ABSTRACT

Title of Thesis: ASSESSING AND MODELING LANDSCAPE CHANGE IN A SENSITIVE HIGH-ELEVATION REGION OF THE BOLIVIAN ANDES

Jodi Brandt, Master of Science, 2004

Thesis Directed By: Associate Professor Phil Townsend, Marine Estuarine Environmental Sciences

This study used remotely sensed land cover and topographic data, maximum likelihood classification, and spectral mixing analysis to characterize current landscape patterns and quantify land cover change from 1985 to 2003 in the Southeastern Bolivian Andes. Current land cover was mapped into 9 classes with an overall accuracy of 89%. The change analysis demonstrated significant gains in bare and cultivated land (4.4% and 4.1%, respectively) at the expense of forest and pasture (losses of 4.8% and 3.9%, respectively). Spectral mixture analysis indicated that communal rangeland degradation (as measured by changes in proportions of green vegetation, non-photosynthetic vegetation and bare soil on the landscape) may have occurred, especially where conversion of land to more productive uses is restricted by soil fertility, topography, and climate. The study demonstrated that remotely sensed data and traditional image analysis techniques can be used to characterize land cover and land cover change in remote, mountainous areas.

ASSESSING AND MODELING LANDSCAPE CHANGE IN A SENSITIVE HIGH-ELEVATION REGION OF THE BOLIVIAN ANDES

By

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1.0 INTRODUCTION

Many regions of the developing world are experiencing profound and rapid change. Adoption of modern standards of living and farming systems in lieu of traditional practices is often accompanied by population growth, resulting in a change in both the type and extent of human activity on the land. The outcome is rapid landscape transformation and the subsequent degradation of water resources. Ideally, the management of the resulting environmental problems is guided by science; however, assessing the implications of landscape transformation in rapidly changing and remote regions of developing countries is difficult because limited field data are available and detailed field analyses are not practical. Therefore, expedient regional assessments must be designed to produce applicable, high-quality scientific data with limited resources so that important landscape dynamics in critical watersheds can be identified and targeted for management, conservation, and continued investigation. In addition, research must be designed and performed as a basis for future research assessing changes in ecological condition of the landscape and water resources.

Ecosystems of the high elevation (3000 – 5500 m above sea level) Central Andes region (Peru, Bolivia, Chile, and Argentina, Figure 1) of South America are extremely vulnerable to climatic factors and anthropogenic activities (Brush 1982). Historically, global climate change cycles have been shown to profoundly influence shifting vegetation zones and hydrologic regimes (Barry and Seimon 2000). In contrast to temperate mountain regions, the South American highlands have a long history of human occupation and landscape transformation driven by anthropogenic activity (Ellenberg 1979; Messerli *et al.* 1997). In recent years, population growth and infrastructure development have caused agricultural intensification and changes in traditional land use practices (Baied and Wheeler 1993; Hamilton and Bruijnzeel 1997; Grau and Brown 2000). Consequently, landscape transformation is occurring in multiple forms and at an accelerated rate. The combined impacts of global climate change and accelerated land use change on hydrologic regimes in this region are of great concern.

Figure 1. Shaded Relief Map of South America (Hearn et al. 2000) Showing Study Site Location.

The utility of remote sensing (RS) and Geographic Information System (GIS) data to explore relationships between terrestrial and aquatic processes has been clearly demonstrated. These are valuable tools for determining how catchment land use, geomorphology, and landscape pattern affect water quality and biotic integrity (Roth *et al.* 1996; Allan *et al.* 1997; Johnson *et al.* 1997; Wang *et al.* 1997; Wang and Yin 1997; Ballester *et al.* 2003). RS/GIS data provides information on current and past landscape patterns, which can be used in models to estimate future landscape dynamics and their affects on hydrologic regime (Allan *et al.* 1997; Miller *et al.* 2002). RS and GIS are especially useful tools in the study of remote regions where extensive field data collection is limited for economic and logistical reasons. For example, the RS/GIS approach has been used successfully in high altitude landscapes to identify watersheds most vulnerable to degradation in the Himalayans (Smadja 1992; Millette *et al.* 1995) and to investigate changes in vegetation zones due to global climate change in (Grace *et al.*2002) .

The study of land cover change using RS in Latin America has mostly occurred in flat, low-altitude, humid rainforest regions. RS has been used to study patterns and rates of deforestation, agricultural conversion, and urbanization with increasing accessibility into and colonization of these vast and previously uninhabited areas (Adams *et al.* 1995; Roberts *et al.* 1998; Ballester *et al.*2003; Lu *et al.* 2003; Roberts *et al.* 2003; Souza *et al.* 2003). In comparison, there are few examples of the use of RS in the mountainous Andean region of Latin America (Washington-Allen *et al.* 1998; Allan *et al.* 2002).

The current study area is in the Central, high-altitude Andes, a region that has been densely populated for thousands of years. The arid climate and mountainous terrain control the ways in which humans can use the land. Soils suitable for agricultural are limited to the flat, moist, fertile soils of the valleys. Forested areas are scarce, and limited to very steep slopes where cultivation or grazing is not possible. Low, seasonal rainfall and cold nighttime temperatures limit agricultural production and forest regeneration. Due to these environmental constraints and the present dense population, land available and appropriate for increased use and production are extremely limited, and potential for land cover conversion is very low. Yet, population and pressure on the land continues to grow, resulting in intensification of current land use along with land use conversion.

The primary objectives of this study are to: (1) identify rates and types of land use and land cover change (LULCC) in a rapidly changing, extremely sensitive region, (2) determine relationships between landscape change and environmental and anthropogenic factors, (3) develop a model that can estimate future change, and (4) determine regions of South America with environmental conditions similar to those of the study site and therefore subject to similar degradation pressures. A variety of geospatial data and methods are used to address these objectives. Shuttle Radar Topography Mission (SRTM) data and a Geographic Information

System (GIS) allow an assessment of the boundaries, topography, and demographic characteristics of the region. Recent and historical remote sensing data facilitate the determination of current environmental conditions as well as the nature and rate of vegetation and land cover change through the past two decades. The Clue-S model framework (Verburg *et al.* 2002) allows the testing of the hypothesized drivers of landscape change. Finally, a multivariate ecoregional analysis of South America will facilitate the identification of regions where environmental conditions are similar to those at the study site and to determine other watersheds where the model can appropriately be applied.

1.1 Environmental Conditions and Hydrologic Regime of the Central High Andes

The environmental conditions and ecosystems of the high elevation (3000-6000 meters a.s.l) cordillera (mountain range) and altiplano (high plateau) regions of the Central Andes are unique. The climate of the region is tropical and dry in that seasonal temperature differences are small and the low annual rainfall (300- 800 mm/yr) occurs almost exclusively during the 4-month rainy season (Seibert 1983). Large diel temperature fluctuations and intense solar radiation at the higher elevations combine with this dry, seasonal precipitation regime to create extremely harsh environmental conditions (Baied and Wheeler 1993). Vegetation has evolved according to this harsh climatic regime. The dominant ecosystem of the Central High Andes is the Puna, or the Highland Andean Grassland (Baied and Wheeler 1993). Vegetation type and distribution in the Puna is driven by elevation and localized wind-driven climatic patterns and include a diverse plant cover of grasses, dwarf shrubs, and peat bog vegetation in local wet areas and spiny shrubs and cactuses, deserts, and salt lakes in the arid regions (Seibert 1983). Vegetation zones below the Puna include the Elfin forest (Pre-puna), the Highland Andean forest, dominated by dwarf and evergreen forests and meadows.

Paleoclimatic and hydrologic studies in the Altiplano of the Central Andes have demonstrated the vulnerability of the hydrologic regime to climatic change (Baied and Wheeler 1993; Barry and Seimon 2000). Modern recharge of groundwater in the area is very limited, and current pools were formed during past humid periods (Messerli *et al.* 1997; Rundel and Palma 2000). Periodic climatic cycles, such as El Niño and the Southern Oscillation (ENSO), drive annual precipitation and river flow variation (Carril *et al.* 1997) and can trigger major flooding events (Depetris and Paolini 1991), which are often the impetus for ecological change and can be disastrous for humans (Hamilton and Bruijnzeel 1997).

The seasonal precipitation regime has a profound impact on stream hydrology and chemistry. Precipitation falls almost exclusively from December to March. Accordingly, large water flows and material fluxes occur during the rainy season, and the magnitude of this seasonal variability depends on basin geomorphology (Wurtsbaugh *et al.* 1985; Wasson *et al.* 1991; Guyot *et al.* 1992; Wasson *et al.* 1998). Basins can be divided into two general types: highly erodible sedimentary formations of the Altiplano and relatively resistant igneous and metamorphic formations of the Cordilleras. Guyot et al. (1992) compared two adjacent Bolivian highland basins of distinct geological origin but similar annual discharge and dissolved erosion rates. Total annual sediment erosion rates were much higher for the sedimentary Altiplano basin due to large sediment fluxes during the rainy season. These sediment fluxes act as a disturbance event to benthic communities of the sedimentary basin and are the primary drivers of benthic community dynamics. In granite basins, seasonal variability is less pronounced, and benthic communities are under biotic control (Wasson, Marin et al. 1998). Phosphorous (P) and nitrogen (N) dynamics are also driven by basin geology. Low N:P ratios of rivers can be linked to the high contribution of dissolved and particulate P from the volcanic and sedimentary formations compared to the relatively low amounts of biologically fixed N contributed by the sparsely vegetated grass and shrublands (Wurtsbaugh *et al.*1985; Carney *et al.*1993) .

1.2 Land Use Practices and Impacts on Watershed Dynamics

1.2.1 Traditional Practices as a Driver of Landscape Change

Throughout the region, traditional agricultural and grazing practices of the ancient Incan civilization still persist today in varying degrees (Ellenberg 1979; Baied and Wheeler 1993).

“Staggered” cropping systems maximize the productive potential of the different elevation zones, and terrace and irrigation systems maximize agricultural production on the steep slopes and with limited precipitation (Hamilton and Bruijnzeel 1997). Cultivation is traditionally performed by hand, causing minimal disturbance of existing vegetation of cultivated fields. In addition, the Incans domesticated the endemic llama and alpaca, specifically adapted to the fragile soils, harsh climate, steep slopes, and low-nutrient vegetation, and which provide wool, meat, dung and labor (Seibert 1983).

Landscape transformation at a regional scale resulted from these traditional agricultural and pastoral practices. Vast areas of grassland (traditionally believed to be the climax vegetation of the Altiplano) are now considered to have replaced natural dense forest (Ellenberg 1979; Laegaard 1992; Kessler 1995; Kok *et al.* 1995; Sarmiento and Frolich 2002). Kessler (1995) studied environmental conditions of distribution of the dominant high altitude forest species *Polylepis* throughout Bolivia and concluded that its distribution is only about 11% of its potential distribution.

1.2.2 Recent Land Use as a Driver of Landscape Change

Land use has changed since the Spanish Conquest (1500’s) and with increased modernization, infrastructure development, and population growth since the 1950’s (Ellenberg 1979; Hamilton and Bruijnzeel 1997). Widespread deleterious affects of changes in land use resulted from the introduction of European domestic animals (Baied and Wheeler 1993; Rundel and Palma 2000). Moreover, an increase in individual property and profit incentives have driven an increase in use of inappropriate, steep sloped lands, and a decrease in the maintenance and use of communal irrigation systems and terraces. These changes also drive a need to increase crop and pasture area, and consequently, the use of fire to clear forest and stimulate pasture growth (Ellenberg 1979).

1.2.3 Effects of Landscape Change

Landscape-scale transformation from forest or shrubland to grassland has profound implications for hydrologic regime at the catchment scale. Vegetation cover and land use are important determinants of infiltration and erosive processes of precipitation, and therefore of biological integrity and stream water quality (Roth *et al.* 1996; Allan *et al.* 1997; Johnson *et al.* 1997; Wang *et al.* 1997; Wang and Yin 1997). Mountain streams are particularly vulnerable to influences of catchment vegetation cover and land use change as highland streams are generally smaller and lower-order, and therefore relatively unable to buffer water flow and material flux variability (Flecker and Feifarek 1994; Monaghan *et al.* 2000). Canopy and litter of natural forests protect the soil from rainfall energy, its tree roots aerate and hold the soil in place, and the forest soils maintain high infiltration rates. With deforestation, total runoff and magnitude of peak flows increase (Likens *et al.* 1970). The decrease in soil water retention and water buffering capacity observed in a catchment in transition from forest to agriculture in the Ecuadorian Andes (Buytaert *et al.* 2002) has great implications for watersheds with steep slopes and thin soils subject to seasonal, episodic rainfall. Permanent replacement of forest vegetation with land uses such as grazing, agriculture, road construction, and human settlements severely compact the soil and reduce its vegetation cover. This results in a decrease in infiltration, evapotranspiration, and stream dry season baseflows, and an increase in overland flow, erosion, stream peak flow, and stream sediment loads (Hamilton and King 1983). Deforestation also drives changes in the physical structure of streams (Karwan *et al.* 2001), which in turn determines factors such as stream discharge, depth, and current velocity that are important factors in nutrient uptake, sediment movement, and biotic integrity (Peterson *et al.* 2001).

Although traditional land uses have caused gradual broad-scale deforestation, they cause relatively little erosion and degradation when compared to more modern practices (Ellenberg 1979; Seibert 1983; Sarmiento 2000). On soils with agricultural land cover, management strategies such as contour cropping and low intensity grazing practices can greatly reduce soil erosion and compaction rates (Seibert 1983; Brooks *et al.* 1991). Carney (1993) demonstrated the ability of traditional raised-bed agricultural fields to use nutrients, moderate seasonal nutrient load variability, and improve stream-water quality in the Lake Titicaca basin of Bolivia compared to stream reaches of the modern flat crop and pasture fields.

Road construction and mining in the region are recent agents of landscape change and watershed deterioration (Seibert 1983). For example, a 500-fold increase in suspended sediment and a 200-fold decrease in total invertebrate abundance was observed downstream of a road construction site in a small tributary of the Coroico River in the Bolivian Andes (Fossati *et al.* 2001).

1.3 Land Use and Land Cover Change Assessment

Remotely sensed (RS) data allows assessment of landscape characteristics at a spatial and temporal scale not possible using other techniques. It can be used to study remote regions where field data collection is prohibitively expensive, and for past time periods for which field data does not exist. RS data is commonly interpreted to classify the landscape into land cover classes, allowing a categorical and quantitative representation of the landscape. In this way, study regions can be compared with each other and with past conditions. The most common classification technique is to categorize an entire study area based on classification algorithms derived from training areas of distinct land uses identified in the field (Lillesand and Kiefer 1994).

A relatively new technique, spectral mixing analysis (SMA), has also been used to characterize landscape composition in regions where historical and contemporary land cover data are scarce. SMA is based on the premise that a landscape consists of a very few pure materials, called endmembers, e.g. water, bare soil, and green vegetation. SMA is used to assess each cell's spectral reflectance according to the type and proportion of each endmember in the pixel. Different land cover types differ in their relative proportion of each endmember leading to differences in spectral reflectance. Land cover classification has been performed based on SMA results, but did not include rigorous assessments of the classification accuracy (Adams *et al.*

1995; Roberts *et al.* 1998; Souza *et al.* 2003). Perhaps its greatest utility lies in its potential to identify differences within broad land cover types. For example, it has proven effective in the classification of successional forest stages (Lu *et al.* 2003), to identify spectral changes occurring with pasture age (Numata *et al.* 2003), and to detect vegetation cover and change in vegetation abundance in a semi-arid region of California (Elmore *et al.* 2000; Okin *et al.* 2001).

1.4 Land Use and Land Cover Change Modeling

Growing awareness of the impact of land cover change on terrestrial and aquatic systems has stimulated considerable interest in the development of LULCC models. LULCC models attempt to predict transitions between defined landscape states (Figure 2). The simplest models calculate transition probabilities from the proportion of change that actually occurred during a specified time interval (Baker 1989; Urban and Wallin 2002). More advanced models incorporate the influence of neighborhood functions and locational characteristics (Turner 1987; Wear *et al.* 1998; Jenerette and Wu 2001; Parker *et al.* 2002; Peterson 2002; Urban and Wallin 2002), socioeconomic factors (Wear and Bolstad 1998; Parker *et al.* 2002), and empirical relationships between land cover and driving factors (Hall *et al.* 1995; Wear and Bolstad 1998).

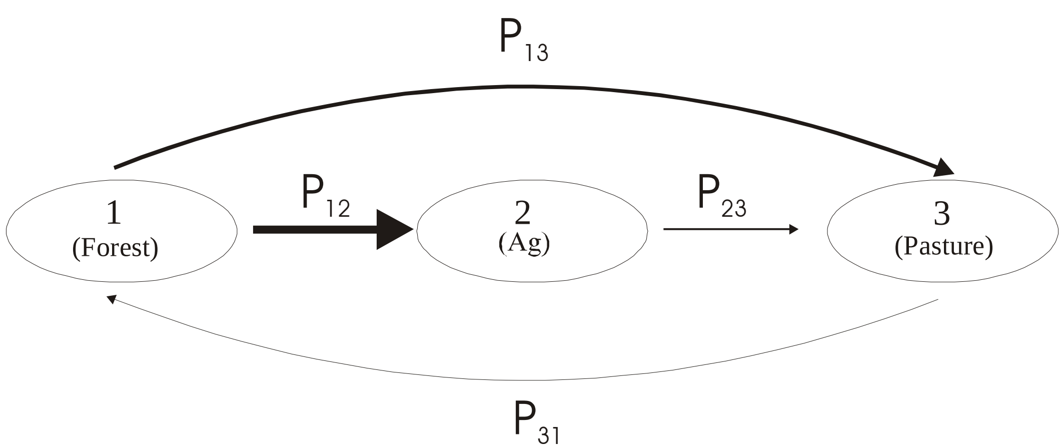


Figure 2. A hypothetical representation of transitions between forest, agriculture, and pasture. Arrows indicate probability (P) of transition between classes.

The CLUE-S modeling framework, used in this study, incorporates several factors shown to influence LULCC (Veldkamp and Fresco 1996; Veldkamp and Fresco 1996; Verburg *et al.* 1999;

Verburg and Chen 2000; Kok *et al.* 2001; Veldkamp and Lambin 2001; Verburg *et al.* 2002; Verburg *et al.* 2002; Verburg *et al.* 2002; Veldkamp and Verburg 2004). Logistic regression models are developed to determine the empirical relationships between landscape composition and environmental and demographic variables. The model then decides the land cover of a cell based on pixel characteristics, the logistic regression, land use conversion elasticity (resistance to change), and overall demand for each land cover. Since demand is determined at the regional scale, the model incorporates a multi-scale allocation approach.

1.5 Ecoregional Theory

Ecoregions are geographical zones where environmental factors combine to form similar ecosystem processes and, possibly, responses to anthropogenic disturbance. The development of the idea of ecosystems as formed by environmental conditions has had implications for biodiversity conservation activities and has been a powerful tool for environmental managers and ecological scientists. Ecoregional theory calls for a switch from species-based conservation to a focus on the persistence of landscape-level environmental processes (Delcourt and Delcourt 1998), and is also the basis in many attempts to predict vegetation and habitat shifts due to global climate change (Davis 1989). It also has been used to highlight regions that are most distinctive in their biodiversity features such as species endemism and species richness (Olson *et al.* 2001). The utility of ecoregional theory in the classification of aquatic systems is a field of current exploration and debate (Gerritsen *et al.* 2000; Hawkins *et al.*2000) .

Ecoregions have been identified using many different approaches, depending on the method and objective of the delineation. One general approach is the determination of regional boundaries based on detailed information about ecosystems at the site level. The most prominent example is the global ecoregional delineation of the World Wildlife Fund (WWF) (Dinerstein *et al.* 1995). It is an intensive and subjective method, in that the delineation is based on collaboration between regional biogeographers, taxonomists, conservation biologists, ecologists, and a diverse set of data sources, including existing habitat classification, vegetation and life zone maps. Similarly, Abell *et al.* (2000) delineated North America into freshwater aquatic ecoregions based on site-specific knowledge of species assemblages in freshwater aquatic environments. Omernik (1987) delineated the U.S. into ecoregions to provide a framework for classification and management of aquatic systems. He used pre-existing maps of land use, potential natural vegetation, land surface form, and soil taxonomy to draw ecoregional boundaries on a single map.

A second general approach to ecoregional delineation is based on environmental factors that contribute to and create variation among ecosystems. For example, Bailey (1983) divided the continental US into ecosystem units where the same kinds of vegetation and soil associations are expected. Approaches of the WWF and Bailey are hierarchical in that successively smaller ecosystems are defined within larger regions. In contrast, a non-hierarchical ecoregional classification addresses ecosystem variability through the clustering of principal environmental factors into similar regions based on the multivariate analyses (Bernert *et al.* 1997; Hargrove and Hoffman 1999). Units are not nested within larger regions, but are defined only by relative similarity.

The non-hierarchical clustering technique is non-subjective in that site-specific knowledge or pre-existing maps are not used, and results are based entirely on the environmental data. Whereas many ecoregional maps represent species biodiversity or actual vegetation cover, clustering approach determines similarity between landscape characteristics, and can be used to investigate various processes, dependent on the focus of interest. For example, clustering has also been performed in other types of landscape classification, such as determination of relative risk to forest fire (Omi *et al.* 1979) or a regional assessment of relative watershed degradation (Jones *et al.* 1997). In the current study, ecoregions were delineated based on topographic and climatic drivers of landscape composition to determine areas of South America with similar environmental characteristics, landscape processes, and response to disturbance and change.

1.6 Research Questions

The study site is a 5,367 km^2 area in southeastern Bolivia encompassing the Sama Mountain Range Biological Reserve (Sama). Sama is a protected area of the Bolivian government established to 1) conserve a representative area of the Puna biome, and 2) protect the headwaters of the Guadalquivir River, that provides water for the city of Tarija and other rural populations (Ayala Bluske 1998). The main threats to the landscape in the region have been identified as: 1) the advance of the agricultural and pastoral frontier caused by population growth and deterioration of existing cropland and pasture; 2) deterioration of the landscape due to unsustainable agricultural practices, overgrazing, and the presence of non-native grazing species; and 3) deforestation due to logging for firewood (Ayala Bluske 1998). To determine the rate, extent, and pattern of landscape transformation occurring in and around Sama due to these processes, my research addressed the following question:

What are the changes occurring on the landscape and their relationship with environmental and anthropogenic factors?

This overall question was investigated by asking the following component questions:

What was the distribution and proportion of land cover/land use in 1985?

What was the distribution and proportion of land cover/land use in 2003?

How was land cover/land use (in both 1985 and 2003) related to environmental and anthropogenic factors?

What was the rate and pattern of land use change between 1985 and 2003? Were rates and patterns of land use change consistent throughout the study area?

How does the rate and pattern of landscape change relate to specific environmental and anthropogenic factors?

Can the rate and pattern of landscape change be accurately quantified?

Can a model be developed that can accurately predict future landscape change in the two study watersheds and to estimate landscape change in other watersheds?

For what other watersheds can the model be used (where are environmental conditions similar)?

1.7 Hypotheses

I hypothesize that environmental and demographic factors combine to drive the pattern of land cover and landscape transformation in the study area.

- Elevation is a primary driver of landscape dynamics. It has been shown in other Andean regions that elevation determines potential vegetation zones which control human land use practices (Etter and van Wyngaarden 2000; Allan *et al.* 2002).
    - The direct effect of elevation will be tested by examining the relationships between LULCC and elevation.
- Slope and aspect influence potential vegetation and human land use, e.g., relatively flat land is more appropriate for agriculture than steep mountainsides.
    - Topographic effects will be tested by characterizing the relationships between LULCC and 1) slope and 2) aspect.
- Along with the constraints that high altitude creates for vegetation, moisture availability also restricts vegetation growth in the Central Andes (Baied and Wheeler 1993). Zones of relatively high moisture or close proximity to water bodies have a higher potential for vegetation and higher potential for use by humans as agricultural land. In addition, stream buffer zones may be more highly impacted by grazing disturbance because streams are an important water source for livestock.
    - Moisture availability will be tested by characterizing the relationships between LULCC and 1) measures of relative landscape moisture and 2) stream buffer zones of varying widths.

- Population density and accessibility influence landscape dynamics. Patterns of human settlement and transit have been shown to correlate with landscape transformation in Latin America (Allan *et al.* 1997) (Hall *et al.* 1995).
    - Anthropogenic effects will be tested by characterizing the relationships between LULCC and 1) population density and 2) proximity to major roads.

I hypothesize that the combined influences of these factors drive LULCC. Therefore, I will also examine the relationship between current land cover classes and hypothesized drivers of LULCC using logistic regression.

2.0 STUDY AREA

The study site is a 5,367 km^2 area in southeastern Bolivia encompassing the Sama Mountain Range Biological Reserve (Sama) (Figure 3). It is part of the Paraná/Plata River basin, the second largest drainage system in South America. Sama is a protected area of the Bolivian government established to 1) conserve a representative area of the Puna biome, and 2) protect the headwaters of the Guadalquivir River, that provides water for the city of Tarija and other rural populations (Ayala Bluske 1998). Sama is managed by the local non-governmental organization, PROMETA, with support from The Nature Conservancy (TNC). Sama encompasses a unique area of the Andean mountain range, the transition between the Eastern Cordillera and the Altiplano (high plain). The reserve encompasses 108,500 hectares, contains four distinct eco-regions, and is home to several floral and faunal species endemic to the unique combination of climate, altitude and geomorphology. In addition to biodiversity, the park region contains the headwaters for downstream rivers and has great importance as a hydrologic regulator for the region.

Within the reserve are 18 indigenous communities containing approximately 5,000 people that still employ traditional land use practices. The region surrounding the reserve has in recent years been experiencing dynamic change. The exploitation of natural gas reserves in Tarija has made the region more prosperous than much of Bolivia, resulting in an increase in immigration, infrastructure, and urban development. Landscape transformation is occurring in multiple forms, resulting in the degradation in both stream water quality and biotic integrity. This study was designed in conjunction with TNC and PROMETA to investigate landscape dynamics and hydrologic processes in the headwater catchments of Sama and the surrounding region which supply water for local communities and for Tarija, a city of 110,000 inhabitants.

