005 -0.123  0.223  0.237  -0.743
0.003
GRUAS:MNPSA97  0.092 -0.194  -0.117  0.277 -0.063 -0.120  0.059  -0.033
-0.714
             MNSLOPE: GRUAS:MNDR GRUAS:MNDH GRUAS:MNDS GRUAS:MNPSA99
GRUAS:MNPSA98
```

```
MNSLOPE
GRUAS
MNDROAD
MNDHW
MNDSMIL
MNPSA99
MNPSA98
MNPSA97
MNSLOPE:GRUAS
GRUAS:MNDROAD  0.145
GRUAS:MNDHW    0.193   -0.484
GRUAS:MNDSMIL -0.405   -0.265    -0.482
GRUAS:MNPSA99 -0.029   -0.114    -0.117     0.081
GRUAS:MNPSA98  0.235    0.012     0.005    -0.098    -0.382
GRUAS:MNPSA97  0.287   -0.276    -0.009     0.121    -0.013         0.043

Standardized Within-Group Residuals:
        Min          Q1          Med          Q3         Max
-0.25453230 -0.04538769 -0.02015482 -0.01124605 71.97665267

Number of Observations: 20085
Number of Groups: 3
```

Appendix 3: OLS Regression - Using household survey data

```
REGRESSION SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION
Data set             : ALLOLS
Dependent Variable   :  VISITS_ENV  Number of Observations:  132
Mean dependent var   :     5.52273  Number of Variables   :   12
S.D. dependent var   :     12.6362  Degrees of Freedom    :  120

R-squared            :    0.301113  F-statistic           :     4.70015
Adjusted R-squared   :    0.237049  Prob(F-statistic)     :5.83937e-006
Sum squared residual:      14730.4  Log likelihood        :    -498.481
Sigma-square         :     122.753  Akaike info criterion :     1020.96
S.E. of regression   :     11.0794  Schwarz criterion     :     1055.56
Sigma-square ML      :     111.594
S.E of regression ML:      10.5638
-----------------------------------------------------------------------
    Variable    Coefficient     Std.Error    t-Statistic   Probability
-----------------------------------------------------------------------
    CONSTANT      1.669351       4.041515      0.4130508    0.6803083
          HA   0.001177797     0.01167344      0.1008955    0.9198055
         BNH  -0.003521154     0.01341821     -0.2624161    0.7934518
         BNL    0.03242963     0.04450745      0.7286338    0.4676461
  DISTANCE_E    0.09046838     0.08584323       1.053879    0.2940552
   POOR_SOIL    0.03336959     0.03782894       0.882118    0.3794762
  LARGE_SLOP   -0.04177523     0.03817152      -1.094408    0.2759676
     DREDCAM  3.393026e-005  0.0006925141     0.04899576    0.9609820
       DCARR   -0.00012253   0.0002500752     -0.4899727    0.6250461
    DSAWMILL  -7.658288e-005  0.0002134411     -0.358801    0.7203716
    DPSAPROT  -0.0002784954  0.0006733896     -0.4135725    0.6799279
        TYPE      15.79214        2.77157       5.697902    0.0000001
-----------------------------------------------------------------------
REGRESSION DIAGNOSTICS
MULTICOLLINEARITY CONDITION NUMBER   12.83739
TEST ON NORMALITY OF ERRORS
TEST                  DF          VALUE            PROB
Jarque-Bera            2           10569.02        0.0000000

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST                  DF          VALUE            PROB
Breusch-Pagan test    11           217.7044        0.0000000
Koenker-Bassett test  11           9.780696        0.5502151
SPECIFICATION ROBUST TEST
TEST                  DF          VALUE            PROB
White                 77            N/A            N/A

DIAGNOSTICS FOR SPATIAL DEPENDENCE
FOR WEIGHT MATRIX : ALLOLSW.GWT  (row-standardized weights)
TEST                           MI/DF       VALUE          PROB
Moran's I (error)            -0.039246    -0.8938187      0.3714188
Lagrange Multiplier (lag)        1        1.4914105      0.2219977
Robust LM (lag)                  1        0.0029417      0.9567462
Lagrange Multiplier (error)      1        1.9603057      0.1614806
Robust LM (error)                1        0.4718370      0.4921433
Lagrange Multiplier (SARMA)      2        1.9632474      0.3747022
```

GLM LOGISTIC MODEL NO SPATIAL TEST INCLUDED