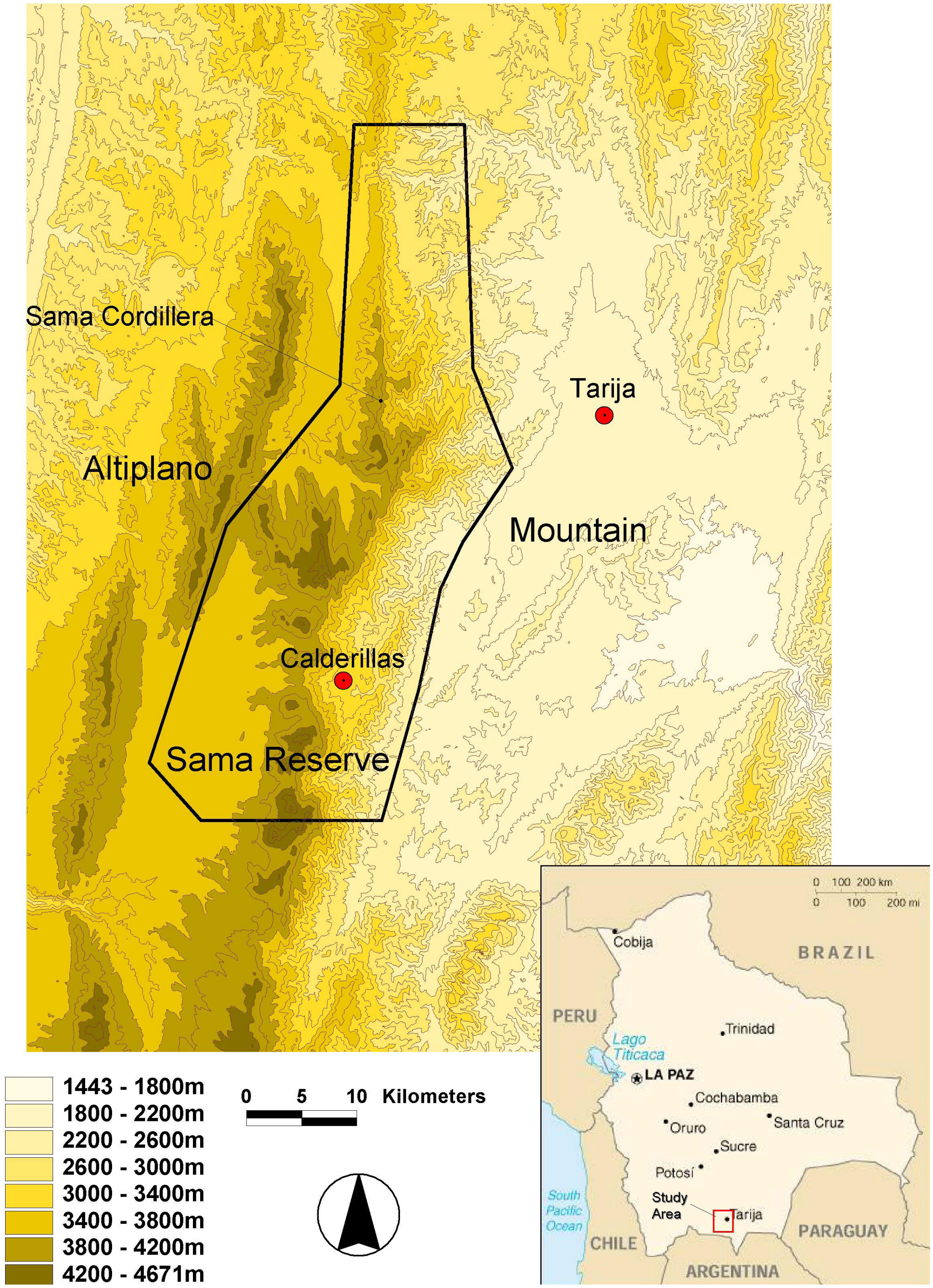


Figure 3. The Sama Reserve and elevation contours in the study area.

2.1 Physiographic Zones

The Sama reserve straddles the north-south trending Sama Cordillera, the highest mountain range in the region. It separates two physiographic zones of distinctly different climatic and topographic characteristics. To the east of the Sama Cordillera lie the steep mountains and narrow valleys of the eastern Andean Cordillera (hereafter referred to as the Mountain region). To the west is the semi-arid, high-altitude plain between the eastern and western Andean ranges (Altiplano), consisting mostly of flat and undulating plains between moderately sloping mountain ranges.

2.2 Climate and Topography

The study area has a seasonal precipitation regime with greater than 85% of the annual precipitation falling between November and March (Carpio *et al.* 2002). Temporal patterns in vegetation growth are controlled by this seasonal precipitation pattern, and all vegetation, except for irrigated agriculture, has limited growth during the dry season. At the onset of the rainy season vigorous growth of all vegetation ensues and continues throughout the wet period.

Elevations climb dramatically from 1400 m at the eastern edge of the study area to 4650 meters at peaks of the Sama Cordillera in the center of the study area (Figure 3, Table 1). The extreme orography drives considerable climatic differences within and between the two physiographic zones. Annual average rainfall in Tarija is low, averaging 500 mm/year (Carpio *et al.* 2002). Air systems move west and rise with the Sama range, and precipitation increases to 1318 mm/year in Calderillas (Figure 3). As the air rises to the top of the Sama mountain range, it is depleted of most of its moisture. West of the Sama range in the arid Altiplano, average annual precipitation ranges from 350-500mm. The Mountain region is at a lower elevation (2367m) than the Altiplano region (3619m), and has a temperate climate with an annual average temperature of 18ºC. The Altiplano has a cold, arid climate with an average annual temperature of 11ºC. Intense solar radiation during the day causes high maximum temperatures while nighttime temperatures commonly drop to below freezing.

Watersheds in the Mountain region drain into the Guadalquivir River and then south into Argentina and the Plata River. The Altiplano region contains two hydrologic systems, 1) Tajzara, an endorrheic region which forms a cluster of lakes, and 2) headwater catchments of the Pilcomayo River, which also drains eventually into the Plata River.

Table 1. Topographic and Climatic Characteristics of the Mountain and Altiplano Regions.

Region	Area (km2)	Elevation (m)			Slope (deg)			Precip. (mm)	Temp. (deg C)
		min	Max	mean	min	max	mean	Avg. Annual	Avg. Annual
Mountain	3357	1491	4623	2367	14	68	11	500-1300	18
Altiplano	1359	2535	4671	3619	11	58	9	350-500	11

2.3 Demography

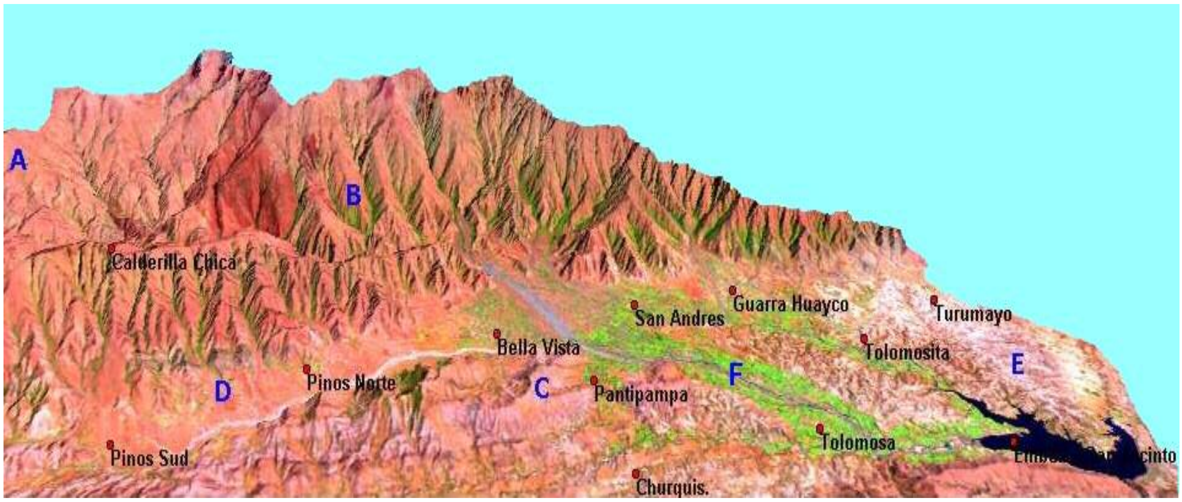
The environmental differences between the two physiographic zones drive differences in patterns of human settlement and activity (Ayala Bluske 1998). In the Altiplano region, arable land is extremely limited. The vast majority of the land is used as rangeland, and apportioned by long tradition to particular communities. The rights to forests and sand and rock deposits are also communally used. Each family has a plot of arable land that they can use in agreement with the rest of the community. The Altiplano is sparsely populated, and its inhabitants are extremely poor (gross income averages 380$US/year). The major economic activity is llama and sheep herding and subsistence agriculture. Seasonal migration to the lowlands during harvest times is common (72%).

Land use patterns and traditions in the Mountain region are considerably different, due to its higher amount of arable land. Agriculture, pasture, and forest plots are generally viewed as private property, although titles to land are not common. Mountain forests and rangelands are communal. The mountain region is more populated and less poor (529$US/year), with a lower rate of seasonal migration (42%), relative to the Altiplano region. Primary economic activities include agricultural production, and cow and sheep herding for crops, meat, leather, and milk for subsistence and for commercial sale.

2.4 Broad Land Use Patterns

The Altiplano landscape is less suited to human habitation than the mountain region. Rocky and shallow soils originating from colluvial sediments of the mountain ranges characterize most of the region. Aeolian soils are common, sometimes in the form of sand dunes, around the saline lakes. The infertile soils and the harsh climatic conditions drive the formation of a vast landscape of grassland, shrub, and cactus vegetation, which is used as communal rangeland. Due to the scarcity of water, there are no irrigation systems. Agricultural production is confined to narrow riparian zones and human habitation occurs in small communities adjacent to perennial watercourses. Forests are extremely rare.

The Mountain region is a more fertile and arable region relative to the Altiplano. Figure 4 shows the Central Tarija Valley portion of the Mountain region divided into several topographic and land use zones: 1) the deep and fertile alluvial floodplain terraces from currently existing watercourses (Zone F), 2) mountain foothills (Zone D), 3) plains made up of erodible fluvio-lacustrine deposits of ancient lakes (Zone E), and 4) steep, rocky, mountains and foothills dissected by narrow valleys (Zones A, B, and C).



Zone	***Topographic Unit***	***Primary Vegetation***	***Land Use***
A	medium mountains	Grassland, valley forest	Communal Rangeland
B	high mountains	Grassland, arbustives	Communal Rangeland
C	low hillsides	Shrubs, grassland	Communal Rangeland
D	foothill plains	Grassland, crops	Pasture, Agriculture
E	Fluvio-lacustrine plains	Churquial	Communal Rangeland
F	alluvial terraces	Crops, pasture, trees	Agric., Pasture, Forest, Homesteads

Figure 4. 3D Model of Landscape Units and Vegetation Types for the Central Tarija Valley of the Mountain Region (from Zonisig 2003)

Agriculture is intensively managed, and confined mostly to the alluvial terraces. However, with increasing development of irrigation systems and increased availability of chemical fertilizers, agricultural expansion is occurring into the foothills and the lacustrine plains. Small-plot, subsistence agriculture prevails, producing a mixed landscape of homesteads, crop fields, pastures, and forest plots. Rotation between crops and pasture from year-to-year is a commonly observed practice. Most of the urban land in the study area is concentrated in the valleys. Small towns, and to a lesser extent the city of Tarija, are also a patchwork landscape of houses, garden plots, neighborhood parks, forest patches, roads, and soccer fields.

The primary land cover in the fluvio-lacustrine plains is a dryland evergreen shrub vegetation commonly known as churquial. It is distinctive for its large spines, which prohibit its consumption by grazing animals. Its presence and density in relation to other vegetation is an indicator of degradation. In areas of low degradation, churquial is mixed with grasses and other shrub and forest vegetation. Severely degraded areas are stripped of all edible vegetation leaving only bare soil and dispersed churquial shrubs. Its ubiquity in the fluvial-lacustrine plains indicates that landscape degradation in the region is not only dependent upon the intensity of use, but also on the vulnerability of the particular landscape unit to degradation. Since these sediments are easily eroded with minimal disturbance, normal grazing pressure has caused a loss of topsoil and extremely eroded gullies and cliffs.

The humid and sparsely populated foothills and mountains support abundant grassland vegetation and are used as communal rangelands. Degraded areas, indicated by bare hillsides or churquial-dominated vegetation, were observed during fieldwork. Springs are abundant throughout the mountains and provide plentiful water for local communities and the city of Tarija. Dense shrub and forest persist in the narrow and steep mountain valleys where the land surface becomes inaccessible for livestock.

3.0 METHODS

3.1 Field Data Collection

Field data for geocorrection and image analysis were collected throughout the study area in January - March 2004. Easting, northing, altitude, and descriptive information were recorded for 35 ground control points (GCP's). To characterize vegetation cover and to test classification accuracies, 85 training points (TP's) and 64 field verification points (FVP's) were collected. TP's were selected in the field as representatives of the various land covers present in the study area. FVP's were randomly chosen prior to fieldwork, and subset to include only points within 2 km of a road. When possible, each point in this subset was visited in the field. However, due to private property boundaries, rugged terrain, and time constraints, many points could not visited. In these cases, the point was collected as close to the coordinates as possible.

In addition to easting, northing, and altitude, I recorded land use and land cover (LULC) observations and took photographs at each FVP and TP to aid in image processing and classification. LULC observations were recorded for an approximate 100 x 100m sampling area surrounding each GPS point. The size of the sampling area was determined by the equation

$$A = P(1+2E),$$

where A is the dimension of the sample area, P is the pixel size (30 meters for Landsat TM imagery) and E is the rectification error (rectification error < 15 m) plus the GPS error (< 15 meters) (Justice and Townshend 1981). When the 100m x 100m sample area consisted of more than one LULC type, a "fuzzy" classification technique was used in field data collection. I determined each land cover type present in the area, its proportion relative to entire sample area, and its ranked class assignment (Gopal and Woodcock 1994).

In addition to FVP's and TP's, incidental points (IP's) were collected as training data for image analysis and classification. IP's included a description of the land cover and its distance and direction from a GPS or reference point while driving or walking.

3.2 Image Selection

Comparison of a dry season (October 31, 1999) and rainy season (April 1, 1985 and April 29, 2003) Landsat (LS) images demonstrated the profound effect of seasonal precipitation on vegetation cycles. During the dry season, most vegetation is senesced, harvested, or extremely reduced due to drought and grazing pressure. Only coniferous tree species and irrigated agricultural plots reflect highly in the near-infrared during the dry season. However, during the rainy season, all vegetation types are vigorously growing and vegetation patterns are more readily detected. Therefore, two rainy season images, April 1, 1985 and April 29, 2003, were used for the LULCC analyses.

The 1985 image was collected with the Landsat-5 TM sensor, whereas the 2003 image was collected with an updated sensor (Landsat-7 ETM). Although the updated sensor was designed to collect spectral information comparable to that collected with the earlier sensor, transformations and spectral enhancements of the bands of different sensors can result in slight variations in representation of spectral information.

3.3 Image Normalization

Spectral normalization is necessary when directly comparing cell values of different images to account for differences in atmospheric conditions, sensor variation, or other factors. Normalization was performed by extracting cell values from both images of temporally invariant areas of extreme brightness and darkness to encompass the entire reflectance range (Collins and Woodcock 1996). A linear regression model was generated and applied to the 1985 image to calibrate it to the 2003 image. The calibrated 1985 image was used for the spectral mixing analysis because cell values from both images were directly compared. The original 1985 image was used for the land cover classification and change analysis because the land cover classifications were derived from each image separately and the cell values were not directly compared.

3.4 Topographic Correction

In areas with mountainous terrain, spectral information of Landsat (LS) bands is influenced by differences in solar illumination on the landscape, causing variable reflectance values for similar vegetation types depending on their topographic location. We attempted several methods of topographic correction to normalize the differences in shaded and illuminated slopes, including an empirical cosine I correction (Meyer *et al.* 1993), the SCS correction (Gu, D., Gillespie, A., 1998) and the C method (Riano et al 2003). The topographic heterogeneity between the two physiographic zones prevented a successful correction of the entire study area. No single topographic correction was effective for both the hilly grasslands of the Altiplano region and steep grass and forest slopes of the Mountain region.

Variability in surface illumination was addressed indirectly by choosing bands for classification that are minimally influenced by shade effects. In some spectral enhancements (e.g. tasseled cap transformation) shading effects were accentuated, whereas others were relatively unaffected. The Soil Adjusted Vegetation Index (SAVI; derived as {LS band 4 – LS band 3} * 1.5/{LS band 4 + LS band 3 + 0.5}) (Huete 1989) and the clay mineral index (derived as the ratio of LS bands 5 and 7) were especially effective at diminishing shade effects, and in these images shaded slopes had similar spectral information as illuminated slopes of the same LULC.

3.5 Geocorrection

The 2003 image was geocorrected using the GCP’s collected during fieldwork. Root mean square (RMS) error for the 2003 image was 5.7 meters (x = 4.0m and y = 4.0m) using 29 field GCP’s. Many field GCP’s were features that have appeared or moved since 1985, such as dirt road intersections, newly constructed asphalt roads, or impoundments. Therefore, the 1985 image was co-registered to the corrected 2003 image. RMS error was less than 1 pixel (21.4 meters) (y = 19.8m and y = 8.0m) using 18 GCP’s.

3.6 Digital Elevation Model

I used a 90m-resolution digital elevation model (DEM) derived by the US Geological Survey (USGS) from data collected in February 2000 on the Shuttle Radar Topography Mission (SRTM). Gaps in the satellite data caused by incomplete SRTM sensor coverage were filled with a DEM developed from 1:50,000 topographic maps of the study area. The 90m DEM was re-sampled to 30m-resolution for use with the 30m-resolution LS images using the nearest neighbor algorithm.

Derivative images of the DEM that demonstrate incident illumination from the sun were compared with the geo-referenced images for co-registration. I measured the offset between the DEM and the image at fifteen points throughout the study area. The DEM was shifted according to the average offset (x = -82.4m, y = 70.4m).

3.7 Cloud and Shadow Masks

Cloud and shadow masks for the 1985 and 2003 images were developed using the software Ecognition version 3.0 (Baatz *et al.* 2003). Ecognition is an object-based image analysis software that considers both spectral characteristics of individual pixels as well as their spectral and geometric context. The masks were applied prior to image processing techniques that are affected by extreme spectral values (e.g. principal components analysis).

3.8 Primary Classification of the 2003 image

Classification of the 2003 image was performed using the image processing software Erdas Imagine version 8.6 (Erdas 2002) using a 2-step methodology incorporating both supervised and unsupervised classification techniques. Supervised classification assigns image pixels to land cover classes based on training areas of known land cover identified in the field. All supervised classifications in this study used the maximum likelihood classification (MLC) parametric rule. During unsupervised classification, the user specifies only the number of classes, and image pixels are assigned to classes at first randamonly, then, iteratively based on their relative similarity using an Isodata algorithm (Tou and Gonzalez 1974). All unsupervised classifications in this study used a convergence threshold of 0.95 (i.e. class assignments are considered stable when greater than 95% of pixels stay in the same cluster between iterations).

Various spectral enhancements were effective in mitigating shade effects and emphasizing spectral information of landscape materials. For example, principal components analysis (PCA) reduces a multivariate dataset to a smaller number of synthetic variables, effectively minimizing noise and accentuating important information. The first step in the primary classification was a supervised classification using a stack of layers least affected by topographic shading effects. The 5 layer stack included 1) PCA of LS bands 1,2,3 (visible bands); 2) PCA of LS bands 5 and 7 (middle infrared bands); 3) Soil Adjusted Vegetation Index (SAVI); 4) clay mineral band, and 5) surface slope. Classes separable with this layer combination were 1) forest and shrub, 2) agriculture 3) abundant grassland in the Mountain and Altiplano regions, 4) sparse grassland in the Mountain and Altiplano regions, 5) bare lacustrine sediments of the Tarija Valley and sand dunes of the altiplano region, 6) urban areas, riverbeds, churquial, and cactus, and 7) water. In this classification, agriculture in the fertile river valleys was identified as one cover class, rather than separated into its actual composition of small plots of rotational crops, pasture, forest, and homesteads. The spectral information in this 5-layer stack was not sufficient to separate the heterogeneous land covers of the intensively managed agricultural regions.

To effectively characterize this mixed landscape, I subset the agricultural class from the initial classification. The agricultural regions of the study area are flat (0-2% slope), and therefore unaffected by illumination and shading effects prevalent in the mountains. I performed an unsupervised classification to divide the agriculture class into 50 classes using a stack of layers with high spectral information for vegetation cover types, including 1) LS band 4; 2) PCA of LS bands 1, 2, and 3; 3) PCA of LS bands 5 and 7, and 4-6) Tasseled Cap bands 1, 2, and 3 (which emphasize the soil, vegetation, and moisture properties of landscape materials, respectively) (Crist and Cicone 1984). Using training data, I manually labeled each of the 50 classes as crops, valley pasture, or forest. I then superimposed the new subset classification onto the original supervised classification.

The final classification consisted of 1) forest and shrub, 2) agricultural crops 3) valley grassland, 4) abundant mountain grassland, 5) sparse mountain grassland, 6) bare lacustrine sediments of the Tarija Valley and sand dunes of the altiplano region, 7) urban areas, riverbeds, churquial, and cactus, and 8) water.

3.9 Secondary Classification of the 2003 and 1985 Images

It was necessary to derive LULC maps with consistent classification schemes from both the 1985 and 2003 images to investigate recent changes in LULC that have occurred in the study area. Two factors prevented the use of the primary classification scheme and methodology for the 1985 image. First, I used transformations and spectral enhancements of the Landsat-7 ETM sensor bands in the 2003 primary classification that did not perform similarly for the 1985 image collected with the Landsat-5 TM sensor. The combination of bands effective in the 2003 image classification produced different landscape patterns in the 1985 image. For example, using the same 5-layer stack of the primary classification, large areas of the Altiplano rangelands classified as forest in 1985, for which there is no historical evidence. The second limitation of the 2-step methodology is its heavy reliance on detailed field data, especially in the agricultural regions. Intensively managed agricultural regions are easily discernible from the communal mountain rangelands in the image due to differences in geometric pattern, topographic location, and spectral reflectance. However, separation of crop fields, small forests, and intensive pasture plots in the flat, fertile valleys requires field data.

A supervised classification for both the 2003 and 1985 images was performed using a 7-layer stack that included the raw LS bands 1,2,3,4,5,7 and slope. The final secondary classification categorized the study area into 1) forest, 2) rotational agriculture and intensive pasture, 3) extensive pasture (open communal grazing), 4) barren, and 5) water. The secondary classification differs from the primary classification in three important ways: 1) it does not distinguish intensive pasture, small tree plots and borders, and cultivated plots in the flat valleys, 2) it lumps sparse and abundant mountain grassland into a single grassland class, and 3) it does not distinguish an urban/churquial/cactus class. However, the secondary classification scheme could be used for both the 1985 and 2003 images, allowing an assessment of land cover change over time.

3.10 Accuracy Assessment

Accuracy assessment for the 2003 primary classification included 109 field reference points. Accuracy assessment for the 2003 secondary classification included 112 field reference points. The classification points and the reference points were compared and quantitatively summarized into a confusion matrix and accuracy assessment report. Classification of the point was considered accurate if the class of the pixel matched the primary land cover class assigned to that point in the field. In the case that the pixel was not classified accurately, and had been assigned a fuzzy land cover classification in the field (i.e. the location could reasonably be labeled as more than one class), a fuzzy classification accuracy assessment was performed. The fuzzy accuracy assessment identifies the proportion of pixels mapped to the best possible class or an acceptable class compared to those that were classified entirely incorrectly.

Data to test the accuracy of the 1985 classification were not available. However, the assumption was made that many areas, such as sand dunes, lakes, roads, the airport runway, and valley forests, were unchanged in both years. Agricultural areas, valley forests, and rangeland have distinct geometric shape and spectral signatures and are easily discernible in the image. Site knowledge and close comparison of the image and the classification allowed an anecdotal accuracy assessment.

3.11 Land Use and Land Cover Change

Land use and land cover change (LULCC) analysis was performed by stacking the secondary classifications of the 1985 and 2003 images and comparing land cover class for each pixel. LULCC was summarized for the entire region, and for the Mountain and Altiplano regions separately. Cloud, cloud shadow, and deep shadow caused by topographic shading were masked from the analysis.

3.12 Drivers of Landscape Change

The relationships between seven environmental and demographic variables and land cover distribution in 2003, as well as and land cover change from 1985 and 2003, were examined. Hypothesized drivers of LULCC dynamics included elevation, slope, aspect, Topographic Convergence Index (TCI) (Beven and Kirkby 1979; Moore *et al.* 1991), distance from a non-ephemeral river, distance from a main road, and population density. Elevation, slope, TCI, and aspect were derived from the DEM. Continuous variables were categorized to allow graphical analysis and interpretation of the data. Elevation was divided into 200m altitudinal zones. Slope was divided into 9 classes of flat (0%), 0.1-2%, 2-5%, 5-8%, 8.1-13%, 13-20%, 20-30%, 30-40%, and >40%. TCI is calculated as $\ln(\alpha/\tan\beta)$, where α = upstream contributing area of a sampling site and β = local slope angle, as normalized by contour length. TCI variously represents relative wetness, drainage characteristics or water supply on a landscape and is often used to distinguish between convergent zones (e.g. lower slopes, coves) where intensive land use may disproportionately contribute to stream quality (Urban 2000; Sturtevant *et al.* in review). The TCI ranged between 20 and 230 and was classed into 20 classes of equal distribution (intervals of 10.5 units). Aspect was divided into 9 classes, with 0 corresponding to flat land, and 1 through 8 as north, northeast, east, southeast, south, southwest, west and northwest, respectively. One hundred meter intervals from roads and rivers were derived from 1:250,000 topographic maps. The population density dataset was derived from the 1992 national census and 1:250,000 topographic maps. Communities and their surrounding area (a 1km-diameter circle) were identified on the map, and assigned the population density reported in the 1992 census. Population densities were categorized into four zones: 1) low (areas greater than 0.5km from a community; 0-5 inhabitants/km^{2,}), 2) medium (5-10 inhabitants/km^2), 3) high (10-15 inhabitants/km^2), and 4) very high (>15 inhabitants/km^2) (ZONISIG 2001).

3.13 LULCC Simulation

The CLUE-S modeling framework, used in this study, incorporates several factors shown to influence LULCC (Veldkamp and Fresco 1996; Veldkamp and Fresco 1996; Verburg et al. 1999; Verburg and Chen 2000; Kok et al. 2001; Veldkamp and Lambin 2001; Verburg et al. 2002; Verburg et al. 2002; Verburg et al. 2002; Veldkamp and Verburg 2004). Logistic regression models are developed to determine the empirical relationships between landscape composition and environmental and demographic variables. The model then decides the land cover of a cell based on pixel characteristics, the logistic regression, land use conversion elasticity (resistance to change), and overall demand for each land cover.

3.13.1 Logistic Regression

The primary empirical component of the CLUE-S model is a statistical analysis relating actual land cover with drivers of landscape change. A binomial logistic regression was performed using a random subset of 2/3 of the classified 1985 image (n = 215,296). The presence or absence of each land cover type was regressed against the hypothesized drivers of landscape change. Results of the regression are then used to estimate the probability of a grid cell for the occurrence of each land cover type, as described by the equation:

$$P_{forest} = \alpha + \beta_1 * elevation + \beta_2 * slope + \beta_3 * TCI + \ldots \beta_n * n$$

Where P_{forest} is the probability of a grid cell for the occurrence of forest. To test the sensitivity of the model to different variables, logistic regression models were derived from 3 different data sets (Table 2): V Set 1) a 4-variable dataset consisting only topographic variables (slope, elevation, tci, and aspect), V Set 2) the 7 hypothesized drivers used in the analysis of LULC change, and V Set 3) a 13-variable data set that included additional coarse-resolution variables of geology, soils, accessibility, land unit, rainfall, and temperature.

Table 2. Variable sets used in the logistic regression analysis.

Variable Set	Variables
V Set 1	Elevation, Slope, TCI, Aspect
V Set 2	Elevation, Slope, TCI, Aspect, Distance from River Distance from Road, Population Density
V Set 3	Elevation, Slope, TCI, Aspect, Distance from River Distance from Road, Population Density Access to Market, Precipitation, Temperature, Geology, Soil Unit, Topographic Unit

3.13.2 Elasticity

Elasticity is a relative measure ranging from 0 to 1 that indicates a land cover class's resistance to change. For example, rotational agriculture has an elasticity of 0 because it can be removed at one place and allocated to another place in the same timestep. As values increase between 0 and 1, they represent an increasing resistance to change. A value of 1 indicates a land cover type that cannot disappear from one pixel to be allocated to another pixel in the same timestep because the its transition requires more than a single timestep. This is appropriate for land cover types that are difficult to convert, e.g., urban settlements and primary forests. Various elasticity sets were used in model simulation to determine the influence of model results to elasticity (Table 3).

Table 3. Elasticity sets used in the Clue-S Model

	Elasticity Value			
Elasticity Set	Forest	Ag	Pasture	Bare
E Set a	1.0	0.6	0.6	0.2
E Set b	0.9	0.2	0.2	0.9
E Set c	0.9	0.9	0.9	0.9

3.13.3 Demand

A non-spatial demand module specifies the amount of each land cover required on an annual basis. This number was derived by calculating the difference between the area of land in each land cover class in 2003 and in 1985. I assumed linear change, and divided the total change in demand that occurred from 1985 to 2003 by the number of years (18) to determine the annual demand for each land cover type.

3.13.4 Allocation

Clue-S uses a spatially explicit allocation procedure that incorporates the logistic regression results, regional demand, and elasticity (Figure 5). Probability maps are derived for each land cover type based on pixel characteristics and logistic regression results. The model then determines the future land cover of a cell based on its actual land cover, the relative probabilities for each land cover type, each land cover's elasticity, and the land use demand. Since demand is determined by the dynamics of the entire study area, the model incorporates a multi-scale allocation approach. Not only the characteristics of the pixel determine its land cover. Overall demand can overrule local suitability. For example, although a cell may have higher probability for agriculture than pasture based on its environmental characteristics, the region as a whole may have a greater demand for pasture.

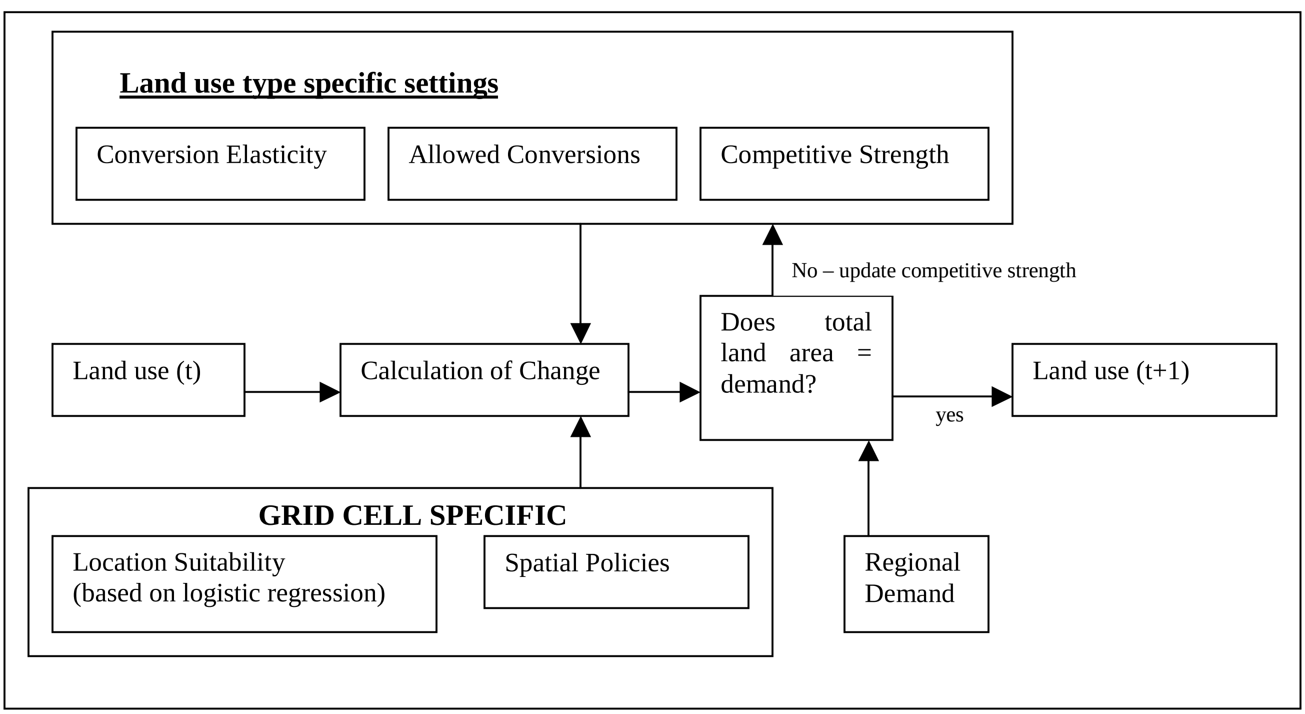


Figure 5. Allocation procedure of the CLUE-S framework (from Verburg et al. 2002)

3.13.5 Simulation and Validation

All datasets were resampled from their original format and resolution to grids of 1-hectare resolution using the nearest neighbor algorithm. Using the 1985 secondary classification as the initial landscape state, land cover was simulated on an annual basis for 18 timesteps to predict land cover in 2003. The model was run for the entire study area, and on the Mountain and Altiplano regions separately, to test the effects of spatial scale. Different combinations of variable and elasticity sets were used to examine the sensitivity of the model. Validation was performed by comparing the simulated land cover in 2003 with the 2003 secondary classification. Results of the comparison were quantitatively summarized in an error matrix and accuracy assessment report.

3.14 Spectral Mixing Analysis

Spectral mixing analysis (SMA), an image analysis technique that quantifies relative abundance of specific landscape components (called endmembers), was conducted to assess landscape change and degradation within land cover classes by determining changes in endmember abundance.

3.14.1 Endmember Selection

Endmembers were selected from the image using the pixel purity index (PPI) (RSI 2000), field data, and analysis of spectral signatures (a pixel's spectral reflectance in each image band). The PPI iteratively scans the principal components of Landsat bands to search for extreme, or pure, pixels. Once the purest pixels were identified using automated routines in the image processing software ENVI (RSI 2000), I determined from its location in the actual image and its spectral signature its representation on the landscape and suitability as an endmember. Target endmembers were: 1) green vegetation (GV), 2) non-photosynthetic vegetation (NPV), 3) bare soil, and 4) shade.

Upon selection of an endmember set, SMA is performed to determine the proportion of each endmember in each pixel. SMA produces a fraction image for each endmember and a band of root mean square (RMS) error values demonstrating the ability of the model to explain the composition of each pixel. Endmember selection is an iterative process, and SMA results are very sensitive to endmember selection. The ability of the endmember set to model the study area is determined by satisfying the following conditions: 1) patterns of fraction images coincide with actual field conditions; 2) endmember fractions for the landscape components of interest are between 0 and 1, indicating that the purest pixels were selected as endmembers; 3) endmember fractions for a pixel sum to one, indicating that the endmember set adequately characterizes the materials in the field; and 4) the error band shows low average RMS error (< 2 units of image brightness). Areas of high RMS error indicate materials that are not adequately modeled by the endmember set.

The final endmember set of green vegetation (GV), non-photosynthetic vegetation (NPV), bare soil, bare rock, and shade/water was extracted from the 2003 image. The GV endmember was taken from an agricultural field in the Tarija Valley. The NPV endmember was taken from a flat area of senesced grass near the runway of the Tarija airport. Due to the aridity and geomorphologic variability within the study area, it was necessary to include two bare ground endmembers to adequately model the images. The soil endmember, taken from a bare, eroded sedimentary cliff north of Tarija, represents the light and erodible lacustrine soils of the Tarija valley. The rock endmember, extracted from a bare ridge top, represents the darker igneous and metamorphic formations of the ridges. The shade/water endmember, although not a physical material, was necessary to account for illumination effects. It was taken from Laguna Tajzara, the deepest and clearest water body in the image, which reflected very little in all TM bandpasses.

The five fraction bands were imported into Imagine for change detection analysis. The bare rock and bare soil fractions were added together to form a single bare ground band. Not all image components can be effectively modeled with the simple endmember model used (e.g. clouds), and therefore some fraction values were greater than 1.0 or less than zero (Adams *et al.* 1995; Elmore *et al.* 2000; Souza *et al.* 2003). All bands were truncated so that any negative values were assigned to be zero and values greater than 1.0 were assigned to be 1.0. Then, all bands were normalized so that for each pixel, the sum of the GV, NPV, soil, and shade bands for each image date summed to 1.0. Following normalization, the shade fractions from both image dates were compared. An overall increase in shade fraction from 1985 to 2003 was evident, possibly due to differences in the sensor or atmospheric conditions on specific image dates. Therefore, shade was removed and the three other endmembers, GV, NPV, and soil, were renormalized to sum to one. Fraction bands from 1985 and 2003 were stacked to perform change detection in endmember fractions on a pixel-by-pixel basis.

3.14.2 Statistical Methods

Average endmember fraction for each land cover class was calculated to determine the coincidence of the land cover mapping with the spectral mixing analysis. For each endmember, I tested whether the average fraction varied according to land cover class using a non-parametric equivalent of a 1-way ANOVA. I then ranked the data and tested for pairwise significant differences among the land cover classes.

The mean and standard deviation were calculated for each fraction change image. Pixels with values between +1 and –1 standard deviation from the mean were considered to be areas of no change to account for potential error due to co-registration, according to the threshold level recommended by Singh (1989) and used by others (Washington-Allen *et al.* 1998; Elmore *et al.* 2000).

3.15 Ecoregional Analysis

3.15.1 Environmental Data

Environmental data available for the clustering analyses included temperature, precipitation, elevation, soil texture, soil depth, slope, and compound topographic index (CTI, a function of the upstream contributing area and the slope of a landscape). Elevation, slope, and CTI were obtained at 1 km resolution (USGS 2000), annual temperature and precipitation at 0.5

degree resolution (approximately 55 km) (Leemans and Cramer 1991) and soil texture, class, and depth data at 1 degree resolution (approximately 110 km) (FAO 1978).

All data were disassembled into cells by transforming them into GIS grids with a common projection [Universal Transverse Mercator (UTM)] and resolution (1 km). Original resolution of the terrain variables was 1 km. Soil texture was re-sampled from 1 degree to 1 km pixels. Excel and S-plus software were used to build a multiple regression model with the 0.5 degree precipitation/temperature data as the dependent variable and latitude, longitude, elevation, slope, and CTI as the independent variables. The regression model and the 1 km terrain data were then used to generate precipitation and temperature data in 1 km pixels. The regression model for temperature had an R^2 of 0.8223 (p-values significant for all independent variables). The regression model for precipitation had an R^2 of 0.4519 (p-values significant for all independent variables).

3.15.2 Multivariate Clustering Technique

The 1-km resolution UTM grids were stacked and the ARC/INFO Version 8.3 (ESRI 2002) commands ISOCLUSTER and MLCLASSIFY used to cluster similar pixels and produce a grid of the classified pixels (Tou and Gonzalez 1974). First, a value for each pixel in the multivariate data space is calculated. Next, kernels are placed randomly in the multivariate data space, and pixels are assigned to the closest kernel. When all pixels have been assigned, new kernel locations are calculated to be the mean of all pixels in its cluster. All pixels are then reassigned based on the new kernel locations. The process is reiterative, and continues until cluster assignments stabilize (i.e. until 95% of pixels remain in the same class between iterations). A grid of all pixels with their final cluster assignments is created.

3.15.3 Validation

Due to the scale of ecoregional analysis, and its use mostly as a descriptive tool, a rigorous, quantitative assessment of the ability of ecoregional delineation to accurately define regions of similar ecological processes is impossible. Ecoregional classifications can be evaluated through comparison with other ecoregional classifications (Bernert *et al.* 1997; Wright *et al.* 1998), independently derived vegetation maps (Host *et al.* 1996; Wright *et al.* 1998), or with actual data (Harding and Winterbourn 1997; Harding *et al.* 1997). For example, Omernik's (1987) delineation has been widely used by scientists and federal agencies, but the adequacy of this map to represent actual variation in stream ecology or vegetation cover measured in the field is inconclusive (Rohm *et al.* 1987; Wright *et al.* 1998; Jenerette *et al.* 2002). I validated my ecoregional delineation by qualitatively assessing the similarity between my map and the WWF delineation of South America (Dinerstein *et al.*1995).

4.0 RESULTS

4.1 Primary Classification of the 2003 image

Figure 6 presents the LULC map for the study area produced from the primary classification of the 2003 image. Comparison of the Mountain and Altiplano regions shows that their distinct topographic and environmental conditions drive differences in landscape pattern. The majority of the Mountain region consists of abundant mountain grassland (55%), but many areas have the climate and soils suitable for agricultural production and forest (Table 4). The floodplain valleys are a patchwork of intensively managed and individually owned agriculture, intensive pasture, forest and homestead plots. In the highly erodible lacustrine sediments around Tarija, sparse grassland, urban settlements and churquiales are common. Portions of this region are so degraded that they are completely bare. The fertile valleys and eroded formations are surrounded by rocky, steep mountain ranges. Mountain hillsides consist largely of communal rangelands of abundant grassland dissected by steep, densely forested headwater and ephemeral stream valleys.

Table 4. Results of primary classification of the 2003 image

Land Cover Class	Mountain	Altiplano
Unclassified	2%	1%
Forest	8%	0%
Crops	4%	1%
Valley grassland	5%	2%
Abundant mountain grassland	55%	12%
Sparse grassland	16%	74%
Urban/churquial/cactus	7%	5%
Bare	1%	4%
Water	0%	0%

The Altiplano region, with its harsh climatic conditions and poorly developed soils, consists mostly of sparse grassland (74%). In the low elevation areas and valleys where moisture accumulates, there is abundant grassland (12%). Those lands classifying in the urban/churquial/cactus class are almost entirely cactus and churquial, as the region is sparsely populated. The bare class (4%) consists of the sand dunes around the lakes. Cultivation (1%) and intensive pasture (2%) is limited to the narrow stream and river floodplains.

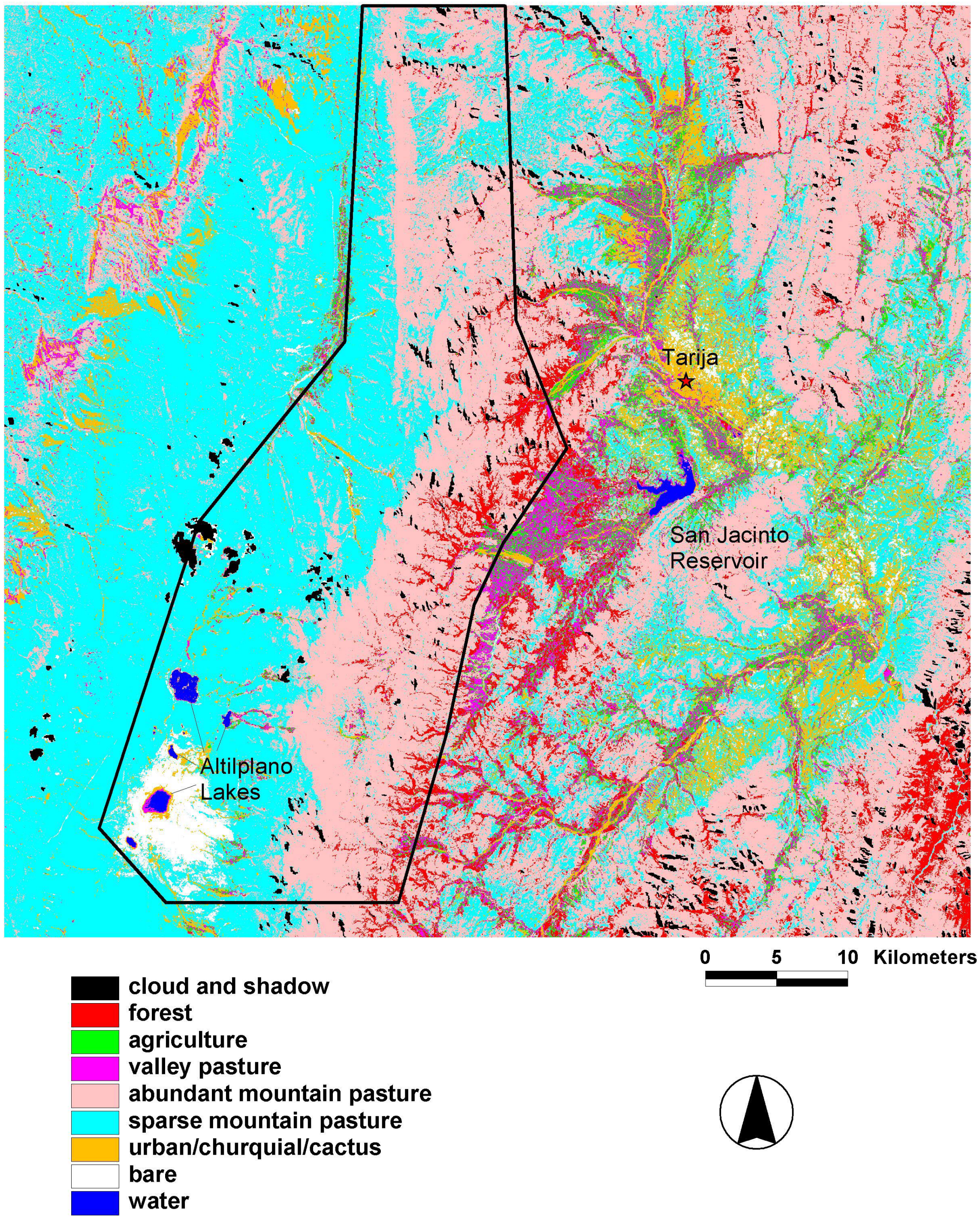


Figure 6. Primary LULC classification of the 2003 image.

Classification accuracy was 89%, with an overall Kappa statistic (KHAT) of 0.85 (Table 5). The fuzzy classification increased the overall accuracy to 95%, with a KHAT of 0.94 (Table 6). The fuzzy classification accuracy indicates whether a classification is reasonable, although not necessarily the best class assignment, for pixels of mixed land cover.

Table 5. Error matrix from comparison of the 2003 primary classification and reference data.

Classification Data	Actual LULC - Reference Data						
	F	A	VG	MG	UC	B	total
F	8	1	1				10
A		13			1		14
VG	3	1	14				18
MG	3	1		48			52
UC		1			12		13
B						2	2
total	14	17	15	48	13	2	109
Producer Accuracy	0.57	0.76	0.93	1.00	0.92	1.00	-
User Accuracy	0.80	0.93	0.78	0.92	0.92	1.00	-
Overall Accuracy	0.89						
KHAT	0.85						

Note: F = forest; A = agriculture; VG = valley grassland; MG = mountain grassland
U = urban/churquial/cactus; B = bare

Table 6. Error matrix from comparison of the 2003 primary fuzzy classification and reference data.

Classification Data	Actual LULC - Reference Data						
	F	A	VG	MG	UC	B	total
F	10						10
A		13			1		14
VG	1	1	16				18
MG		1		51			52
UC		1			12		13
B						2	2
total	11	16	16	51	13	2	109
Producer Accuracy	0.91	0.81	1.00	1.00	0.92	1.00	-
User Accuracy	1.00	0.93	0.89	0.98	0.92	1.00	-
Overall Accuracy	0.95						
KHAT	0.94						

4.2 Secondary Classification

The secondary classification scheme was used for both the 1985 and 2003 images, allowing an assessment of land cover change over time. Broad land cover patterns of the secondary classification were very similar to those of the primary classification (Table 7, Figure 7). The secondary classification differs from the primary classification in three important ways, 1) it does not distinguish intensive pasture, small tree plots and borders, and cultivated plots in the flat valleys, 2) it lumps sparse and abundant mountain grassland into a single pasture class, and 3) it does not distinguish an urban/churquial/cactus class.

Table 7. Results of secondary classification for 1985 and 2003.

	ENTIRE STUDY AREA		**MOUNTAIN**		**ALTIPLANO**	
Land Use Class	1985	2003	1985	2003	1985	2003
forest	7%	3%	9%	4%	0.1%	0.0%
ag	9%	11%	12%	16%	5%	3%
pasture	77%	75%	75%	71%	82%	84%
bare	7%	10%	5%	9%	11%	13%
water	0.4%	0.2%	0.0%	0.1%	1%	0.3%

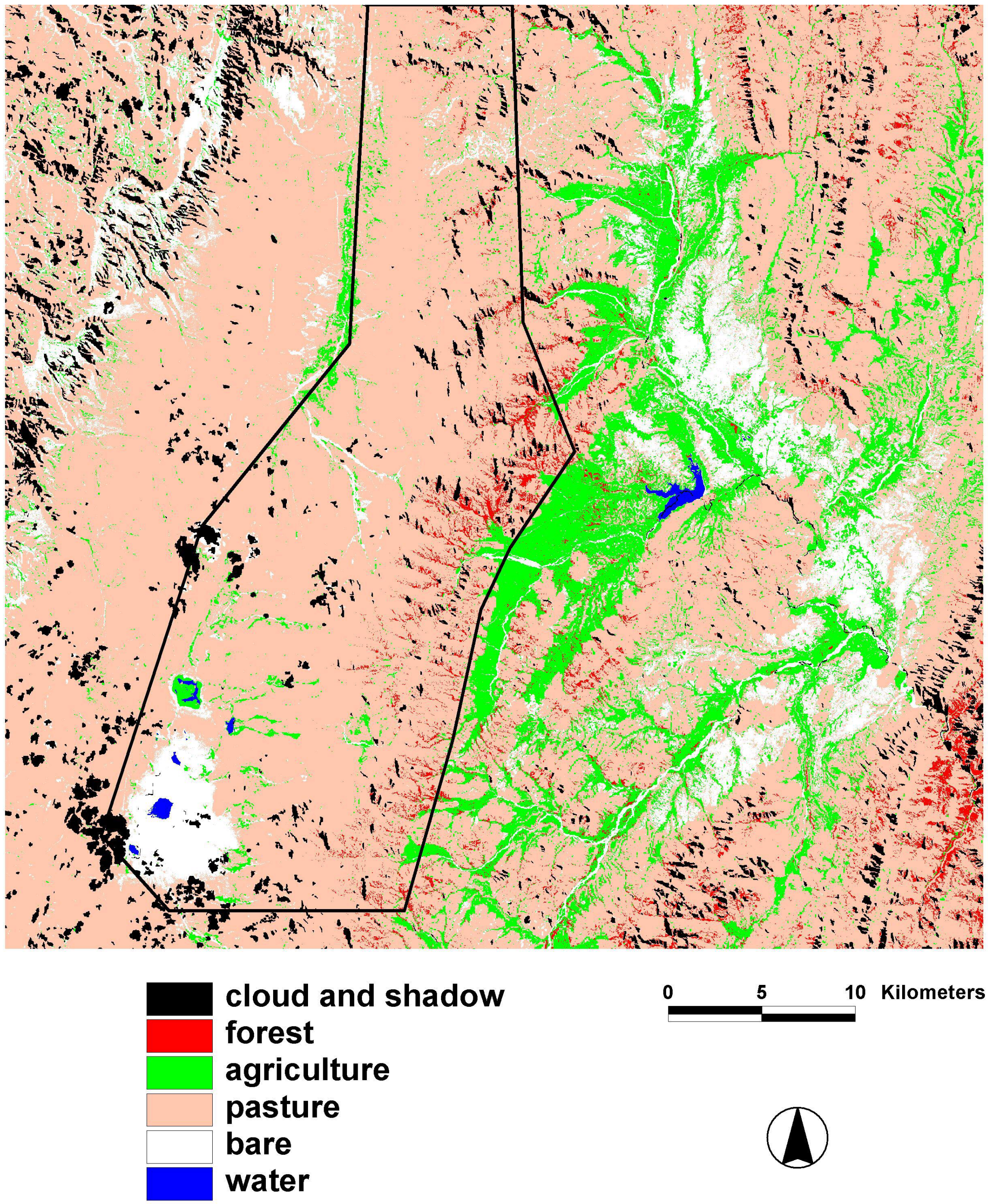


Figure 7. Secondary LULC classification of the 2003 image.

Overall classification accuracy of the secondary classification was 88%, with a Kappa statistic (KHAT) of 0.82 (Table 8). The fuzzy classification increased the overall accuracy to 93%, with a KHAT of 0.89 (Table 9).

Table 8. Error matrix from comparison of the secondary classification and reference data.

Classification Data	Actual LULC - Reference Data				
	F	A	P	B	total
F	6				6
A	7	37	1	1	46
P	2	2	41		45
B			1	14	15
total	15	39	43	15	112
Producer accuracy	0.40	0.95	0.95	0.93	-
User Accuracy	1.00	0.80	0.91	0.93	-
Overall	0.88				
KHAT	0.82				

Note: F = forest; A = agriculture; P = pasture; B = bare

Table 9. Error matrix resulting from comparison of the secondary fuzzy classification and reference data.