```
> surv1.glm.logit.d<-glm(TYPE ~
VISITS_ENV+DREDCAM+DCARR+DSAWMILL+DPSAPROT, family = binomial(link=logit),
data = surv1) > summary(surv1.glm.logit.d)
Call:
glm(formula = TYPE ~ VISITS_ENV + DREDCAM + DCARR + DSAWMILL +
    DPSAPROT, family = binomial(link = logit), data = surv1)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-2.45465  -0.33347  -0.07653   0.06364   2.35555

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept) -1.317e+00  9.773e-01  -1.348 0.177720
VISITS_ENV   2.046e-01  5.308e-02   3.855 0.000116 ***
DREDCAM      2.968e-04  1.835e-04   1.617 0.105797
DCARR       -6.396e-05  7.043e-05  -0.908 0.363823
DSAWMILL     1.237e-04  7.065e-05   1.750 0.080049 .
DPSAPROT    -1.904e-03  5.348e-04  -3.561 0.000369 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 154.691  on 131  degrees of freedom
Residual deviance:  63.734  on 126  degrees of freedom
AIC: 75.734

Number of Fisher Scoring iterations: 7
```

Appendix 4: OLS regressions for test of convergence among Cantones

```
Test for convergence of PSA contracts among Cantones in CR
REGRESSION: SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION
Data set            : Cantones_SPO5_Clip
Dependent Variable  :   LNPSA2000  Number of Observations:   81
Mean dependent var  :   -0.862362  Number of Variables   :    4
S.D. dependent var  :    0.519998  Degrees of Freedom    :   77

R-squared           :    0.058034  F-statistic           :      1.5813
Adjusted R-squared  :    0.021334  Prob(F-statistic)     :    0.200722
Sum squared residual:     20.6312  Log likelihood        :    -59.5443
Sigma-square        :    0.267937  Akaike info criterion :     127.089
S.E. of regression0.63:  0.517626  Schwarz criterion     :     136.666
Sigma-square ML     :    0.254706
S.E of regression ML:    0.504684
-----------------------------------------------------------------------
    Variable    Coefficient     Std.Error    t-Statistic   Probability
-----------------------------------------------------------------------
    CONSTANT    -0.6458498      0.1249443      -5.169102    0.0000018
   LNPSA1997    0.03358115     0.06956918      0.4827016    0.6306787
  LNREF19997    0.02902686     0.07673361      0.3782809    0.7062622
   LNMAN1997     0.2187042      0.1344565        1.62658    0.1079123
-----------------------------------------------------------------------

REGRESSION DIAGNOSTICS
MULTICOLLINEARITY CONDITION NUMBER   5.039603
TEST ON NORMALITY OF ERRORS
TEST                  DF          VALUE            PROB
Jarque-Bera            2           213.6816        0.0000000

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST                  DF          VALUE            PROB
Breusch-Pagan test     3           15.87285        0.0012041
Koenker-Bassett test   3            3.56214        0.3127918
SPECIFICATION ROBUST TEST
TEST                  DF          VALUE            PROB
White                  9           10.95234        0.2789902