Classification Data	Actual LULC - Reference Data				
	F	A	P	B	total
F	6				6
A	4	40	1	1	46
P	1	1	43		45
B				15	15
total	11	41	44	16	112
Producer accuracy	0.55	0.98	0.98	0.94	-
User Accuracy	1.00	0.87	0.96	1.00	-
Overall	0.93				
KHAT	0.89				

Field data were not available to assess classification accuracy of the 1985 image (Figures 8 and 9). Historical information collected during fieldwork was considered along with close analysis of the image and allowed an anecdotal accuracy assessment. Overall landscape patterns of the distribution of mountain rangelands, floodplain agriculture, and valley forests of 1985 match those in 2003. Certain features have remained unchanged from 1985 to 2003, such as sand dunes, altiplano lakes, major roads, the airport runway, and the city of Tarija (Figure 8) and classified accordingly in both years. In addition, land cover changes characterized in the classified image matched patterns of known agricultural development and forest regeneration. For example, a known area of forest plantation and protection by the airport runway since 1985 was accurately represented by both classifications. Agricultural development, especially around and downstream of the San Jacinto reservoir constructed in the late 1980's, is also evident in the classifications (Figure 8).

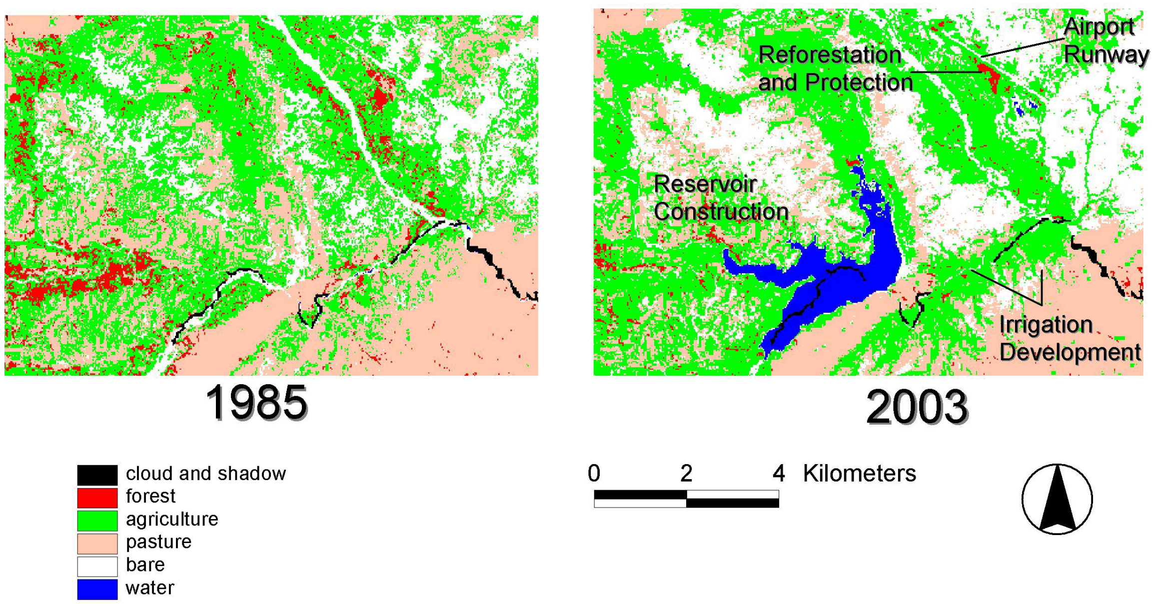


Figure 8. Qualitative accuracy assessment of the 1985 classification was performed by verifying known unchanged (airport runway) and changed (reforestation/protection, irrigation development, and reservoir construction) areas in both the 1985 and 2003 secondary classifications.

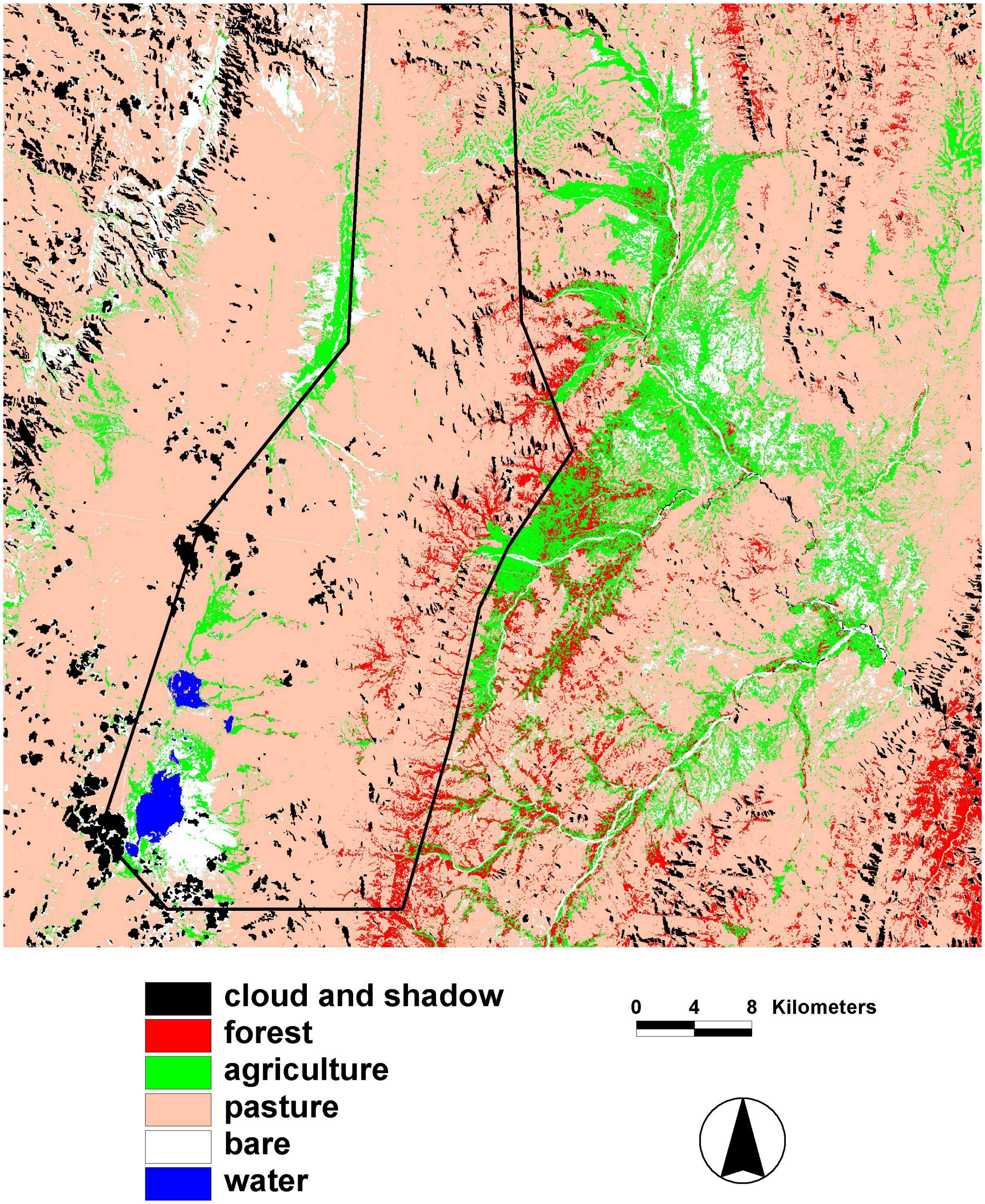


Figure 9. LULC classification of the 1985 image.

4.3 Land Use Change

The 1985 and 2003 classifications were used to quantify proportions of the study area that have experienced land cover conversion during this time period. Conversion classes that represented at least 1% of the entire study area, and their proportions for both the Mountain and Altiplano regions, are shown in Table 10. For both regions, the majority of the landscape in 2003 did not change from 1985. Only 14% of the Altiplano region has experienced land use conversion, compared to 23% of the mountain region.

Table 10. Land Use Conversions as a Proportion of the Mountain and Altiplano Regions.

Land Use	**LAND USE CONVERSION 1985 - 2003** Mountain	Altiplano
No Change	77%	86%
Pasture to Agriculture	5%	1%
Forest to Pasture	5%	<1%
Pasture to Bare	3%	3%
Agriculture to Bare	3%	2%
Forest to Agriculture	2%	<1%
Pasture to Forest	2%	<1%
Agriculture to Pasture	1%	2%
Bare to Agriculture	1%	<1%
Bare to Pasture	1%	3%
Water to Bare	<1%	1%

Table 11 presents net changes in land use as a proportion of each region and as a proportion of 1985 composition. Net land use conversion as a proportion of the entire region is higher in the Mountain region compared to the Altiplano. The Mountain region has experienced a 4.8% decrease in forest, a 4.4% increase in bare land, and a 4.1% increase in agricultural land. Compared to the land cover in 1985, forest has decreased by more than half, and bare ground has almost doubled. Net changes in land cover for the Altiplano include a 2% loss in agricultural land, a 2% gain in bare land, and a 1% gain in pasture land. Although small as a percentage of the entire Altiplano region, the rate of change as a proportion of the region in 1985 is very high. For example, the reduction in forest was almost 100%. The shrinkage of the Altiplano lakes accounts for the 80% reduction in water. The increase in water in the Mountain region (992%) is a result of the construction of the San Jacinto reservoir.

Table 11. Net Changes in Land cover as a Proportion of the Entire Region and as a Proportion of Land Cover in 1985 of the Mountain and Altiplano Regions

Land Cover Class	Percent of Region 1985	2003	Change Over Time as proportion of region	Change over time as proportion in 1985
MOUNTAIN				
forest	9.1%	4.4%	-4.8%	-52%
ag	12%	16%	4.1%	35%
pasture	75%	71%	-3.9%	-5%
bare	4.6%	9.1%	4.4%	96%
water	0.01%	0.14%	0.1%	992%
ALTIPLANO				
forest	0.09%	0.01%	-0.1%	-90%
ag	5.4%	3.4%	-2.0%	-38%
pasture	82%	84%	1.2%	1%
bare	11%	13%	2.0%	19%
water	1.4%	0.28%	-1.1%	-80%

4.4 Drivers of Land Cover Change

I performed the analysis of the hypothesized drivers of LULCC on the Mountain region only because of 1) high rates of observed recent land cover change and 2) high potential for future change. Figures 10 through 12 are highly simplified and provide descriptive information on the relationship between LULCC and each hypothesized driver. Continuous variables were classed in order to examine broad trends in the data. Figure 10 demonstrates current land cover as a function of the driving variables, and figures 11 and 12 show land cover conversion as a function of driving variables. Consistently, the largest conversion class was land that had not undergone conversion (NC = No Change). The range of the y-axis of figure 11 is 0 to 100%, and demonstrates the relationship between NC and the drivers. Figure 12 reduces the range of the y-axis, omitting the NC class and highlighting the other conversion classes.

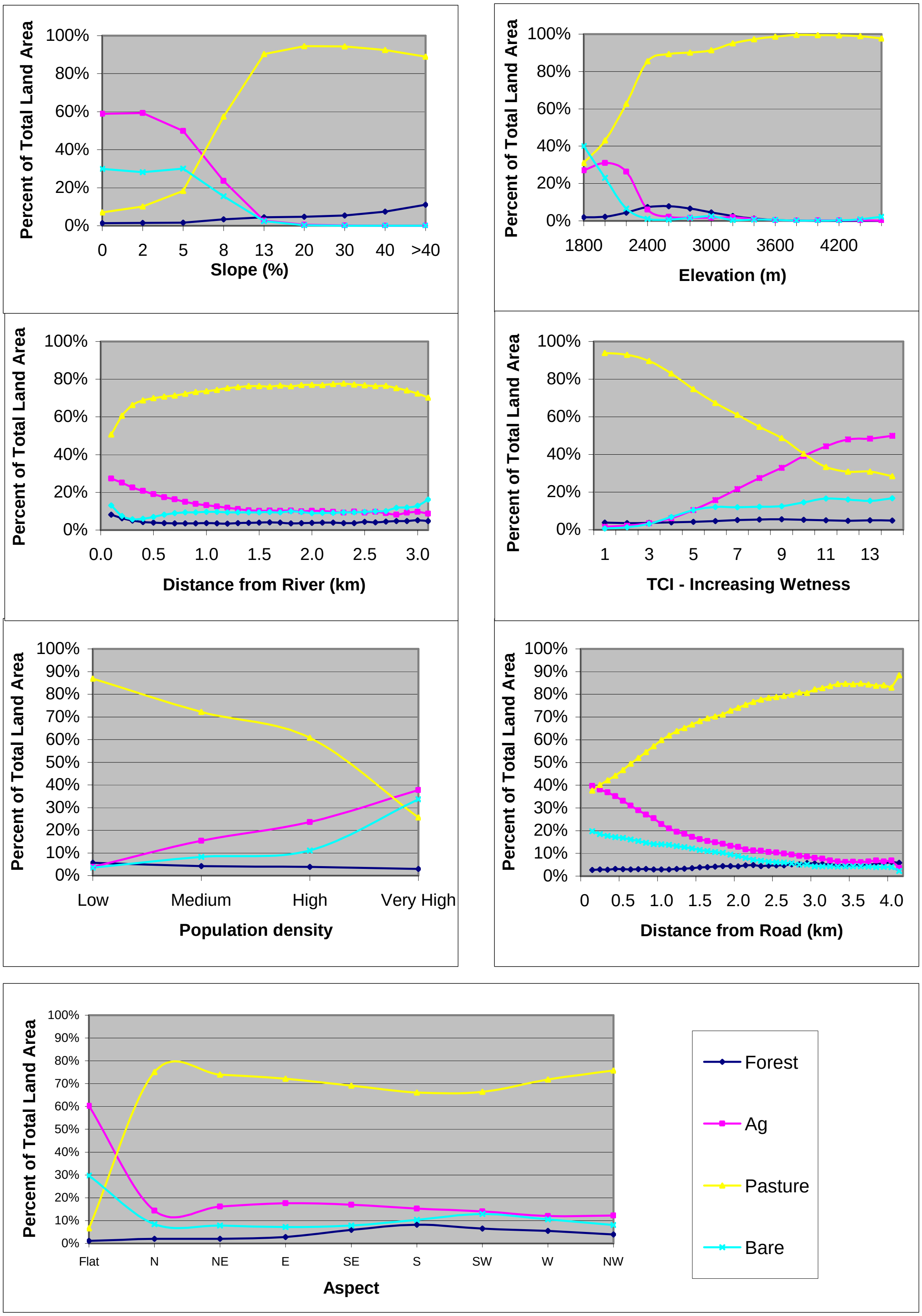


Figure 10. Percent of total land area for each land cover class as a function of topographic and demographic drivers of landscape change.

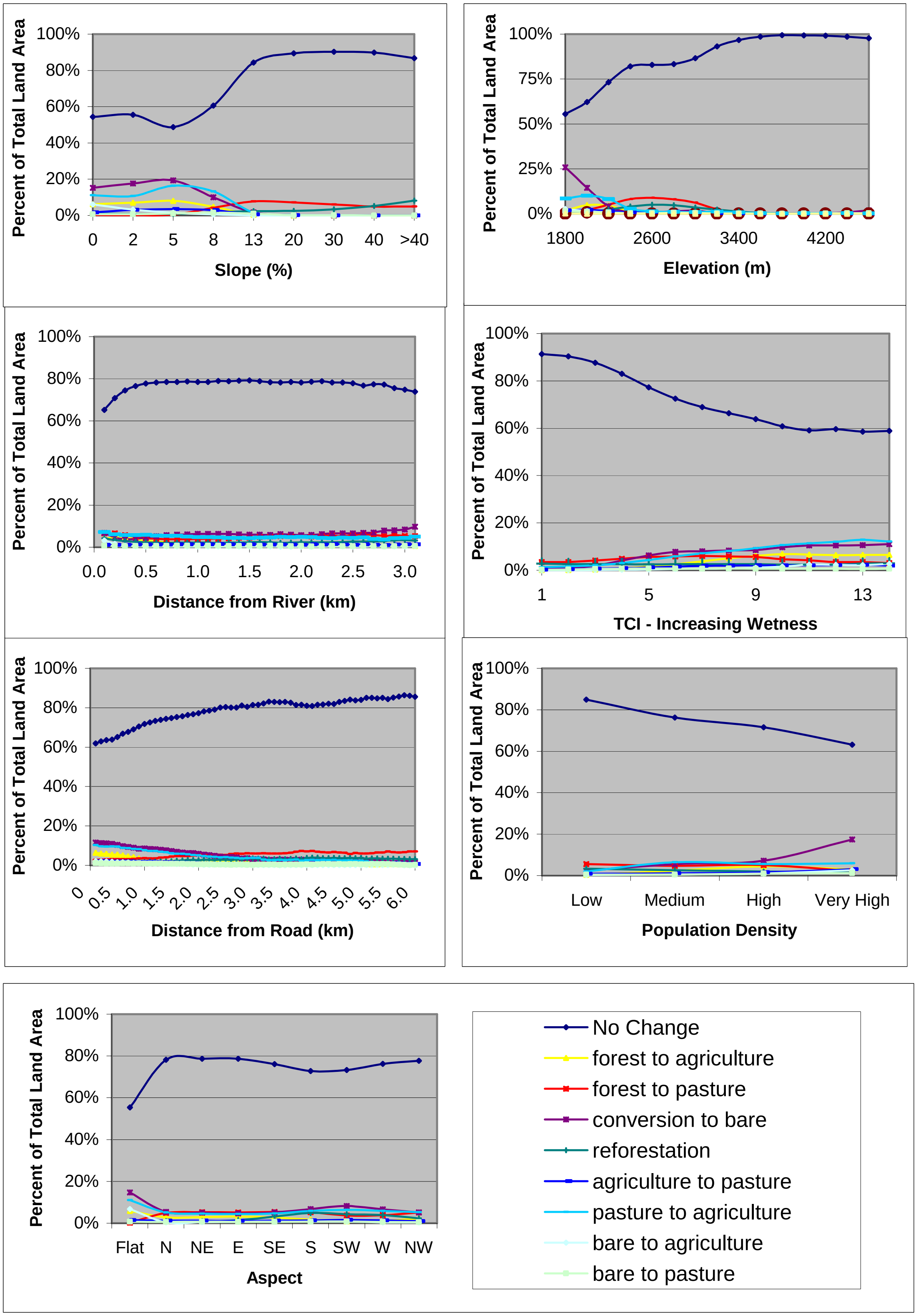


Figure 11. Percent of total land area for each conversion class as a function of topographic and demographic drivers of landscape change.

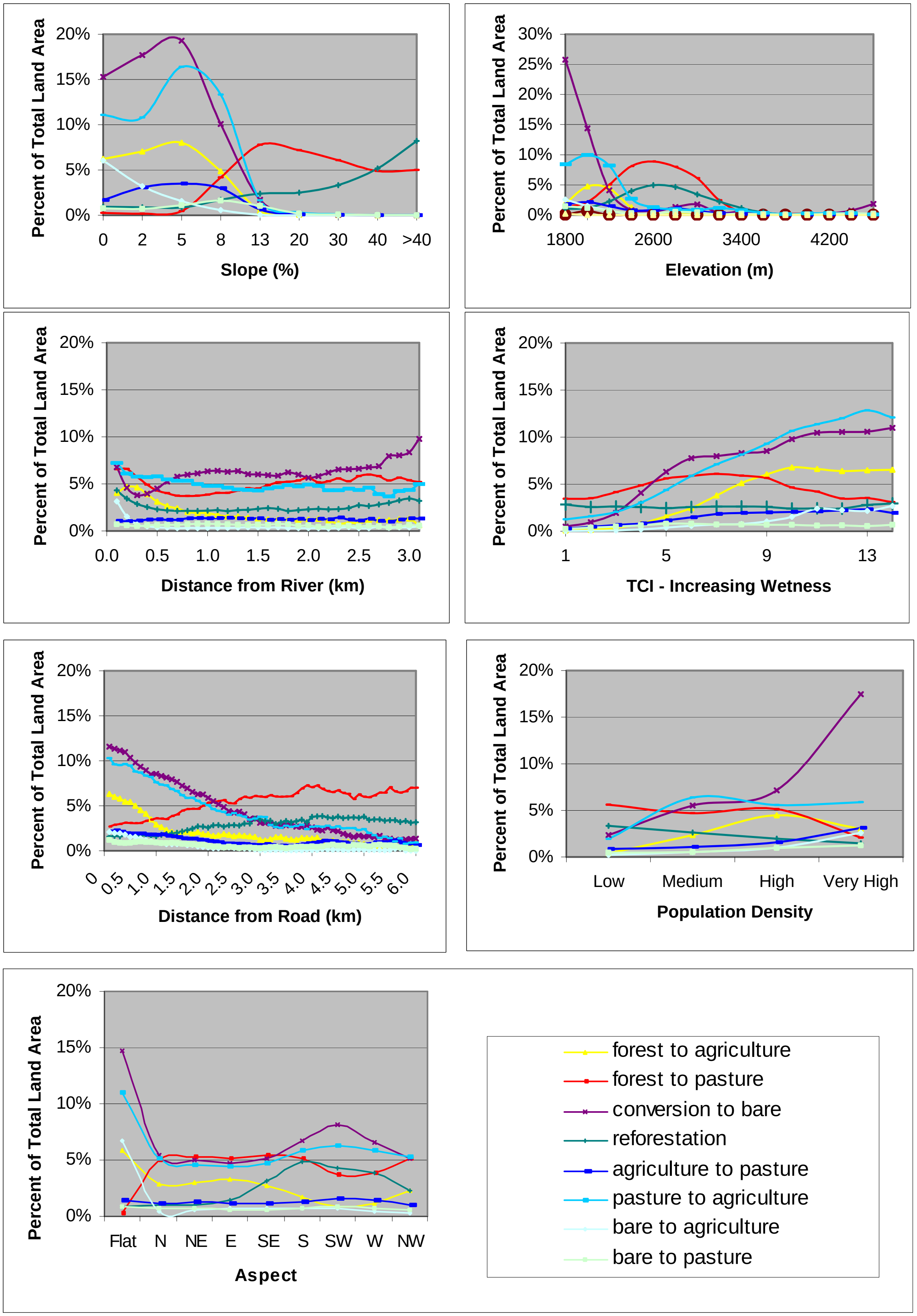


Figure 12. Percent of total land area for each conversion class (excluding No Change) as a function of topographic and demographic drivers of landscape change.

4.4.1 LULCC as a function of elevation

The proportion of the landscape in each cover class changes according to elevation (Figure 10). Bare land, pasture, and agriculture are equally distributed on the landscape at the lowest elevations (< 2000 meters). Above 2000m, pasture increases dramatically, and agriculture and bare land decrease to less than 5% of the landscape above 2600m. Above 2400m, pasture is ubiquitous (> 85% of total landscape). Forest proportions peak at 2200 to 3000m.

Patterns of observed land cover change also show similar trends and elevation thresholds (Figures 11 and 12). The NC class increases with elevation at especially high rates in the 1800m to 2400m elevation zone. Between 2400 and 2800m, and above 3200m conversion rates are low. Above 3200, less than 5 percent of the landscape is experiencing change.

4.4.2 LULCC as a function of Slope

The proportion of the landscape in each cover class changes according to slope (Figure 10). Pasture and forest are positively related to slope, whereas agriculture and bare land decline on steeper slopes. Agriculture and bare ground are the dominant land covers on the flatter slopes (0%, 0-2%, and 2-5% slope classes), but then decline abruptly on land with greater than 5% slope. Cultivated and bare land is virtually non-existent on lands with a slope greater than 13%. The decreases in agricultural and bare land are complemented by an abrupt increase in pasture for slopes greater than 5%. By 13% slope, pasture covers greater than 90% of all land. Pasture reaches its highest proportion at 95% of the total landscape in the 13-20% slope class, and then decreases slightly for the steepest slopes. The proportion of forest land increases steadily from very low proportions on the flattest lands to greater than ten percent of the landscape on the steepest slopes.

Steep land is less vulnerable to land cover conversion than flat and moderate slopes (Figures 11 and 12). Approximately 50% of land with 0 to 8 percent slopes experienced a change in land cover, with the highest rate of change (55%) occurring in the 2-5% slope class. The rate of land cover conversion decreases dramatically in the 5-8% slope class, and levels off at slopes greater than 13%. The most prominent conversions occurring at the lower slopes are conversion to bare ground, pasture to agriculture, and forest to agriculture (Figure 12). All three peak in the 2-5% class and then decline to very low rates of change. The conversion of forest to pasture was low in the lower slopes, but peaks in the 8-13% slope class where agricultural production is unsuitable.

4.4.3 LULCC as a function of aspect

There are clear differences in the patterns of LULCC between sloped lands and those with no measurable aspect (flat land). On flat lands, agriculture (60%) and bare (30%) dominate, but decrease considerably on inclined surfaces (Figure 10). Flat land has a much higher rate of land cover conversion than steeper areas (Figure 11). On sloped land, the relationship between aspect and LULCC is not clear, but it appears that aspect is influencing landscape dynamics. For example, forest is greatest on the SE, S, and SW facing slopes, whereas agriculture is highest on the NE, E, and SE slopes (Figure 12).

4.4.4 LULCC as a function of proximity to major rivers

Land cover patterns are dynamic in the approximately 1km river buffer zone, and relatively stable further than 1km away from a river (Figure 10). Forest and agriculture decline and pasture increases moving further away from perennial surface water sources (Table 12). Agriculture is most prevalent closest to the rivers, indicating the use of rivers for irrigation. Bare ground is at its highest proportion in the 100m buffer zone, due to the wide, rocky river channels created by high flows in the rainy season.

Table 12. Land cover distribution in successive riparian buffer zones.

Buffer Zone	Forest	Ag	Pasture	Bare	Water
0 - 100m	8%	27%	51%	13%	1%
100m - 500m	5%	22%	66%	7%	0%
500m - 1km	4%	15%	72%	9%	0%
>1km	4%	10%	76%	10%	0%

Land cover conversion was not highly sensitive to distance from a major river, although it appeared most dynamic within a 500m-buffer zone (Figures 11 and 12). Land experiencing conversion is at the highest rate of 55% changed in the 0-100m buffer, probably due to shifting river channels. Steady decrease in land conversion occurs from 0 to 500 meters from rivers, where it levels out. In the 0-500m buffer region the dominant conversions are pasture to agriculture, forest to pasture, forest to agriculture, and conversion to bare, indicating a heavy conversion to agriculture and deforestation close to an irrigation source.