DIAGNOSTICS FOR SPATIAL DEPENDENCE
FOR WEIGHT MATRIX : WEIGHTS2.GAL  (row-standardized weights)
TEST                          MI/DF       VALUE          PROB
Moran's I (error)           0.021078     0.7703440      0.4410957
Lagrange Multiplier (lag)       1        0.8471874      0.3573492
Robust LM (lag)                 1        5.3814938      0.0203514
Lagrange Multiplier (error)     1        0.1550400      0.6937648
Robust LM (error)               1        4.6893464      0.0303502
Lagrange Multiplier (SARMA)     2        5.5365337      0.0627707
```

CHAPTER IV - SCALE ELEMENTS IN ENVIRONMENTAL ASSESSMENT OF REGIONAL POLICIES

Luis Eduardo Carrasco

1 ABSTRACT

Since the 1970s multiple research efforts around the world have focused on identifying potential environmental, economic, and social impacts of development. It is well understood that local project assessment approaches fail to identify or, worse, quantify indirect or cumulative effects when they do not provide an appropriate baseline framework to understand the local and the regional environment as a connected entity. A conceptual approach based on several environmental assessment and spatial analysis tools suggests that we need to consider multi-scale methods that can help describe the different processes that occur within a region. This would help project managers and researchers to better evaluate ongoing regional policies by retrieving a wide characterization of the application and impacts of policies within the whole geographical spectrum. Within each policy assessment, these methods could evolve into a framework for environmental management practices at both local and regional scales that could be updated with new information through time. We analyze two regional policy case studies: poverty targeting in Sri Lanka, and ecosystem services in Costa Rica.

Keywords: Strategic Environmental Assessment, Environmental impact analysis, Environmental impact assessment, GIS, Multilevel analysis, Multiscale analysis, poverty targeting.

2 INTRODUCTION

The US National Environmental Policy Act (NEPA) of 1969 established the first effort from a developed country to avoid, minimize, or control environmental impacts of human development. Since then, many countries in both the developed and developing world have established their own environmental regulations and processes of environmental impacts qualification. The process, norms, and practice have evolved since then to incorporate newer methodologies to assess impacts according to the nature of projects. This evolution has helped to recognize different realms that need to be treated in an environmental study, such as biophysical, social and economic realms. Each of these environmental realms could be affected by direct, indirect and cumulative impacts.

Direct impacts are, as the name implies, those actions that affect another element directly and that are easily identifiable as, for example, an oil spill in the ocean would immediately pollute water. Indirect impacts, also known as secondary impacts, are those that occur as an ensuing effect of a direct impact. For instance, fish entering the area of an oil spill could die as an indirect consequence of it, as oil affected the water first. Reduced tourism or transit on an oil spill area is an example of indirect environmental economic impact on the local economy. Cumulative impacts are those that manifest themselves when aggregated events of the same nature affect the environment. For instance, stream pollution within a watershed can through time produce high levels of a pollutant at the point of discharge of that watershed. One of the main similarities between indirect and cumulative impacts is the spatial scale of their occurrence which is larger than that of direct impacts.

In most practice, environmental impact studies are bound to budget constraints and short timeframes imposed by agency planning cycles. Emphasis goes to assessing direct impacts of a biophysical nature, rather than other impacts whose nature is more complicated and less surely predictable. Most environmental assessment practitioners have experience primarily with methodologies designed to assess direct impacts. Such impacts are relatively easy to identify and to link to a source. Moreover, environmental assessment methodologies are adapted to the short timelines preferred by regulatory agencies.

On the other hand, indirect and cumulative impacts are harder to identify and define. Even when these are defined, it is sometimes hard to associate them with a particular source. Assessment of indirect and cumulative impacts requires more time and resources, and methodologies available are just starting to be implemented.

Hunsaker (1998) suggests that since the requirement for identification of cumulative impacts, the main problem to deal with was assessment and management. Early EIS professionals working under the NEPA framework noticed that effectively assessing CI required a complex institutional framework involving Federal, State, NGO, private, and public elements. To date, however, the assessment of CI has not yet reached the effectiveness desired.

Nevertheless, the need for and importance of assessing cumulative and indirect impacts is widely accepted, so there have been some advances in European countries, as well as in Canada, Australia, and recently in the U.S. One example of methodologies to assess indirect and cumulative impacts can be found in Strategic Environmental Assessment (SEA) (Partidario and Clark 2000) and the Guidance for Assessing ICI (The Louis Berger Group 2001) document used by the North Carolina Department of Transportation in the United States. As different approaches to assessing indirect and cumulative impacts have been tried, literature indicates that assessing indirect and cumulative impacts requires considering the effects of the following:

1. Scales of the study (spatial and temporal) (Joao 2002, Dube 2003, Deverman 2003)
2. Boundary definition for spatial and temporal scales (McGarigal et al. 2001, Finnveden et al. 2003)
3. Stages of occurrence of impacts (Dube 2003)
4. Connecting the assessment with sustainability goals (Dube 2003, Backhaus et al. 2002, Bruhn-Tysk and Eklund 2002)
5. Using a measurable indicator of sustainability (Backhaus 2002)

As a consequence of trying to address shortcomings of EIA, Strategic Environmental

Assessment (SEA) was conceptualized as a systematic process for evaluating the environmental quality, and consequences, of alternative visions and development intentions incorporated in policy, planning or program (PPP) initiatives. Consequently, SEA approaches have been used for a variety of analysis of policies, plans, or programs (Table 1).

Table 1. Examples of PPP where SEA approach has been used

Country	Source	Type of SEA	Sector	Main analysis and assessment tools
Germany	Kleinschmidt and Wagner (1996)	Sectoral SEA	Energy (wind farms)	Field data collection and GIS
US	Webb and Sigal (1996)	Sectoral SEA	Environmental restoration and waste management programme of nuclear facilities	Risk assessment, modeling
EU	Dom (1996)	Sectoral SEA	Trans-European transport networks	Emissions modeling, GIS, socioeconomic assessment
Netherlands	Verheem (1996)	Sectoral SEA	10 year waste management programme	Impact matrices, weighing tables
Nepal	Khadka et al (1996)	Sectoral SEA	Forest Management Plan	GIS, weighing tables, experts opinions
UK	Rumble and Therivel (1996)	Comprehensive Area Based Plans	County Council's Structure Plan	Impact matrices, cost benefit analyses
Sweden	Asplund and Hilding-Ridevik (1996)	Comprehensive Area Based Plans	Municipal land-use planning	Impact matrices, GIS, travel demand model, field surveys
Ireland	Bradley (1996)	Comprehensive Area Based Plans	Structural funds	Not explicit
Canada	Campbell	Comprehensive Area Based Plans	Crop Insurance	Economic impact analysis, experts opinions,
Germany	Dalkmann and Bongardt (2004)	Undefined	Federal transport infrastructure planning	Environmental risk analysis, Cost benefit analysis, Feasibility analysis
Spain	Jiliberto et al (2004)	Undefined	Urban Planning	Impact matrices
Taiwan	Liou and Yu (2004)	Undefined	National Water Resource Development Plan	Impact matrices and indicators
Sweden	Nilsson et al. (2005)	Sectoral SEA	Waste incineration tax proposal	Qualitative assessment, LCA, site-specific assessment

SEA was developed to include different goals focused at the regional level and not at the project level. One most relevant advantage of SEA over project EIA is that SEA has the potential to analyze indirect and cumulative impacts effectively (Partidario and Clark 2000, Finnveden et al. 2003, Annandale et al. 2001). Moreover, the advantage of using SEA as an alternative to project EIA in the case of regional development policies is that goals could be defined by a larger involvement of different stakeholders at a regional level, taking this complicated task away from local agencies.

Thus, in order to address cumulative and indirect impacts within an EA context, SEA represents a potential alternative to study these types of impacts. However, scale elements surrounding spatial analysis of indirect and cumulative impacts need to be further studied. This could be accomplished, in part, by closely paying attention to current application of SEA in cases where scale elements are crucial. Lessons drawn from such an exercise could lead to improvement in treatment of indirect and cumulative impacts within SEA generally.

2.1 DATA SOURCES FOR SEA

Given the broad nature and the variety of tools for SEA, data sources are multiple and disparate, could be qualitative or quantitative: socio-economic surveys, expert surveys, census data, wildlife surveys, water, air and soil surveys, as well as recorded information in databases, and GIS. These data could be produced during the assessment or acquired from governmental or other institutions.

With increased use of digital data, Vanderhaegen and Muro (2005) advocate for the extended use of spatial data in both EIA and SEA. For instance, the EU started in 2004 a plan for providing the policy infrastructure to provide spatial data for its PPP and projects called INSPIRE. The authors mention that most tools used in EIA and SEA (such as matrices tables, checklists, ranking and weighting systems and relationship systems lack the ability to show spatial and temporal dimension. For that reason assessments should use GIS more extensively. The main problems are access to data, unavailability of data, integration from different sources, time and cost for spatial analysis. It is important to highlight that access to GIS data and software is widely increasing, especially since Open Source software is being adopted in both developing and industrialized countries. This means that use of GIS in EA can increase as well. Under this scenario, it becomes crucial to pay more attention to scale issues in EA and try to overcome them in its future practice. Specifically, issues cited earlier regarding spatial and temporal scales of the study (Joao 2002, Dube 2003, Deverman 2003) and boundary definition for spatial and temporal scales (McGarigal et al. 2001, Finnveden et al. 2003) should be taken into consideration for development of impact assessment tools.