4.4.5 LULCC as a function of TCI wetness index

Agriculture, pasture, and bare land covers are influenced by the relative wetness of the landscape (Figures 10, 11, and 12). Agriculture and bare land covers increase, and pasture decreases, steadily with increasing TCI. Forest does not change with changes in TCI (Figure 10). The percentage of land experiencing conversion increases steadily with increasing wetness. The most dominant conversions occurring in the wetter regions (classes 10-15) are conversion of pasture and forest to agriculture, and conversion to bare.

4.4.6 LULCC as a function of proximity to major roads

The distance of a land unit from a major road represents its accessibility. There is a strong relationship between road access and land cover. Pasture increases with distance from roads, while forest, agriculture, and bare land decreases as accessibility decreases (Figure 10).

Road access also drives land cover conversion, especially urbanization, agricultural conversion, and desertification. Overall land cover change decreases as distance from a major road increases (Figure 11). Conversion to bare, conversion of pasture to agriculture, and the conversion of forest to agriculture declines, while the conversion of forest to pasture increases (Figure 12). Further than 2 km from a road, the conversion of forest to pasture, probably in the steep valleys where cultivation is inappropriate, is the most prominent LULCC process.

4.4.7 LULCC as a function of population density

Population density influences land cover and land cover conversion. Agriculture and bare ground increase while pasture decreases with higher population densities. There is an apparent threshold between High and Very High population density where the proportion of bare ground increases dramatically. Land cover conversion increases steadily with increasing population density. In the most densely populated areas, conversion to bare and conversion of pasture to agriculture are the dominant processes. In the less populated regions, conversion of pasture to agriculture, conversion to bare, and conversion of forest to pasture are the most common changes.

4.5 Model Simulation

The primary empirical component of the CLUE-S model is the logistic regression relating actual land cover with potential drivers of landscape change. Slopes, intercepts, and R^2 values from the logistic regression are shown in Table 13. Low R^2 values, especially for the forest and bare classes, indicate that the variables included in the model account for a limited amount of the variability observed on the landscape.

Using the 1985 classification as the starting landscape condition, land cover change was simulated on an annual timestep for 18 years using several different scenarios. First, LULCC for the entire study area, including both the Altiplano and Mountain regions, was simulated. Overall accuracy from modeling the entire study area was 73% (Table 14). Comparison of the model simulation and the 2003 image classification showed that the simulation misallocated the bare ground in the Mountain Region (mostly a product of urbanization and pasture degradation in the fluvial plains) to the Altiplano region. Subsequent simulations were run on the separate regions. Separation of the two regions improved the accuracy of the simulation for the mountain region (Figures 13 and 14). However, the model was unable to simulate land cover change in the Altiplano region because the rate of change in the region is very low.

Table 13. Results of the logistic regression of spatial distribution of land cover (n = 215296).

Driver	Forest	Agriculture	Pasture	Bare
Constant	-1.32267	-1.01858	0.055	1.51
	Beta			
Aspect	-0.00038	-0.00051	0.00087	0.00044
Population density	0.02081	0.26404	-0.3841	0.2506
Distance from road	0.00010	-0.00007	-0.00002	-0.00002
Distance from river	-0.00021	0.00001	0.00016	0.00014
Elevation	-0.00087	0.00062	0.00077	-0.00159
Slope	0.02099	-0.51547	0.08964	-0.2441
TCI	0.00887	0.00073	-0.012	-0.00458
R-Square	0.02	0.26	0.23	0.08
Percent Concordant	61.8	92.3	82.0	86.2

Table 14 shows the differences in model performance with various elasticity and variable sets. Comparison of the entire study region simulation with the Mountain region simulation using the same variable and elasticity set shows that overall accuracy increased to 76% with the separation of regions, with the largest improvement in the prediction of the bare ground class (40% accuracy versus 29%). Agriculture and pasture were also predicted more accurately, but accuracy for forest composition decreased. As demonstrated in the LULCC analysis, pasture is by far the largest class, and therefore, overall accuracy and KHAT values are particularly influenced by the ability of the model to simulate the pasture class.

Table 14. Model verification using different drivers and elasticity factors (best simulation in bold).

Simulation	KHAT	Overall	Forest	Ag	Pasture	Bare
Entire study area, V Set 3, E Set a	0.33	0.73	0.26	0.49	0.84	0.29
Mountain Region Only:						
V Set 1, E Set a	0.46	0.75	0.16	0.56	0.88	0.37
V Set 2, E Set a	0.47	0.75	0.16	0.56	0.88	0.37
V Set 2, E Set b	***0.48***	***0.76***	***0.17***	***0.58***	***0.88***	***0.45***
V Set 2, E Set c	0.43	0.74	0.20	0.54	0.86	0.36
V Set 3, E Set a	0.47	0.76	0.17	0.57	0.88	0.40
V Set 3, E Set b	0.47	0.76	0.17	0.58	0.87	0.43
1985 Land Cover Classification	0.47	0.77	0.41	0.47	0.90	0.37

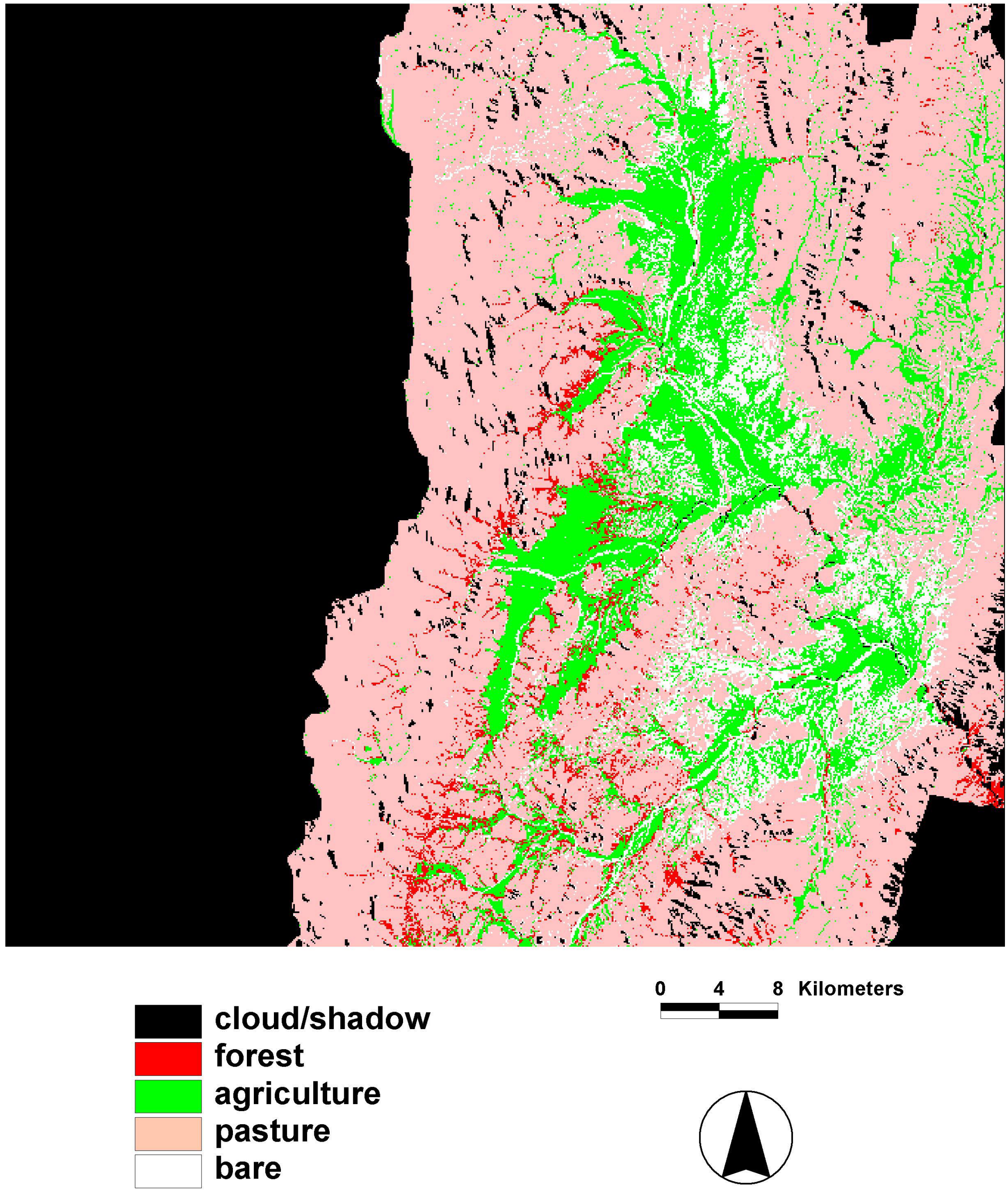


Figure 13. Results of simulation of land cover in 2003 in the Mountain region only.

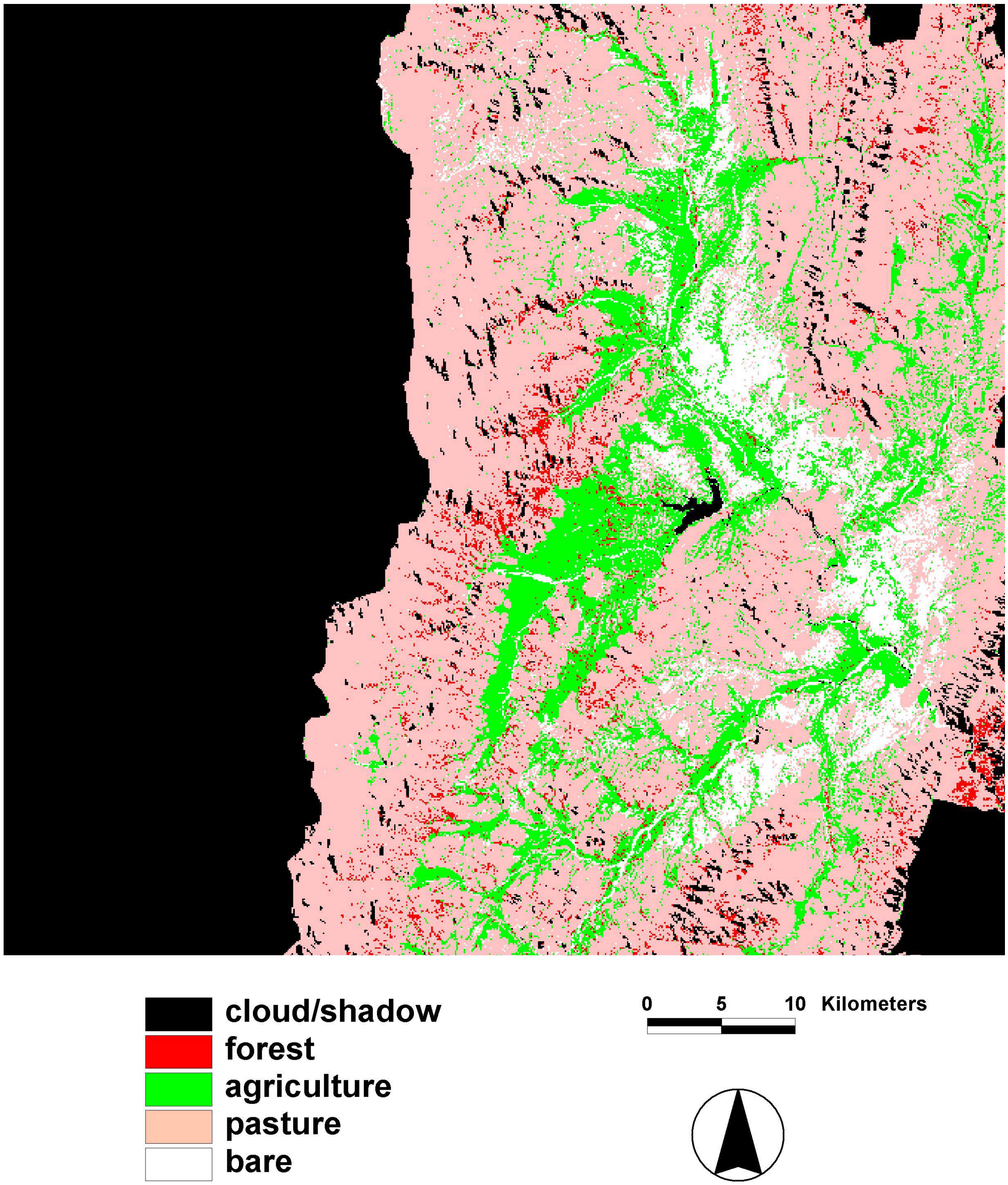


Figure 14. Actual land cover in 2003 according to the Secondary LULCC classification (resampled to 1 ha resolution).

Model simulations for the mountain region were influenced by changes in the elasticity set and, to a lesser degree, the variable set. In general, the terrain and demographic variables (V Set 2) performed the best of the three variable sets. Elasticity Set A was used in combination with all 3 variable sets, resulting in slight differences in accuracy. V Set 2 used with Elasticity Set B produced the best overall accuracy, the highest KHAT, and best accuracy in the agriculture, pasture, and bare classes. However, V Set 2 used with E Set C was the most effective at predicting forest (0.17 versus 0.20). The intercepts and slopes of the logistic regression for each variable in Variable Set 2 are shown in Table 13.

Land cover in 1985 was a good predictor of 2003 land cover (overall accuracy = 77%). It was more effective at predicting forest presence than any of the model simulations. Since the 1985 map was used as the starting point for the simulations, and forest composition was halved by 2003, this high forest accuracy represents an overestimation of forest at the expense of decreased ability to predict agriculture and bare ground.

4.6 Spectral Mixing Analysis

Spectral mixing analysis (SMA) was performed to determine relative proportions of green vegetation (GV), bare soil, and non-photosynthetic vegetation (NPV) throughout the study area. Various characteristics of the study area, including the prevalence of the "mixed pixel", changes in land cover condition (e.g. pasture degradation) and the absence of field data for 1985, called for the use of SMA to investigate landscape dynamics. Instead of a subjective assignment of land cover class to the pixels, the proportion of each endmember can be quantified for each pixel in both images, allowing assessment of changes in endmember proportions.

Others have investigated the ability and limitations of SMA to accurately quantify vegetation cover in semi-arid environments (Elmore *et al.* 2000; Okin *et al.* 2001). Elmore et al. (2000) determined that estimates of percentage of live cover in a LS pixel is accurate to within +/- 4% (one sd from the mean), and that estimates of change in live cover are accurate to within +/- 3.8% (one sd from the mean). SMA correctly determined the sense of change (i.e. positive or negative) in 87% of the samples. Okin et al (2001) found that SMA can accurately model vegetation cover at proportions greater than 10%.

4.6.1 Comparison of LULC Classification with Endmember Fractions

4.6.1.1 MOUNTAIN REGION

Average endmember proportions for each LULC class were calculated for the Mountain region in 1985 and 2003 (Table 15, Figure 15). In both years**,** average endmember fractions were significantly different in each land cover class. In 1985, soil fraction is very low in forest (0.04). It increases in the other land cover classes, reaching a maximum in the bare land class (0.52). GV fraction complements the soil fraction well, with the highest value in the forest class (0.51), and the lowest value in the bare class (0.13). NPV trends are more ambiguous. NPV represents many different components on the landscape, and therefore many different processes can affect its pattern (Adams *et al.* 1995; Roberts *et al.* 1998; Okin *et al.* 2001). In the current study area, NPV on the landscape includes senesced pasture, mature annual crops, perennial crops (grape trees), woody material from living vegetation (tree branches, cactus), and plant material from dead vegetation (debris from deforestation or from crop harvest). Its variability is highly dependent on vegetation stage (Numata *et al.* 2003) as well as land use practices. For example, a deforestation event will result in an immediate decrease in GV. However, the trend in NPV fraction will depend on whether the branches and dead leaves are left on the landscape (increased NPV), or scavenged for firewood (decrease in NPV and increase in soil fraction).

It is important to note the differences in the image dates when comparing fraction results of the two different years (April 1, 1985 versus April 29, 2003). The rainy season in this region is both pronounced and short, with greater than 85% of the precipitation falling between November and March (Carpio *et al.* 2002). At the beginning of April, rainfall has been plentiful and moisture available for vegetation growth is still abundant. Conversely, at the end of April available moisture has already become limited. It is a dynamic period in environmental conditions, and considerable changes in vegetation development that alter relative proportions of

GV and NPV (e.g. plant maturity and senescence) in response to these dynamic environmental conditions almost certainly occur. Therefore, the decrease in GV fraction in the agriculture class (from 0.33 in 1985 to 0.21 in 2003) and the accompanying increase in NPV (0.42 in 1985 to 0.62 in 2003) is potentially a result of advanced crop senescence in the 2003 image, rather than an indicator of degradation. Fraction changes over time for the other land cover classes are discussed in detail later in this paper.

Table 15. Mean endmember fractions for each land cover class in the Mountain region in 1985 and 2003.

Mountain Region				
1985				
Land Cover	Soil	GV	NPV	Description
Forest	0.04	0.51	0.45	very low Soil, high GV, high NPV
Ag	0.25	0.33	0.42	moderate Soil, moderate GV, moderate NPV
Pasture	0.25	0.25	0.50	moderate Soil, moderate-low GV, high NPV
Bare	0.52	0.13	0.34	high Soil, low GV, moderate NPV
2003				
	Soil	GV	NPV	Description
Forest	0.03	0.36	0.61	very low Soil, high GV, high NPV
Ag	0.17	0.21	0.62	low Soil, moderate GV, high NPV
Pasture	0.27	0.09	0.64	moderate Soil, low GV, high NPV
Bare	0.55	0.03	0.42	high Soil, low GV, moderate NPV

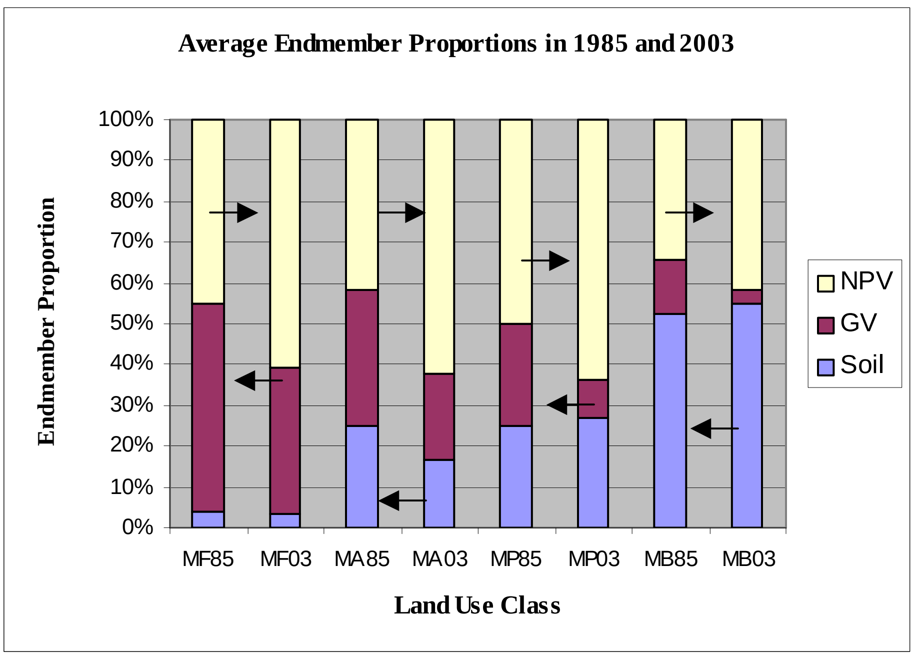


Figure 15. Mean endmember fractions for each land cover class in the Mountain region in 1985 and 2003. MF = Mountain Forest, MA = Mountain Agriculture, MP = Mountain Pasture, MB = Mountain Bare.

4.6.1.2 Altiplano Region

Average endmember proportions for each LULC class were calculated for the Altiplano region in 1985 and 2003 (Table 16, Figure 16). In both years**,** average endmember fractions were significantly different in each land cover class. All pairwise comparisons were significant in 1985 except for the NPV fraction in forest and pasture, and the NPV fraction for forest and bare. In 2003, all pairwise comparisons were significant except for the GV fraction of the forest and agriculture class. It is important to note that the forest class was very small in both 1985 and 2003, consisting of 0.09% and 0.01% of the landscape, respectively.

Trends for 1985 look very similar to those in the Mountain region. Forest has the lowest average soil fraction (0.08), and the highest GV fraction (0.60). Soil fractions increase and GV fractions decrease in the agriculture, pasture, and bare classes. Bare ground has the highest soil fraction (0.54) and the lowest GV fraction (0.11).

In 2003, relative endmember proportions deviate from 1985 patterns for the pasture and bare classes. Pasture has a higher average soil fraction (0.68) than bare ground (0.59), and lower GV fraction (0.02) than bare ground (0.03). This deviation from the patterns observed in the Altiplano region in 1985 and in the Mountain region in both years is probably due to limitations of the SMA to correctly model vegetation cover at very low proportions. Both Elmore *et al.* (2000) and Okin *et al.*(2001) found that SMA was unable to accurately model vegetation cover at very low percentages. The average proportion of GV in the pasture (2%) and bare ground (3%) classes in the Altiplano region in 2003 are well below the 10% GV fraction threshold determined by Okin et al. (2001).

Table 16. Mean endmember fractions for each land cover class in the Altiplano region in 1985 and 2003.

Altiplano Region				
1985				
Land Cover	Soil	GV	NPV	Description
Forest	0.08	0.60	0.32	very low Soil, high GV, moderate NPV
Ag	0.35	0.27	0.37	moderate Soil, moderate GV, moderate NPV
Pasture	0.53	0.15	0.32	high Soil, moderate-low GV, moderate NPV
Bare	0.54	0.11	0.36	high Soil, low GV, high NPV
2003				
Land Cover	Soil	GV	NPV	Description
Forest	0.09	0.31	0.60	very low Soil, high GV, high NPV
Ag	0.34	0.22	0.45	moderate Soil, moderate GV, moderate-high NPV
Pasture	0.68	0.02	0.30	high Soil, low GV, moderate NPV
Bare	0.59	0.03	0.38	high Soil, low GV, moderate NPV

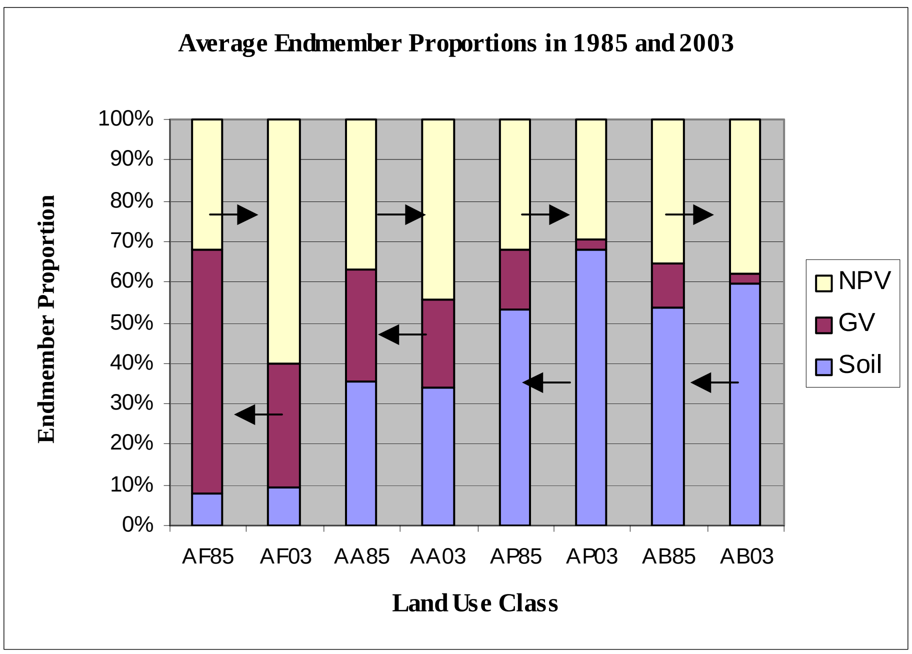


Figure 16. Mean endmember fractions for each land cover class in the Altiplano region in 1985 and 2003. AF=Altiplano Forest, AA = Altiplano Agriculture, AP = Altiplano Pasture, AB = Altiplano Bare.

4.6.2 Comparison of SMA and LULCC

4.6.2.1 Mountain Region

The change in endmember fraction for each land cover conversion class was quantified to determine how endmember proportions change with land cover conversion (Table 17). Changes in endmember proportions occurred in areas that have not been converted, possibly due to vegetation maturity, climatic conditions, or degradation within a land cover class. For example, there was a decrease of 0.14 in GV fraction complemented by an increase of 0.16 in NPV for areas that were forest in both 1985 and 2003. In order to isolate endmember fraction changes due to land cover conversion, fraction changes were calculated relative to areas of no conversion, and rounded to one significant figure for simple comparison. For example, areas converted from forest to agriculture experienced a 0.27 gross loss in GV, but only a 0.13 loss relative to forest that was not converted (rounded to 0.1).

Table 17. Average change in endmember fraction for each conversion class and normalized endmember fraction changes for the Mountain region.

Conversion Type	Change in Soil Fraction	**Change in Soil Fraction Relative to NC**	Change in GV Fraction	**Change in GV Fraction Relative to NC**	Change in NPV Fraction	**Change in NPV Fraction Relative to NC**
Forest Conversion						
No Change	-0.01	**-**	-0.14	**-**	0.16	**-**
For-Ag	0.03	**0.0**	-0.27	**-0.1**	0.25	**0.1**
For-Past	0.05	**0.1**	-0.28	**-0.1**	0.24	**0.1**
For-Bare	0.34	**0.4**	-0.50	**-0.4**	0.16	**0.0**
Agricultural Conversion						
No Change	-0.01	**-**	-0.18	**-**	0.19	**-**
Ag-For	-0.09	**-0.1**	-0.10	**0.1**	0.20	**0.0**
Ag-Past	0.19	**0.2**	-0.17	**0.0**	-0.01	**-0.2**
Ag-Bare	0.13	**0.1**	-0.17	**0.0**	0.04	**-0.2**
Pasture Conversion						
No Change	0.04	**-**	-0.16	**-**	0.13	**-**
Past-For	-0.06	**-0.1**	-0.08	**0.1**	0.14	**0.0**
Past-Ag	-0.06	**-0.1**	-0.10	**0.1**	0.17	**0.0**
Past-Bare	0.06	**0.0**	-0.14	**0.0**	0.09	**0.0**
Bare Conversion						
No Change	0.05	**-**	-0.08	**-**	0.04	**-**
Bare-For	-0.33	**-0.4**	0.21	**0.3**	0.13	**0.1**
Bare-Ag	-0.21	**-0.3**	0.06	**0.1**	0.16	**0.1**
Bare-Past	0.05	**0.0**	-0.07	**0.0**	0.03	**0.0**

Clear and expected trends are obvious in the Soil and GV fractions. Soil fractions increase and GV fractions decrease with forest conversion. Conversion of forest to bare shows the largest increase in soil fraction (0.4) and decrease in GV (-0.4). In the agriculture class, soil fraction decreases and GV fraction increases with conversion to forest. Soil fraction increases with agriculture conversion to both pasture and bare. A decrease in soil fraction occurs with the conversion of bare ground to agriculture (-0.3) and forest (-0.4), accompanied by increases in GV.

4.6.2.2 ALTIPLANO REGION

The change in endmember fraction for each land cover conversion class was also quantified for the Altiplano region and normalized relative to areas of no change (Table 18). Patterns in the Altiplano are similar to those in the Mountain region. Only the pasture and bare classes deviate from expected patterns due to very low GV proportions in 2003. Conversion to agricultural and bare land to forest was extremely low and not included in the analysis.

Table 18. Average change in endmember fraction for each conversion class and normalized endmember fraction changes for the Altiplano region.

Conversion Type	Change in Soil Fraction	**Change in Soil Fraction Relative to NC**	Change in GV Fraction	**Change in GV Fraction Relative to NC**	Change in NPV Fraction	**Change in NPV Fraction Relative to NC**
Forest Conversion						
No Change	-0.04	**-**	-0.23	**-**	0.28	**-**
For-Ag	0.12	**0.2**	-0.31	**-0.1**	0.19	**-0.1**
For-Past	0.32	**0.4**	-0.43	**-0.2**	0.11	**-0.2**
For-Bare	0.17	**0.2**	-0.48	**-0.2**	0.32	**0.0**
Agricultural Conversion						
No Change	0.10	**-**	-0.16	**-**	0.08	**-**
Ag-For	Not Analyzed					
Ag-Past	0.38	**0.3**	-0.20	**0.0**	-0.18	**-0.3**
Ag-Bare	0.27	**0.2**	-0.17	**0.0**	-0.10	**-0.2**
Pasture Conversion						
No Change	0.14	**-**	-0.13	**-**	0.00	**-**
Past-For	-0.17	**-0.3**	-0.04	**0.1**	0.22	**0.2**
Past-Ag	0.01	**-0.1**	-0.11	**0.0**	0.11	**0.1**
Past-Bare	0.10	**0.0**	-0.17	**0.0**	0.08	**0.1**
Bare Conversion						
No Change	0.09	**-**	-0.08	**-**	0.00	**-**
Bare-For	Not Analyzed					
Bare-Ag	-0.08	**-0.2**	-0.09	**0.0**	0.18	**0.2**
Bare-Past	0.16	**0.1**	-0.07	**0.0**	-0.08	**-0.1**

Various factors complicate the interpretation of the SMA results. In this study, I considered simple and substantial differences in GV and Soil within a land cover class as indicators of degradation. However, various processes can influence endmember composition, such as changing species composition and climatic conditions. To some extent, these results should be considered exploratory, as necessary ground data to validate changes through time within classes did not exist.

4.7 Ecoregional Analysis

4.7.1 South America

Ecoregions were delineated based on topographic and climatic drivers of landscape composition to determine areas of South America with similar environmental characteristics, landscape processes, and response to disturbance and change. The initial analysis used the variables of elevation, temperature, precipitation, slope, and the wetness index. I clustered these variables into various numbers of classes ranging from 5 to 40 classes. Figure 17 shows the results of this clustering analysis into 9 classes. Although vague landscape patterns are discernible, such as the Andes mountain range, the Venezuelan highlands, and the Brazilian highlands, the clustering analysis was not successful because adjacent pixels were generally assigned to different classes and actual clusters were not formed.

Consultation of the literature aided in the determination of appropriate variables for subsequent clustering analyses. In the identification of customizable ecoregions of the southeastern US, Hargrove and Luxmoore (1997) used six variables important to tree growth: annual temperature, annual precipitation, elevation, and three soil parameters, including plant-available water content, total organic matter, and total Kjeldahl nitrogen. Clinebell et al. (1995) found very strong relationships between vegetation biodiversity and precipitation patterns in his examination of tree species and environmental data from 69 lowland forest plots throughout South America. Annual rainfall, rainfall seasonality, and available soil nutrient concentrations were the most important variables in accounting for variation in species richness.

Accordingly, I selected temperature, precipitation, soil texture, and elevation from my limited suite of variables. Analysis using this new data stack into shows that clustering results vary greatly depending on the input variables (Figure 18). Increasing representation of detail results as the number of classes grows, and experimentation demonstrated that the ISOCLUSTER algorithm could identify a maximum of 40 distinct classes using these 4 variables (Figure 19).

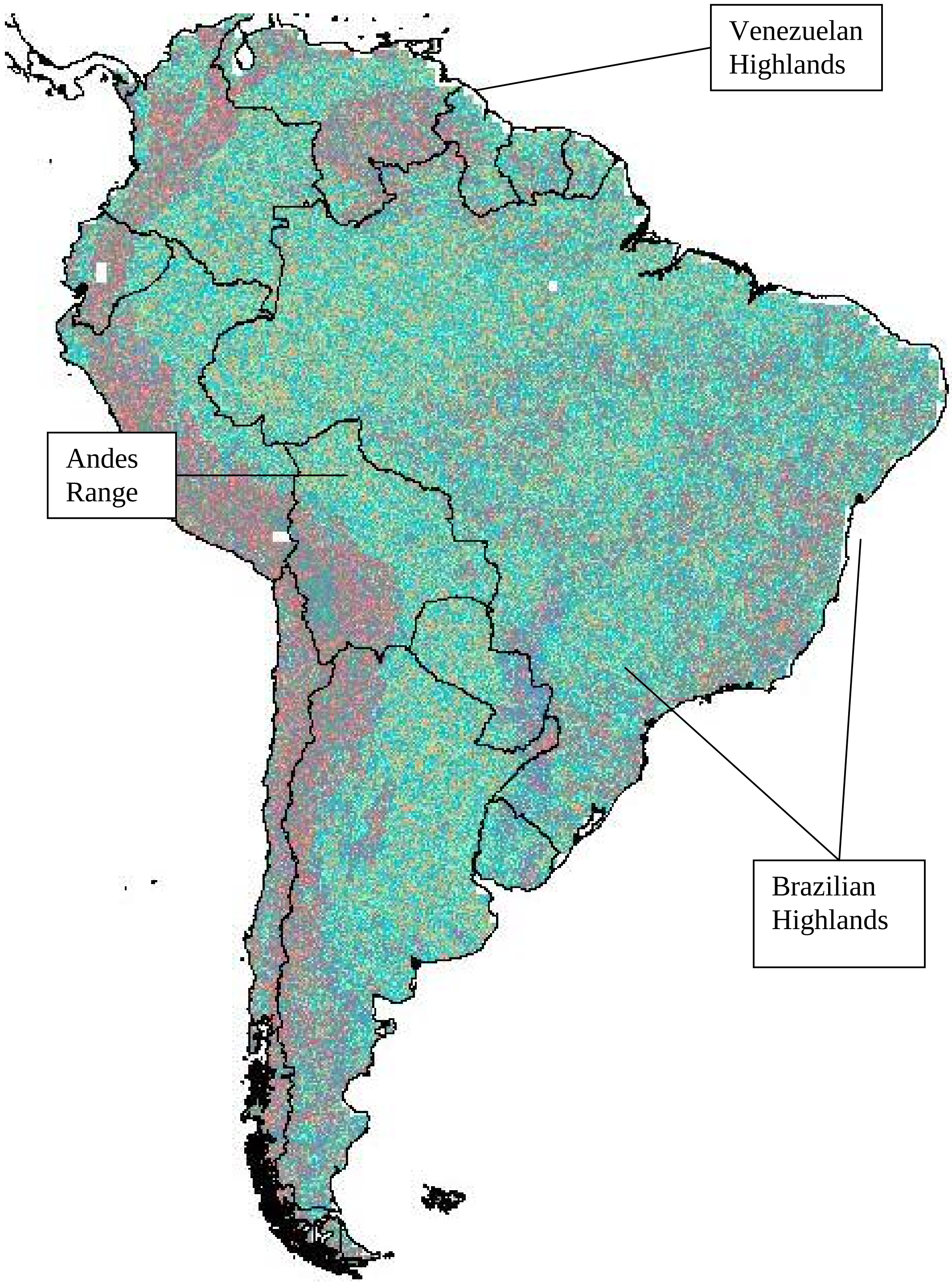


Figure 17. Results of 16-class clustering analysis using 5 variables: precipitation, temperature, elevation, slope and wetness index.

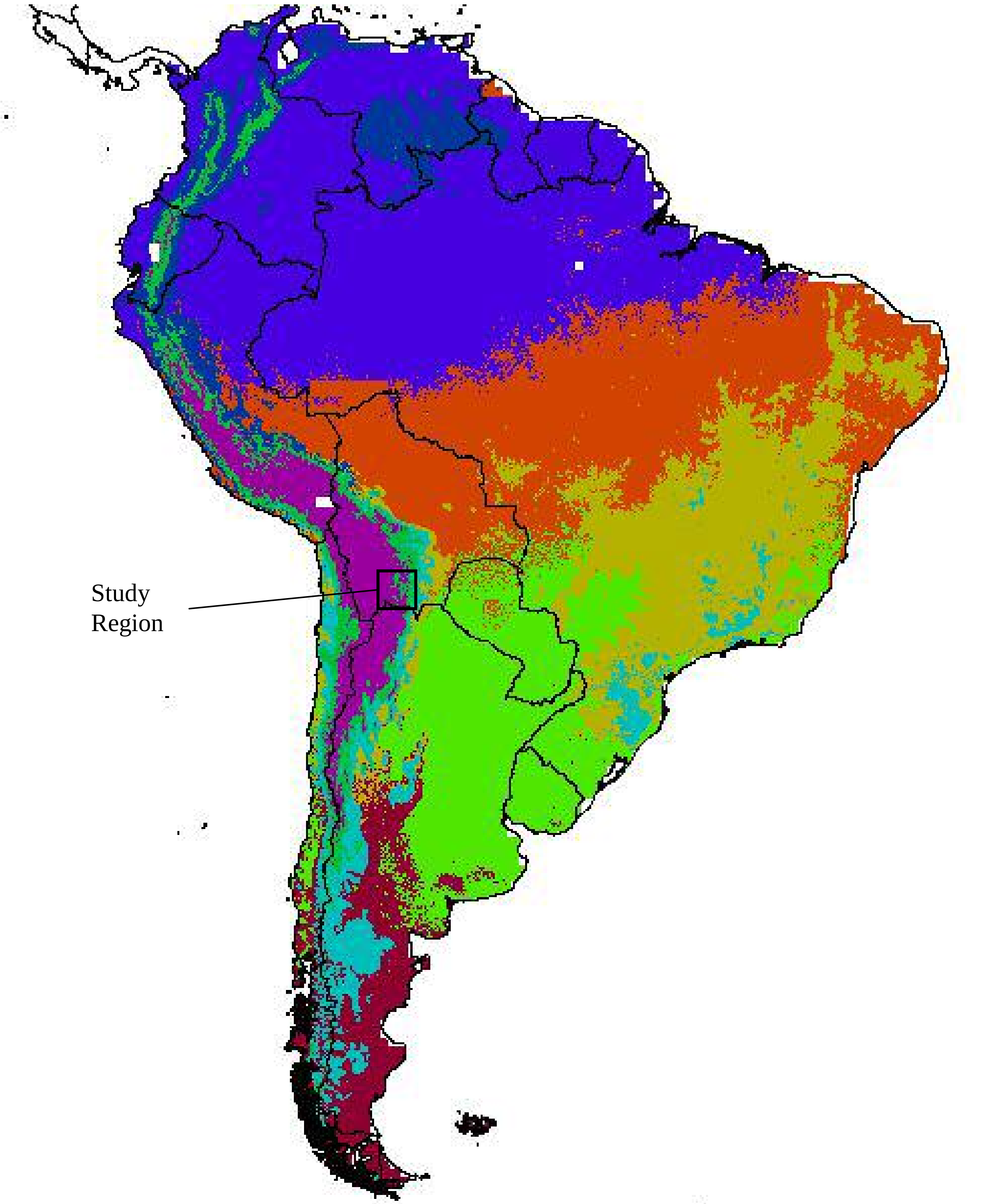


Figure 18. Results of 9-class clustering analysis using revised stack of variables.

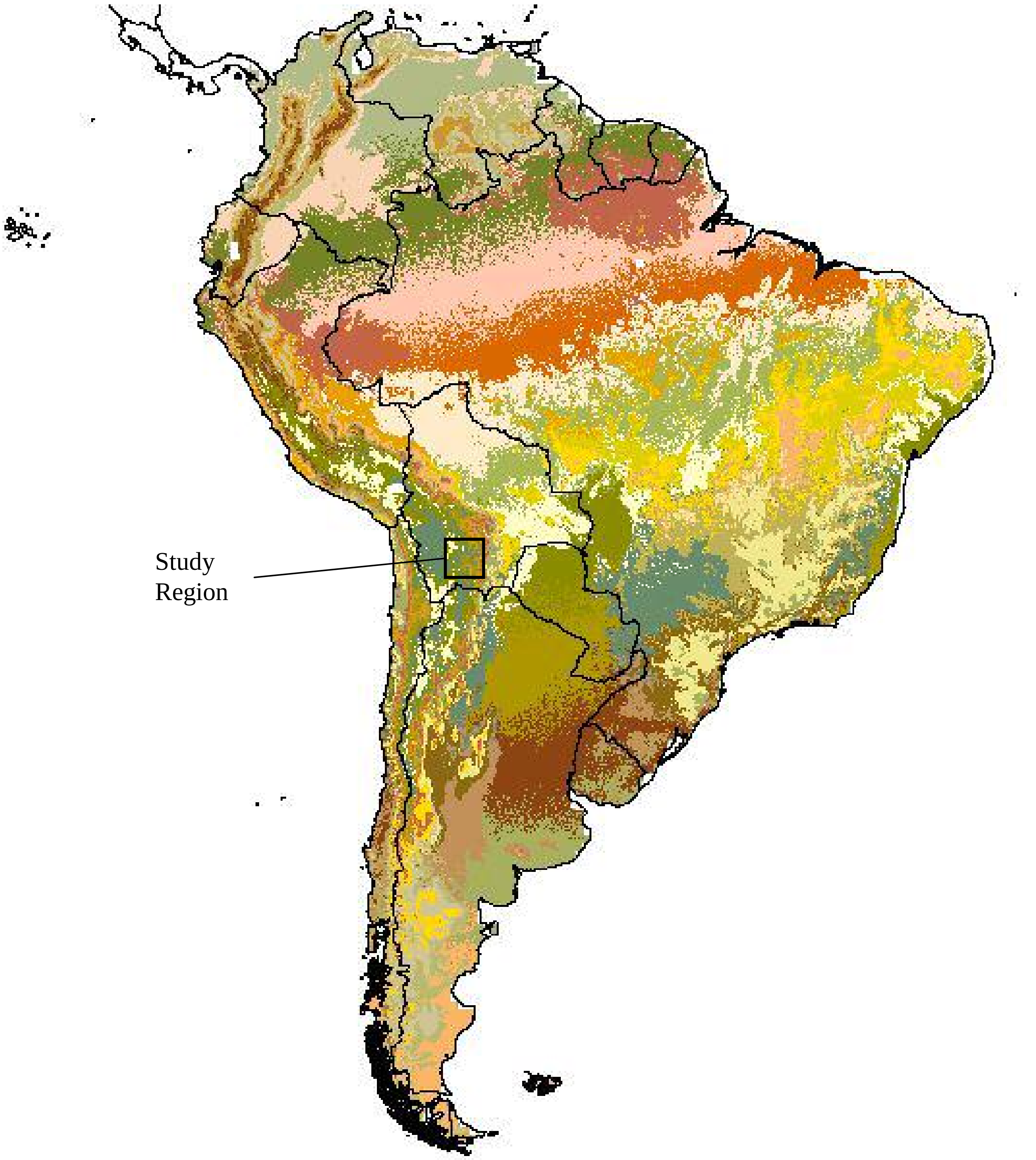


Figure 19. Results of 40-class clustering analysis

The WWF ecoregional map identifies approximately 100 classes throughout South America (Figure 20). More detail is represented by the WWF map than the cluster maps for many regions. For example, northern South America is delineated into several small ecoregions on the WWF map. Divisions are less numerous and ecoregions are more continuous on the cluster maps, especially the 9-class and 16-class (Figure 21) cluster maps. For northern South America, the 40-class cluster map most closely resembles the WWF ecoregion map. However, for other regions the clustered maps are more detailed. For example, the Cerrado ecoregion is large and continuous on the WWF map, whereas a single, clear, continuous class is not created in the 40-class or the 16-class cluster maps. For the Cerrado ecoregion, the 9-class cluster map most closely resembles the WWF ecoregion map. The differences between the maps created by the 2 methods may be due to the ability of the WWF approach to identify areas of known distinct biodiversity, whereas the clustering technique cannot represent very localized patterns of diversity because it is based on a limited number of variables at a broad scale resolution. On the other hand, the more detailed division of the WWF map could result from bias due to the subjectivity of experts consulted or differences in the scale and resolution of their data sources.

WWF also created a habitat map, which condenses the ecoregional delineation into 16 general habitat types (Figure 22), which allows a comparison of the 16-class cluster map with the 16-class WWF habitat map. Broad-scale patterns of the divisions are remarkably similar, which is to be expected since broad-scale habitat formation is driven by broad spatial and temporal scale environmental factors. Close comparison reveals distinct fine scale differences that may be due to the subjective approach of the WWF habitat map or to the low-resolution data used in the cluster analysis. A key feature in the comparison of these two maps is their different representation of habitat boundaries. The WWF map divides the continent into discrete units with definite boundaries. On the other hand, the 16-class cluster map shows a more realistic representation of habitat transition zones. For example, in northern South America, the transition from the yellow class to the blue class moving from north to south does not occur abruptly. There is a transition zone containing both blue and yellow pixels. This gradual transition between classes portrays a more realistic representation of habitat gradients on a real landscape.

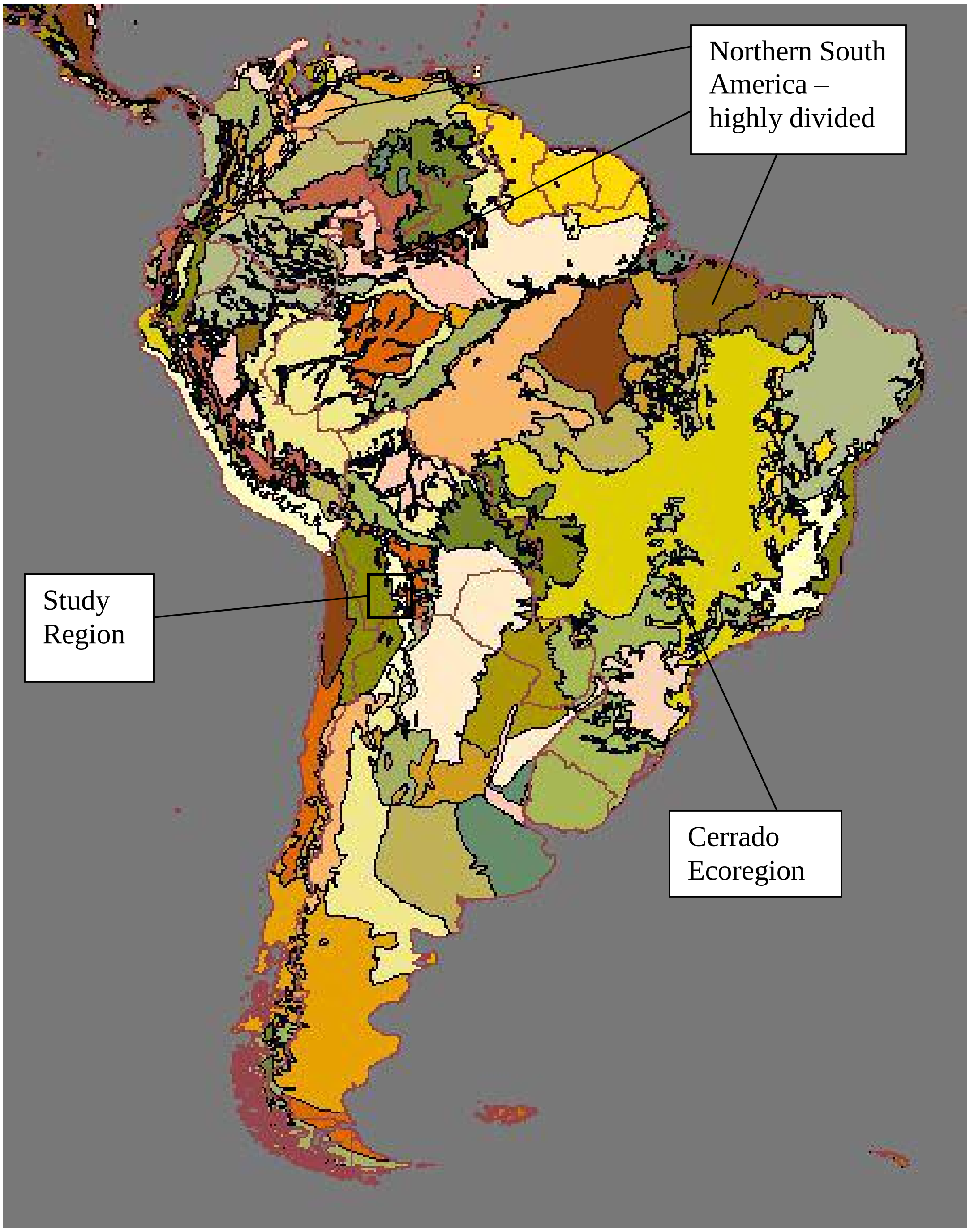


Figure 20. WWF Ecoregional Map of South America

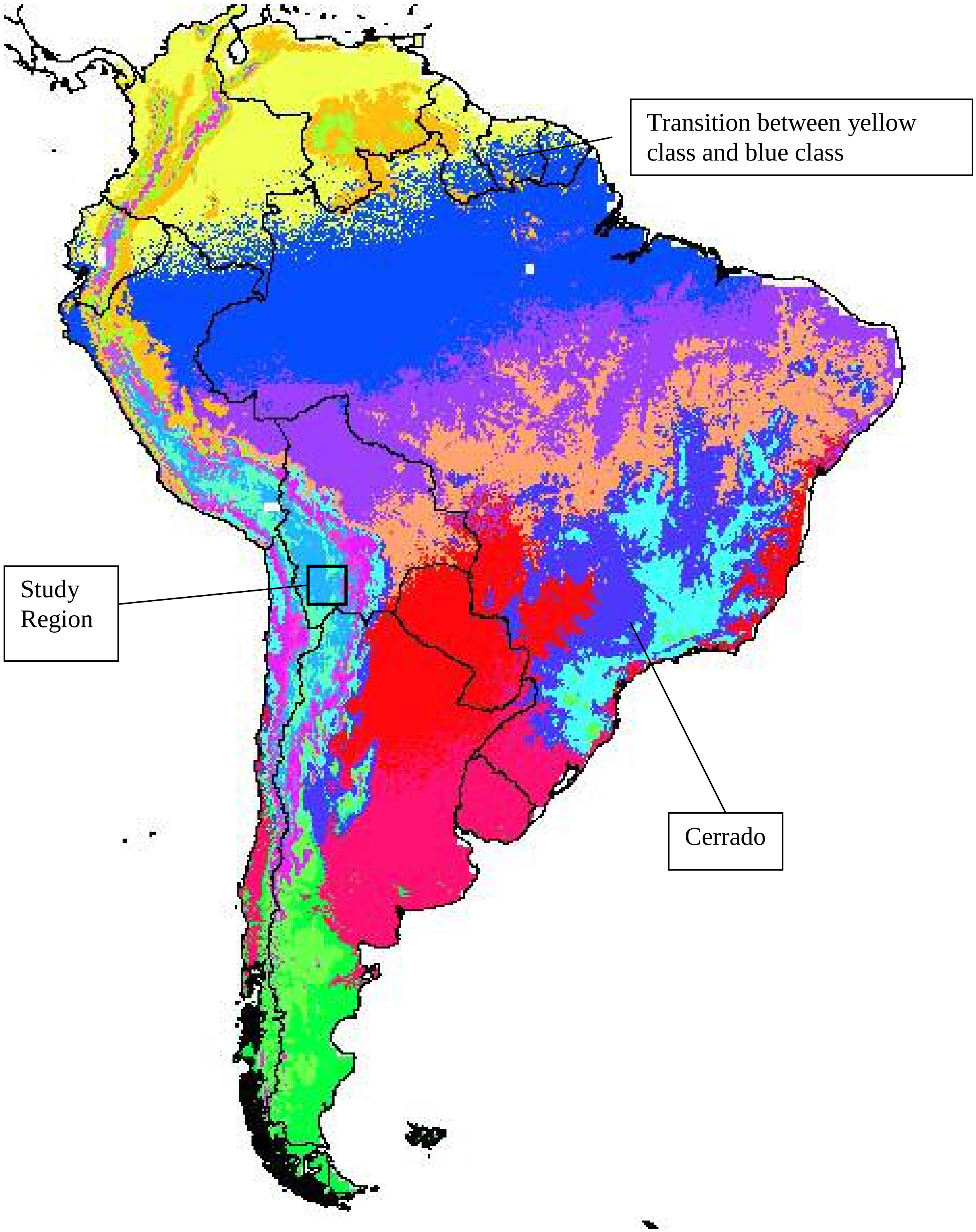


Figure 21. Results of the 16-class clustering analysis.