The tools that seem most useful for conducting such assessments are geographic information systems. Yet such systems ultimately depend upon the data available for building the systems. Uniting different data types into GIS and proceeding to attempt assesments may not be feasible in all cases without serious qualifications.

Collectively, the goal was to extract useful ideas relevant to (1) the application of environmental assessment in regional and subregional policies and (2) the current use of geographic information systems in this context. Based on the findings and discussions of each chapter, the most important lessons to be taken into consideration when using GIS as a tool for environmental assessment are summarized below in terms of subject.

2.2 TYPE OF ENVIRONMENTAL ASSESSMENT

The two case studies treated in Chapters 2 and 3 reflected programs or policies at the national or regional level that, because of their large geographical extent or scale[1] could or should be addressed with SEA. The case studies are each subject to a national or regional program or policy. No cases were identified where a project-level EIA alone could address its objectives. Thus, we needed to pay attention to environmental elements, relationships and impacts that could manifest at different (geographic) scales. Once we reached this understanding we needed to make sure that these elements were incorporated in the environmental assessment approach.

2.3 TYPE OF IMPACTS

Environmental impacts were defined from two points of view. The first position involves what the observer can list as potential environmental impacts before suggesting a policy that

1 There is difference between cartographic and geographical scale. Small cartographic scale refers to a large area, whereas small geographical scale refers to a small extention (Sheppard and McMaster, 2004).

intends to mend certain problems. The second position relates to the observed impacts of a proposed policy. The first position may better resemble the way impacts are outlined in an environmental impact statement, as the extent of their perceived implications is usually local. Assessment of impacts from a proposed policy needs to include how the policies will affect the ongoing environmental processes that we want to fix and also list other direct, secondary or cumulative impacts that could arise from the application of the proposed policy.

The poverty targeting case study involved urban environments and dealt principally with social impacts. The environmental service case study was of rural nature and comprised impacts to forest cover and associated ecological impacts that extend to urban areas.

The two policies assessed intend to affect agents that directly caused environmental issues. Policy can affect water infrastructure design to expand water availability and indirectly improve people's welfare. National policy can affect people's land use decision making to help protect forest cover and indirectly produce ecosystem services. In the long term it can improve the quality of those services, even though ecosystem services processes or their impacts may not be fully identifiable or understood. In the long-run, these are top-to-bottom strategies to tackle environmental impacts that could work by implementing monitoring and mitigation measures targeted to geographical units of small extent.

2.4 ENVIRONMENTAL IMPACTS MANAGEMENT PROCESSES

The policy and program processes studied involved prevention, mitigation, and monitoring of environmental impacts. Prevention of impacts is present in both case studies. For instance, ecosystem services intend to abate CO_2 emission countrywide. The poverty targeting case study did not preclude prevention of other (social) impacts, but this process may escape the objectives or the scope of these policies. The two case studies included a mitigation process which tries to address environmental impacts of human development. Ecosystem services payments include monitoring processes which involve medium to long term commitments to evaluate those environmental conditions that we would like policy to modify.

2.5 POLICY THEORETICAL SCOPE, SCALE OF IMPLEMENTATION AND SCALE OF IMPACTS

Policy theoretical scope is the geographical extent to which the policy is expected to generate cumulative positive impacts by adjusting environmental conditions. In the two case studies the geographical extent was regional.

Policy scale of implementation is the scale at which each regional policy is directly applicable. For the case of poverty targeting this scale was identified as the neighborhoods that needed improved access to water. For the case study of ecosystem services this scale referred to each parcel under protection contract.

Policy scales of impacts are those geographical and operational extents at which different impacts of policy implementation (positive and negative impacts) may manifest. Direct and indirect impacts are likely to manifest at a smaller (subregional) scale than cumulative impacts. The latter could manifest at a larger (regional) scale.

It was necessary to identify these elements within each policy scenario. By doing so it was possible to define spatial analysis methods that would better describe these policies.

2.6 SCALE OF PROBLEMS ASSESSED

The scaler elements of each of the scenarios were classified as resolution, geographic, operational and temporal. The temporal scale of the poverty targeting case study was assumed to be cross-sectional. The ecosystem services case study had temporal scale elements due to the presence of cumulative impacts.

In the case of poverty targeting, we tried to define neighborhoods based on household geostatistical data. Therefore, the resolution of the element household needed to be very fine. Since the elements to map were clusters of households or a neighborhood, then the geographical scale is small. The operational scale is the scale at which we can define the phenomenon *poverty* or *lack of water supply* to occur on the ground which could or not match the geographic scale. In poverty targeting the focus could be at the extent of neighborhood or larger, depending on how many neighborhoods are detected, and the total extent of the area of interest.

In the ecosystem services case study, three different resolutions were used. The finest one was at the level of households and their parcels. Coarser ones reflected the extension of deforestation countrywide as an aggregate of smaller observations while another assessment used medium resolution remote sensing analysis. The operational scale of this case study was much more complex than the poverty targeting case. First we needed to define the extent of the geographical relationships or dependencies between a landowner and environment in the context of his individual decision making process towards land use change. In essence, selecting a scale to measure the success of the program depended on indicators used and the processes that we want to evaluate. A single scale assessment may not be able to describe accurately a complex multilevel process. A different operational scale is the one at which we would like to measure the success of the policy, whether in terms of protected forest nationwide or of ecosystem services, which may differ across the country.

2.7 METRICS OR INDICATORS

Metrics or indicators here define what was measured or estimated within each case study. In the poverty targeting study, the main target was a sector of the population that is selected based in proxies such as overall expenditures or water expenditures. In the ecosystem services case study, the main targets were ecosystem services. As there is no standard currency to measure them, we assumed that by tracking change in forest areas we are tracking change in ecosystem services in the same direction.

On the other hand, relationship indicators are connections between elements which suggest an order in which they could be approached. These metrics are useful from a scale point of view because by analyzing each relationship we could identify those cases in which we would require a cross-scale examination, either temporal or multilevel. In the poverty targeting case study this relationship was "policy-infrastructure-water allocation-population welfare". In the ecosystem services case it was "policy-landowner dynamics-forest cover protection-environmental services".

2.8 DATA CHARACTERISTICS

The characteristics of the data used in each of the case studies differ in a number of ways. However, infrastructure, social and environmental data used in these analyses were public. In general this is the case with spatial data of low resolution.

Dimension refers to whether the data could be geo-referenced in any way regardless of whether a datum could be located in a single X, Y coordinate or as a centroid of a lattice polygon. In that sense, part of the data used was spatial. We used data from georeferenced household surveys (geostatistical data) and other data which, even though extracted from non-spatial databases, could be related to lattice polygons of large extension and still be useful for the analysis performed.

The temporal (longitudinal) data used were minimal mostly because of unavailability. In the ecosystem services case study it was important to have temporal data on different types of contracts, namely reforestation, management, and protection in order to assess relationships among them. The second set of temporal data was the area deforested from 1997 to 2000, which was publicly available and prepared for this type of analysis.

One of the challenges encountered when trying to find readily useful temporal data was that different non-standardized datasets were available to be used for regional analysis but not subregional analysis.

Most of the data were used in cross-sectional analysis for the two case studies. This seems to be the most feasible type of analysis to run at any time, especially when temporal data are limited or unreliable. However, lacking temporal data could affect our interpretations of analysis if we do not complement them with any background data, spatial or not. For instance, it is hard to contrast forest recovery to ecosystem services payments without data on forest cover variation.

Accuracy is an important issue that can be affected in different ways (e.g. when data are passed on from institution to institution through time). Several of the GIS datasets for the ecosystem services and poverty targeting case studies did not present metadata; important details relevant to how these datasets could be used (range of scale of application, resolution) were missing. Medium accuracy was present in low resolution land cover land use data as well as some of the property data for the ecosystem services case study. Survey data from households were meant to have high accuracy, but intrinsic errors of sampling and manipulation could have increased this error in different ways, so their expected high accuracy was reduced.