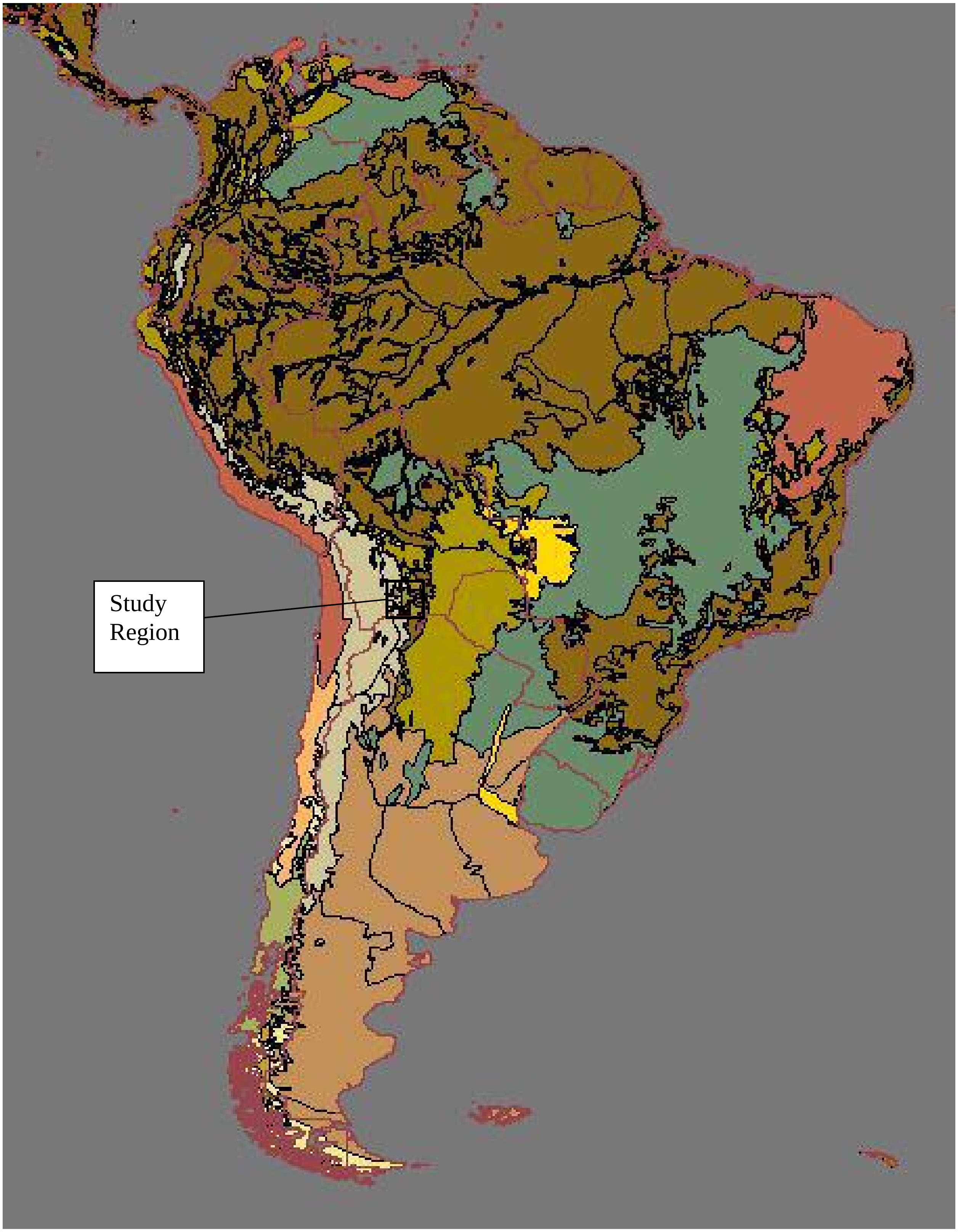


Figure 22. WWF Habitat Map of South America

4.7.2 Bolivia

The next figures show Bolivia on the WWF ecoregion map, the WWF habitat map, and the 16-class cluster map (Figures 23, 24, and 25). A visual comparison of the classification of the Bolivian highlands region for the three maps shows several key features. General patterns (e.g. size, shape, location) of the Altiplano, steep valleys, and vegetation zones are similar for the 3 maps. The 16-cluster map detects more variability in an east-west direction, whereas the WWF ecoregion map represents more variability in the north-south direction as the mountain grassland habitat changes from Wet Puna to Puna to Dry Puna. This variability is absent in the WWF habitat map and the 16-class cluster map and clusters are relatively continuous moving from north to south. Again, these differences could be caused by the broad-scale climate data used in the cluster analysis or the arbitrary nature of boundary definition of the WWF maps.

Classes 3, 14, 15, 16 are the dominant regions in my study area (Figure 25). Classes 7 and 13 are in close proximity to the study area. Figure 26 is a dendrogram demonstrating the distance measures between the 16 classes formed from the cluster analysis. It is apparent that classes 3, 14, 15, and 16 form a distinct branch of the dendrogram. They have relatively small distance measures between them (2 – 6 units), and have a relatively high distance measure (~19 units) from the other branches. Other regions of South America that also cluster into classes 3, 14, 15, and 16 should have similar environmental conditions as my study area. The dendrogram demonstrates that although classes 7 and 13 are close to the study area, they are distinct from classes 3, 14, 15, and 16. Figure 27 shows the various highland regions of South America and their cluster assignments. The Orinoco highlands (eastern Venezuela) cluster in classes 11 and 12 and the Brazilian highlands cluster into classes 1 and 13, implying that environmental conditions are distinct from those at my study site.

Therefore, environmental conditions of my site are very unique and are restricted to the high-elevation Andes region. However, Andean highlands as far north as western Venezuela and

Colombia, and as far south as Central Argentina and Chile, cluster into classes 3, 14, 15, and 16. Therefore, the results of some of the change analyses and modeling may be germane to other areas, when controlling for differences in economic and social factors.

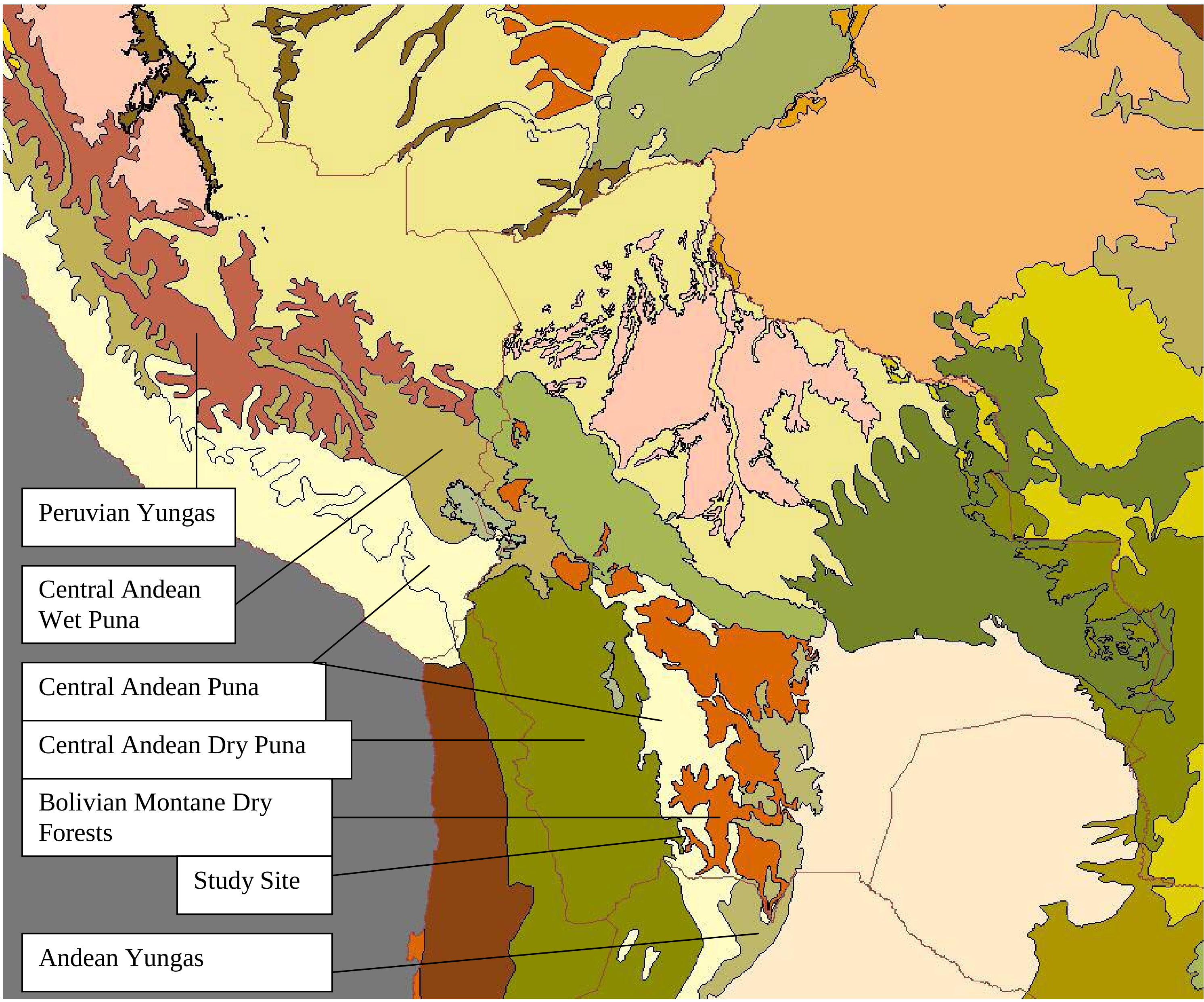


Figure 23. WWF Ecoregional Map showing Bolivian Highland Ecoregions and the location of the study site.

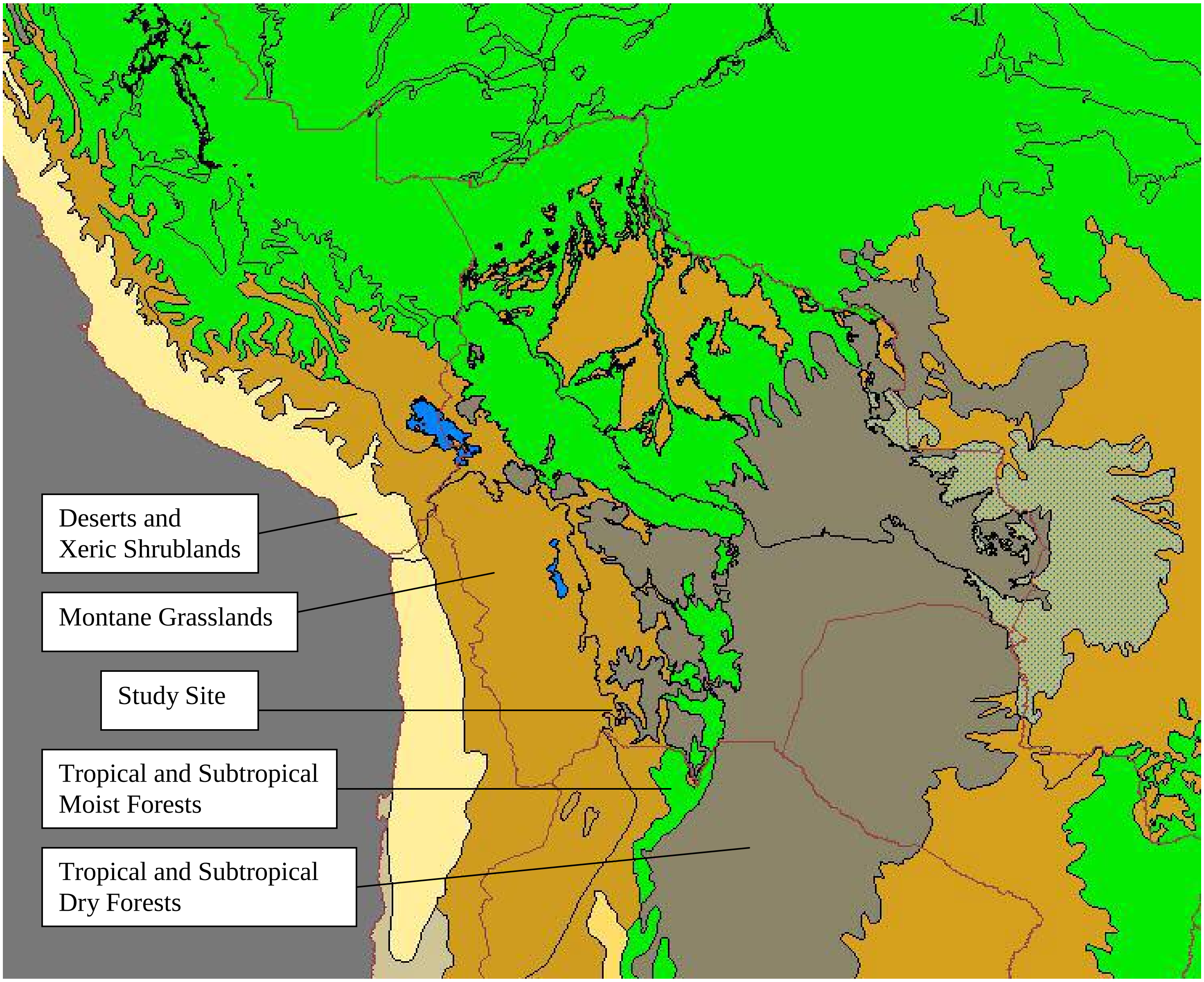


Figure 24. WWF Habitat Map showing Bolivian highland habitats and the location of the study site.

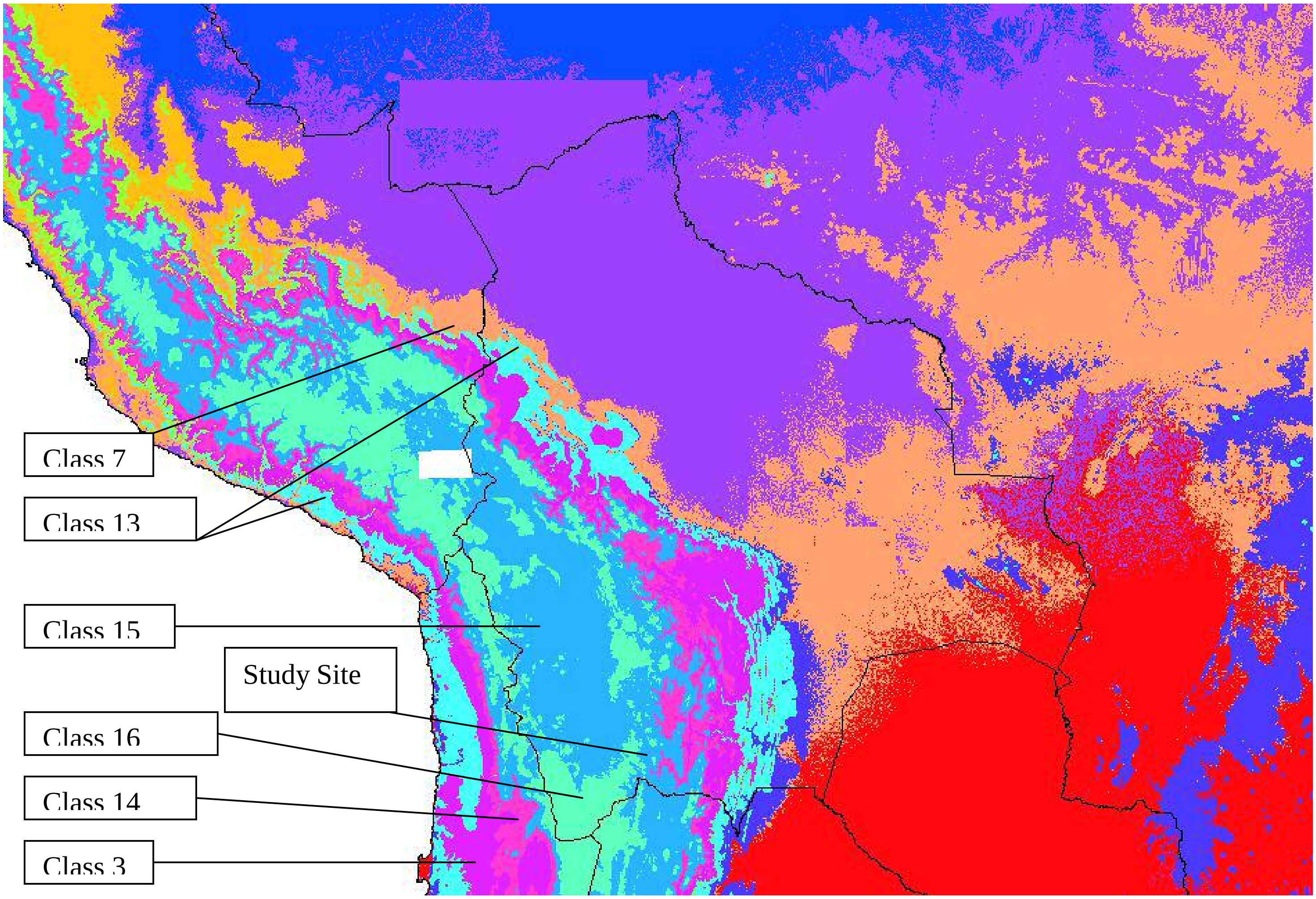


Figure 25. 16-class cluster map showing Bolivian Highland classification and the location of the study site.

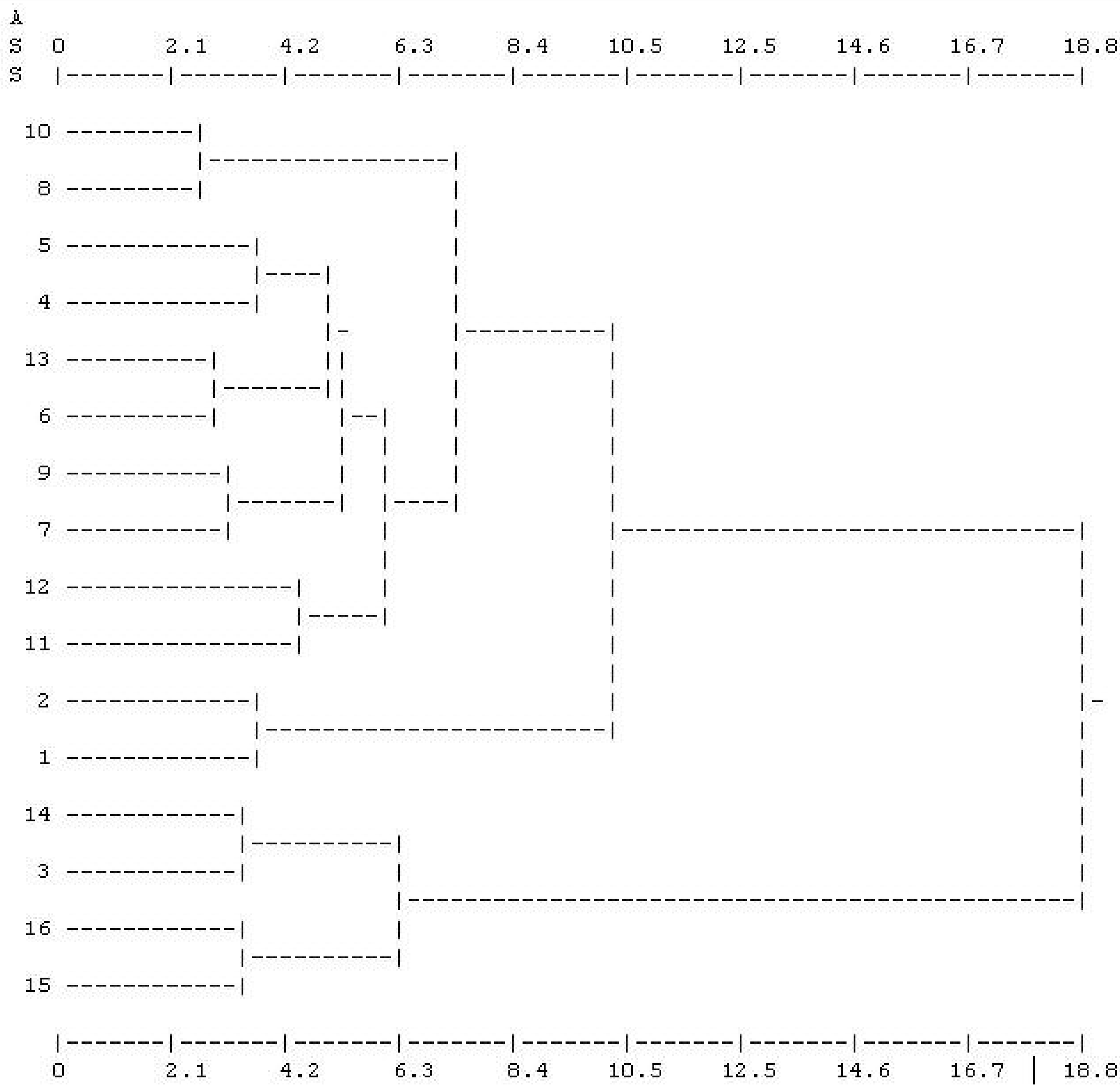


Figure 26. Dendrogram of the 16-class Cluster Analysis. The y-axis shows clusters 1 through 16 and the x-axis shows the difference measures between the clusters. The clusters in the study site region (classes 3, 14, 15 and 16) form a distinct branch of the dendrogram.

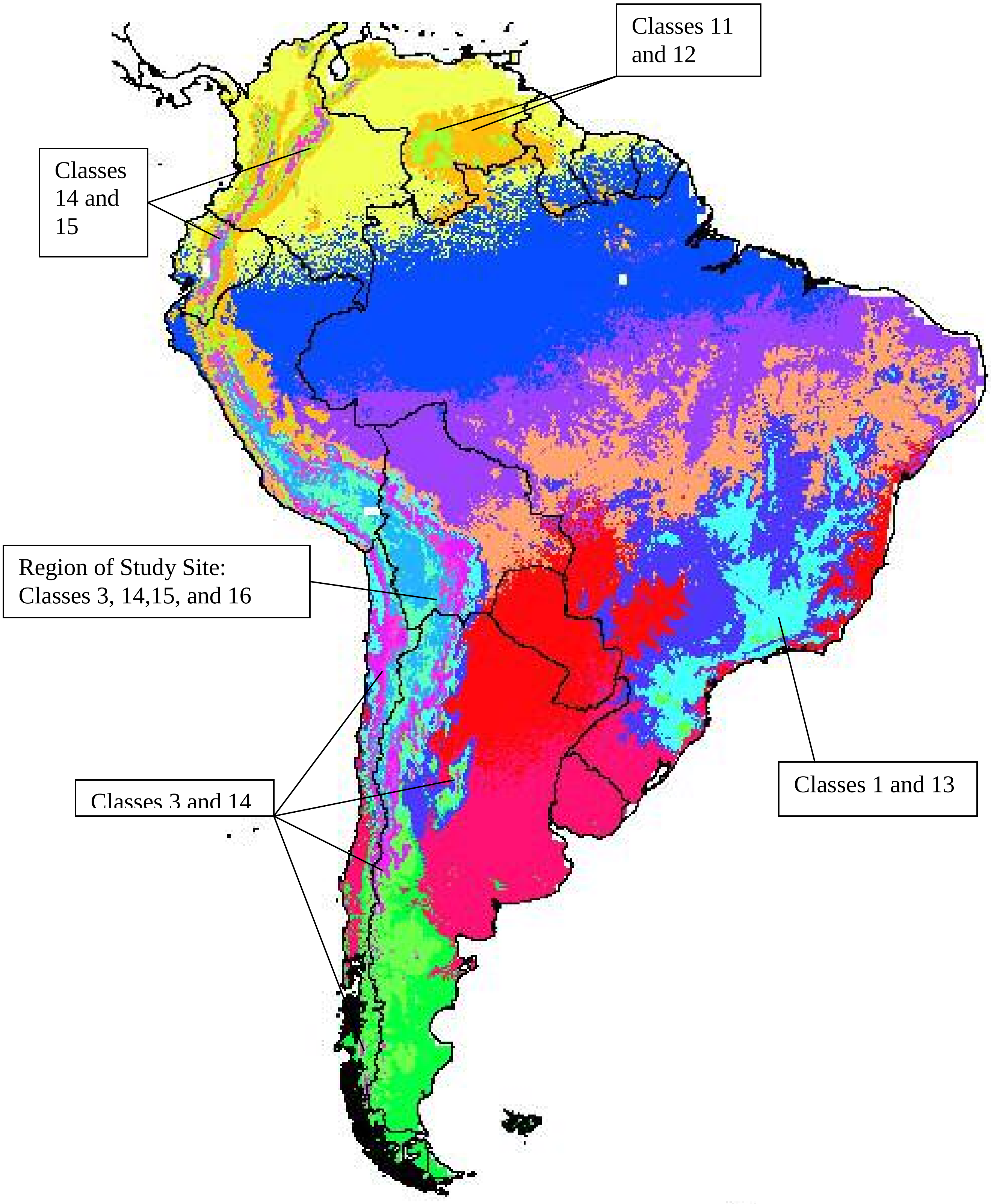


Figure 27. The 16-class cluster map showing classification of the various highland regions of South America.

5.0 DISCUSSION

The Andean region of South America has been densely populated for thousands of years. The majority of its inhabitants are subsistence farmers using traditional agricultural and pastoral practices especially adapted to these sensitive mountain ecosystems. With changes in land use practices and increased population pressure, the precarious balance between humans and the land is threatened. Once degraded, vegetation and soil regeneration is restricted by climatic and topographic conditions, leading to the loss of productive topsoil, which is irreversible on anthropogenic time scales. The result of landscape degradation in arid, vulnerable environments is two-fold: 1) the productivity of the land is severely and permanently diminished and 2) the hydrologic cycle is disturbed. In a region where people depend on untreated surface water for drinking, household use, and irrigation, the decrease in dry season stream flows and the contamination of drinking water with harmful pathogens are devastating consequences of landscape degradation.

The assessment of regional patterns of land use and land cover conversion (LULCC) is the first step in developing sound land management plans. One objective of this study was to test whether land cover in the current study area could be accurately characterized using limited field data, remotely sensed land cover and topographic data (Landsat and Shuttle Radar Topography Mission), and traditional image analysis techniques. A regional fine-scale landscape analysis would be logistically impossible in any other way due to constraints in financial resources and accessibility. Similar techniques have been applied throughout the developing world, but almost exclusively in flat, humid, low-elevation regions. Application of these techniques to the current study area, or other high elevation regions of South America, is not documented in the published literature.

In addition to the inherent challenges of conducting research with extremely limited resources in a remote region of a developing country, various unique characteristics of the study area complicated efforts to accurately evaluate land cover using remotely sensed data.