Geographic extent, availability and resolution go in different directions, mostly for economic reasons. Household surveys used in this study were performed in a relatively small area. The resolution of these data, however, is of the highest since it captures the minimum unit relevant to the objectives of the analysis. This is usual since the cost involved in collecting georeferenced data is high. Other data used, in particular existing GIS data sets, belonged to a larger geographical extent, but of course, with reduced accuracy and resolution.

The completeness of datasets used varied by case study, scale of assessment and resolution required. Specialized surveys in the case of poverty targeting and ecosystem services were usually very consistent. However, completeness of records was an issue during data preparation, since incomplete records had to be eliminated, directly affecting prediction power as the resulting dataset size would be smaller. Public records were usually more incomplete in the case of the ecosystem services study. This was a serious issue because it forced assumptions about the data which otherwise would leave us with a large part of the dataset in a useless state. However, these datasets still have useful information for analysis, but we needed to take into consideration that statistical significance might not mean much under these circumstances in terms of testing hypotheses. But they might identify relationships worthy to assess.

2.9 ANALYSIS TOOLS USED

Despite some of the problems with data accuracy, resolution and completeness, it was possible to run different types of analysis via geographic information systems, spatial statistics, or other mathematical operations. This study suggests that the validity of any of these operations was carefully interpreted based on the characteristics of the data used (spatial or aspatial) and their limitations. However, very few tools were readily available for multi-level analysis, and spatial statistics, especially in terms of incorporating spatial lag and spatial error into multilevel modeling.

2.10 RESULTING CONCEPTS

2.10.1 SCALE

We used fine scale data to build neighborhood maps according to proximity of indicators values. This way we attempted to reduce bias by not using administrative boundaries. Additionally, it was important to understand the relationships between elements or variables of an environmental problem--direction or flow of their effect--in order to understand geographical or operational scale and apply sound analytical methods. In that sense, geographical or operational scales of policy, human dynamics, ecosystem and economic processes were important to define early in the assessment in order to correctly choose the type of analysis to be run and therefore the type of data to request or produce.

On the other hand, single scale assessment of regional policy outcomes was biased or incomplete if not complemented with analysis at other scales or multiscale (multilevel) analysis. An analysis using a second scale helped understand the problem better, and helped identify research bias regarding relationships of spatial nature that we would otherwise have not expected. This is particularly important because practical uses of multiscale analysis are being explored with more attention. Use of complementary analyses at complementary scales was useful as well to understand environmental dynamics and human dynamics interactions when variables were generated or specified at differing scales.

2.10.2 STRATEGY

In terms of strategy, use of advanced techniques in spatial analysis helped to develop alternative poverty mapping techniques as in the case of poverty targeting. Specifically, household targeting bias could be reduced with spatial data and mapping methods of fine resolution when fine resolution data were available.

In the case of ecosystem services, multilevel spatial analysis helped monitor current regional policies relationships and collect important input from different factors that were perceptible only by using a smaller geographical scale or a finer resolution. These results help identify strategic factors that could help understand how success of targeting at the local level, by rural extension (visiting and educating landowners) and existence of a close visual reference of the program's goal at the household level, are linked to success of the program's goals at the regional level. At the same time these results helped understand why using complementary scales of analysis is important for improving overall strategy.

3 RECOMMENDATIONS

When considering data needs and possible methods for using environmental assessment and GIS to address most types of impacts successfully, regional policy researchers and environmental managers need to bear in mind:

- Spatial and temporal dimensions within an environmental problem are fully understood.
- Policy-environment relationships need to be placed in the context of scale and time. Paying attention to these concepts is important to know if a policy application context is composed by cross-scale processes that need to be assessed carefully; i.e. if direct, indirect, and cumulative impacts are present.
- Consider a flexible scale framework in which to apply environmental assessment. It is up to the researcher to define the different scales (operational or geographical) in order to define analytical and spatial data needs.
- While complementary results from using multiscale assessment could be important, the researcher has to be careful in extrapolating analysis results across different scales.

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