Topographic heterogeneity confounded attempts at topographic correction and complicated land cover classification. Limited collection of field data for geocorrection and land cover mapping introduced error and bias into the analysis. "Mixed pixels", areas with different land covers comprising an image cell, are prevalent. Finally, both change in landscape condition (e.g. pasture degradation), as well as land cover conversion, are occurring within the study area. This study demonstrated that, despite these challenges, land cover and landscape change in the study region cover could be effectively characterized using established techniques and limited field data.

5.1 Development of a Regional Land Cover Map

Land cover in 2003 was mapped into 9 classes with an overall accuracy of 89%. Compared to the overall accuracy, the forest (57% omission error) and agriculture (76% comission error) classes contained considerable error. The major sources of classification error were 1) image registration error, and 2) the inability to separate areas of mixed land cover at a very fine scale, including small agricultural plots and narrow strips of forest.

Co-registration error between the GPS locations and the images is a common source of classification inaccuracy. Permanent, accessible ground points that were identifiable in the image were very limited throughout the study area. Isolated pixels often classified out as forest adjacent to, but not exactly aligned with, the exact GPS training point location. The fuzzy classification accuracy accounted for these co-registration errors. If a feature described in the field notes (e.g. a plot of forest) was represented in the classification but not on the exact pixel of the GPS point, it was counted as accurate in the fuzzy classification. This accounts for a considerable improvement when considering the fuzzy classification producer's accuracy for the forest class (90%).

Mixed pixels are also common sources of classification error. In many cases of mixed pixels, neither the basic nor the fuzzy classification is accurate. For example, a 50 x 50 meter forest plot surrounded by pasture can be represented in three pixels of mixed forest and pasture. These three mixed pixels are classified in the field as forest (in the basic classification) and pasture (fuzzy classification). However, due to their mixed composition, their spectral signature may resemble the agriculture class more than either the forest or pasture class. If the pixels classify as agriculture, they are incorrect for both the regular and the fuzzy accuracy assessment. This problem was evident in the agriculture class, as there was only a slight improvement in accuracy from the basic assessment (76%) to the fuzzy assessment (81%).

The assessment of regional, fine-scale land cover patterns had not previously been performed for this region. Managers and scientists can use this classification as 1) a reliable map of current land cover from which to base land management plans, 2) a foundation for future land use change monitoring, and 3) the basis for a stream survey designed to examine the relationship between streams and their watersheds.

5.2 Trends in Land Cover Conversion

The secondary classification methodology was developed to allow classification of both the 1985 and 2003 images and the subsequent analysis of rates, trajectories, and drivers of land cover change in the region. The secondary classification represents a profound loss in detail relative to the primary classification. It is unable to distinguish 1) intensive pasture, small tree plots and borders, and cultivated plots in the flat valleys, 2) sparse from abundant mountain grassland, and 3) an urban/churquial/cactus class. Overall accuracy (88%) and producer's accuracy for agriculture, pasture and bare ground (>90%) were quite good for the secondary classification. However, forest composition was poorly predicted in the secondary classification (40% basic, 55% fuzzy). Small forest plots and tree boundaries in the intensively-used, floodplain valleys are classified as agriculture since there was no attempt to further separate forest, pasture and crop plots in the secondary classification. However, the secondary classification methodology did produce consistent and comparable landscape patterns for both the 1985 and 2003 images, allowing the assessment of land use and land cover conversion (LULCC).

The Altiplano region has experienced minimal LULCC, probably due to environmental conditions that severely restrict land use activities. The Mountain region has experienced increases in both agricultural and bare land at the expense of forest and pasture (Figures 28 and

29). Agricultural expansion is a result of forest clearing and the development of irrigation systems. The construction of the San Jacinto reservoir after 1985 provided a perennial water source and stimulated development of irrigation canals around and downstream of the reservoir.

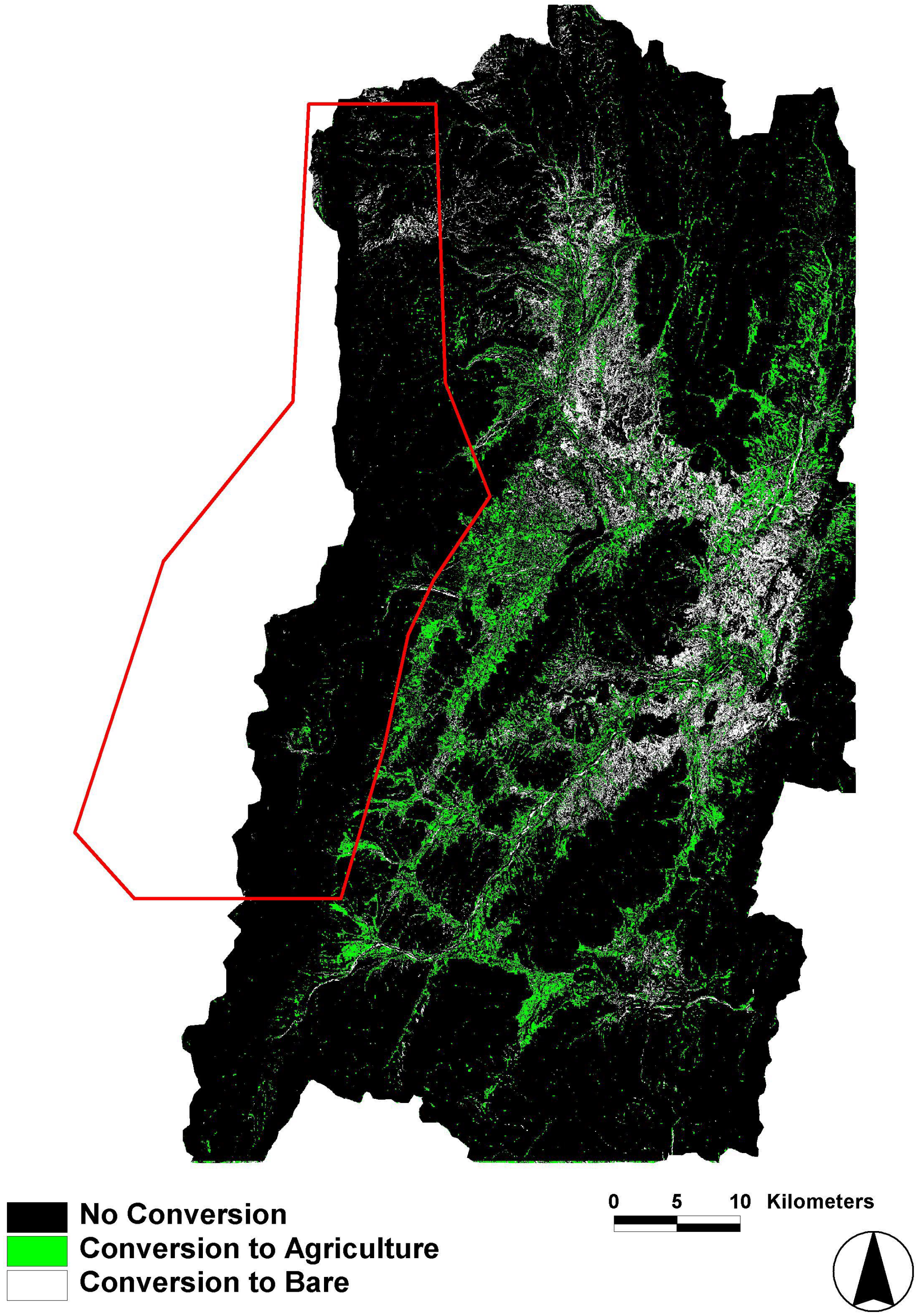


Figure 28. Areas converted to agriculture and bare ground in the Mountain region.

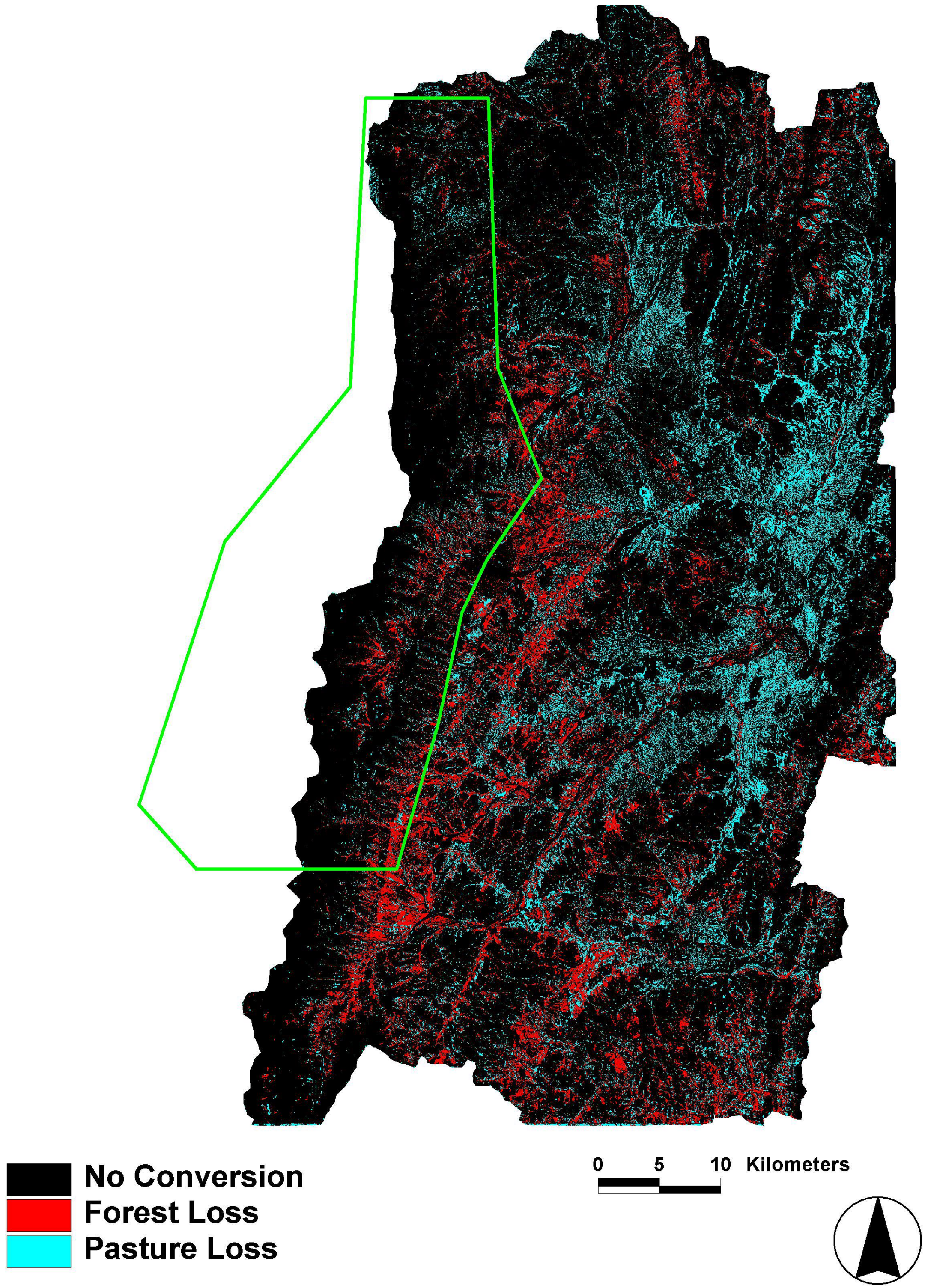


Figure 29. Areas converted from forest and pasture in the Mountain region.

Continued irrigation development and agricultural conversion is limited by topographic and climatic conditions. The proportion of agriculture as a function of elevation and slope suggests that within the Mountain region there are discrete zones where agricultural production is possible (Figure 9). Cultivated land is most common between 1600 and 2000 meters and on flat land (0-5% slope). At elevations above 2000m and slopes greater than 5%, the proportion of the landscape in cropland plummets, indicating topographical thresholds for agricultural production.

Forest cover in the Mountain region was halved between 1985 and 2003. Deforestation occurred throughout the study area, with the most accessible areas suffering alarming forest loss (Figures 10 and 11) and only the steepest, most inaccessible terrain maintaining forest cover (Figures 9). Forest loss was high in the flat, low elevation areas due to agricultural conversion and at intermediate slopes and elevations due to pasture conversion (Figure 11). At current rates, forest in the Mountain region will disappear by 2020.

The extent of bare land doubled in the Mountain region between 1985 and 2003. The large increase in bare land is both surprising and alarming because desertification is permanent on anthropogenic time scales. Regeneration of topsoil on steep, arid slopes will take hundreds to thousands of years. Much of this desertification has occurred in communal rangelands in the densely populated area around the city of Tarija (Figures 28 and 29) and where agricultural land and population density are at their highest (Figures 10, and 11). Interestingly, although steep slopes and arid conditions generally make landscapes more vulnerable to erosion and desertification, bare ground is clearly more prominent on flat slopes and on land with high moisture levels (i.e. TCI) (Figure 9). Bare ground closely corresponds to the prevalence of agriculture in the wettest and most highly populated areas, indicating that intense agricultural use and high population densities are driving desertification.

This study showed that alarming deforestation and desertification at a regional scale has occurred in the last 20 years and that future agricultural development is limited by topography.

The analysis suggests that with continuation of present population density, land use practices, and management, complete forest loss and eventual desertification of all of the communal rangeland is inevitable. At current rates of change, forest in the mountain region will disappear by 2020 and complete desertification of the communal rangelands will take less than 300 years. These dramatic landscape transformations will have disastrous consequences for both landscape productivity and the hydrologic cycle, decreasing both the quantity of base flows and the quality of surface water. Urgent measures to manage grazing practices in this area and to protect remaining forests must be implemented to avoid continued deforestation and desertification in the immediate future.

5.3 Changing Condition of Communal Rangeland

Spectral mixing analysis (SMA) was performed to determine changing proportions of green vegetation (GV), bare soil, and non-photosynthetic vegetation (NPV) as indicators of changes in landscape condition, especially in communal rangelands. The degradation of pasture as a result of overgrazing is a subject of much debate in traditionally pastoral regions throughout South America (Ellenberg 1979; Brush 1982; Seibert 1983; Laegaard 1992; Baied and Wheeler 1993; Kessler 1995; Kok *et al.* 1995; Messerli *et al.* 1997; Rundel and Palma 2000; Sarmiento 2000; Buytaert *et al.* 2002; Sarmiento and Frolich 2002). Deterioration of the landscape due to unsustainable agricultural practices, overgrazing, and the presence of non-native grazing species is considered one of the most dangerous threats to Sama and the surrounding area (Ayala Bluske 1998). Others contend that empirical data does not support the hypothesis of landscape deterioration as a result of unsustainable grazing practices in the Bolivian Altiplano (Washington-Allen *et al.* 1998; Preston *et al.*2003) .

The land cover change analysis clearly demonstrated that bare ground is replacing intensively used communal rangeland at a rapid rate (Figures 28 and 29). However, the conversion analysis allowed no assessment of changes in landscape condition leading to desertification. From a management perspective, the identification of areas in the process of degradation is essential to prevent irreversible conversion and erosion.

To address the question of rangeland deterioration in my study area, I first determined whether differences in landscape composition within a land cover class could be detected by comparing proportions of green vegetation (GV), non-photosynthetic vegetation (NPV), and soil in the two different physiographic regions. The significant differences in the climatic and geomorphologic conditions of the Mountain and Altiplano regions drive distinct differences in vegetation composition. Specifically, the predominant grassland vegetation of the Altiplano is the Paja Brava, a fibrous, yellowish-brown tall grass that grows in dispersed tufts surrounded by rock and bare soil. Grassland in the Mountain region consists of abundant, green, short grasses that provide continuous cover on the soil surface.

Comparison of endmember fractions between the two physiographic regions illustrated expected differences in communal rangeland composition as well as differences in the other cover classes (Figure 30). Pasture soil fractions in the Altiplano region (0.53) are much higher than those in the mountain region (0.25), consistent with field observations. Soil fractions are higher for Altiplano cropland (0.35) relative to Mountain cropland (0.25), and GV fractions are lower (0.27 vs. 0.33, respectively). Differences in forest composition are also evident, with higher NPV fractions in Mountain forest (0.45) than Altiplano forest (0.32). These results compare well with differences in crop type, forest species composition, and plant vitality observed in the field.

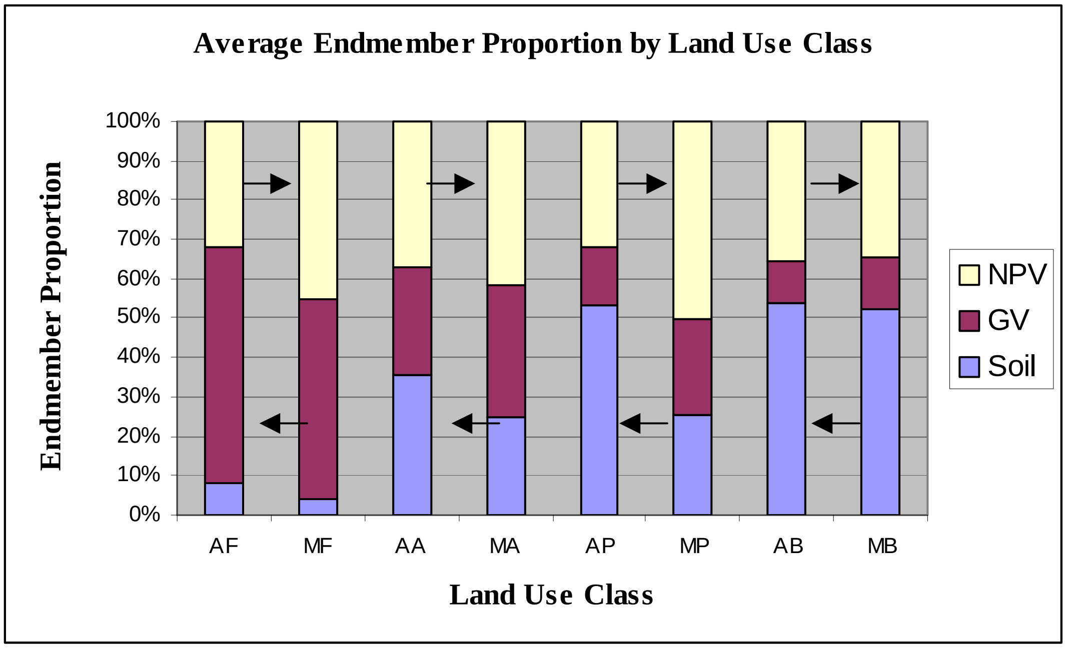


Figure 30. Average endmember proportions in each land cover class for both regions. AF = Altiplano Forest, MF = Mountain Forest, AA = Altiplano Agriculture, MA = Mountain Agriculture, AP = Altiplano Pasture, MP = Mountain Pasture, AB = Altiplano Bare, MB = Mountain Bare

These results demonstrate that differences in class condition can be detected from relative endmember proportions. Thus, I next explored change in landscape condition over time in areas that did not experience land cover conversion. In the Mountain region, there are consistent losses in GV replaced by gains in NPV in the forest and agriculture classes, accompanied by a slight decrease in soil fraction (Table 19). This may be attributed to vegetation maturity and senescence, because loss of GV due to degradation in agricultural and forested land would intuitively be accompanied by higher soil fractions (e.g. forest degradation due to tree extraction). The pasture and bare classes show a different pattern. The loss of GV cannot be entirely attributed to senescence, as the gain in NPV does not fully account for GV loss. Instead, a gain in soil is partially responsible for the loss in GV, indicating actual degradation.

Table 19. Changes in endmember fractions for areas that did not experience land cover conversion for the Mountain region.

Land Cover Type	Change in Soil Fraction	Change in GV Fraction	Change in NPV Fraction
NC Forest	-0.01	-0.14	0.16
NC Agriculture	-0.01	-0.18	0.19
NC Pasture	0.04	-0.16	0.13
NC Bare	0.05	-0.08	0.04

The Altiplano region shows a similar, but more pronounced, pattern for areas that have not experienced land cover conversion (Table 20). As in the Mountain region, the loss in GV in Altiplano forest is accompanied by a gain in NPV and a loss in soil, typical of leaf maturation (Adams *et al.* 1995; Lu *et al.* 2003). The agriculture class has experienced a larger gain in soil than in NPV, which is most likely due to a post-harvest image date in 2003. The pasture and bare classes experienced a loss in GV, but no increase in NPV. Instead, loss of GV is accounted for completely by an increase in soil fraction, indicating substantial vegetation loss and bare soil gain.

Table 20. Changes in endmember fractions for areas that did not experience land cover conversion for the Altiplano region.

Land Cover Type	Change in Soil Fraction	Change in GV Fraction	Change in NPV Fraction
NC Forest	-0.04	-0.23	0.28
NC Agriculture	0.10	-0.16	0.08
NC Pasture	0.14	-0.13	0.00
NC Bare	0.09	-0.08	0.00

Both the Mountain and Altiplano regions show vegetation loss and bare soil gain in the communal rangelands, but the suggestion of degradation is much stronger in the Altiplano than in the Mountain region. The land cover conversion analysis detected little change in the Altiplano region. However, the SMA results indicate a large region in the process of desertification. Immediate action to identify the conditions and manage the grazing practices driving this wide-scale degradation is necessary.

5.4 Identification of Areas of Extreme Change

I used the SMA results to identify areas of moderate change (1 – 2 standard deviations from the mean change) and extreme change (greater than 2 standard deviations from the mean change) in green vegetation (GV) (Figure 31). Obvious, extreme changes in GV occurred in the Altiplano lakes due to changing water levels. Moderate and severe GV loss is evident in the Central Tarija Valley and mountain headwater stream valleys where deforestation was observed from the land cover conversion analysis. Extreme increases in GV fraction have occurred both in the recently developed agricultural areas below the San Jacinto reservoir and in the upper Victoria watershed, which supplies greater than 90% of the potable water for the city of Tarija.

The upper Victoria was subject to the same anthropogenic pressures (i.e. communal grazing and sparse habitation) as the rest of the medium and high ridges of the Mountain region until the late 1980's, when main access to the upper watershed was blocked with a steel gate and 24-hour guarded access. The guarded access and daily patrol of the entire watershed above the gate has curtailed livestock grazing and human activity. Therefore, the Upper Victoria has been undisturbed (relative to its surroundings) for the past several years, providing a valuable reference area for the rest of the study region. The regeneration of the protected area, in contrast with the wide-scale vegetation degradation of adjacent, unmanaged watersheds, indicate the ability of local management activities to influence landscape processes.

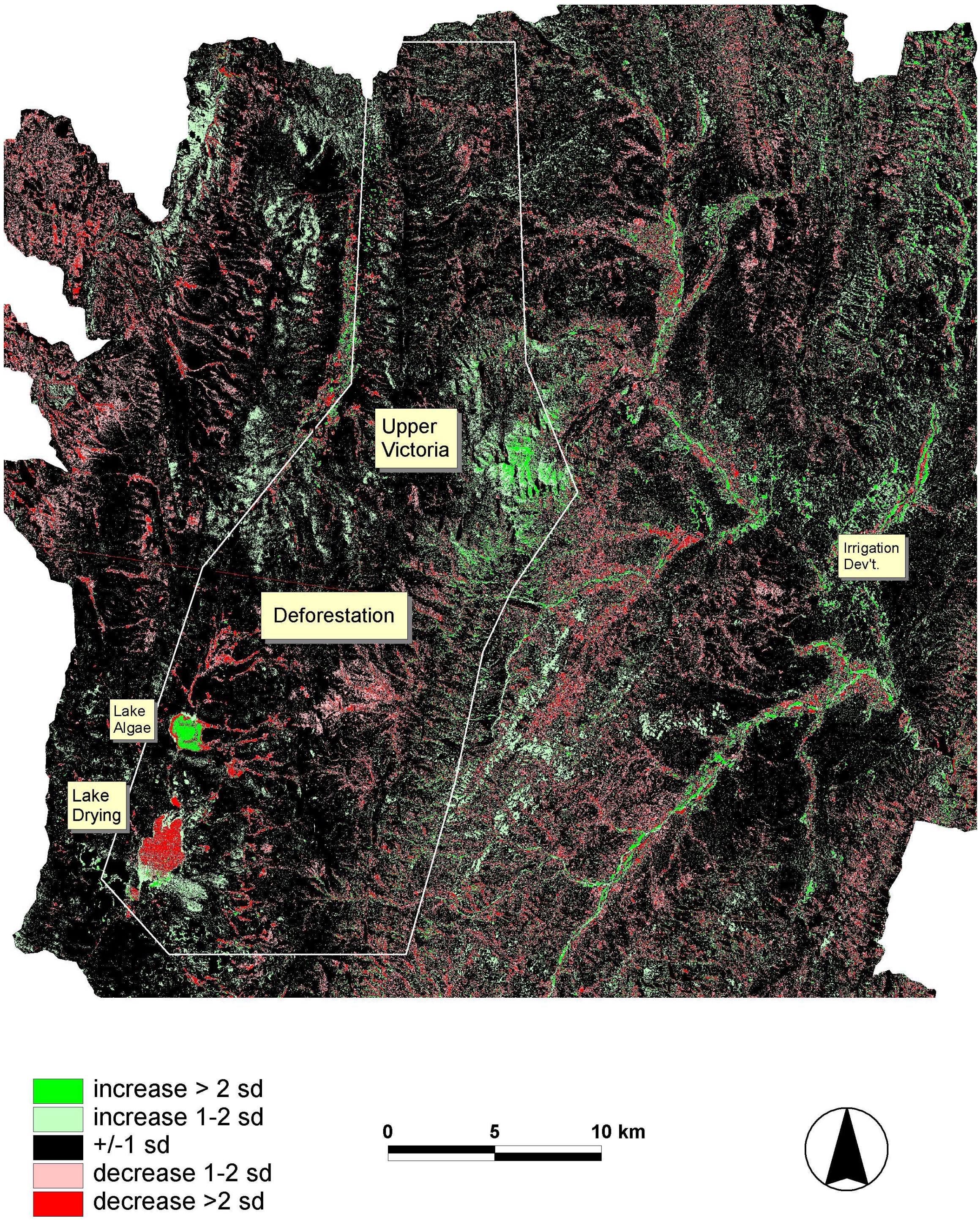


Figure 31. Change in GV endmember fraction from 1985 to 2003.

5.5 Extrapolation to National and Continental Scales

Remote sensing (RS) technology and analysis techniques allowed a fine scale regional analysis of land cover change based on very few field observations at a temporal and spatial scale that would otherwise be impossible. Conducting similar research for all of South America would be prohibitively resource-intensive. Using a multivariate clustering technique of basic environmental drivers, I identified ecoregions of South America where topographic and climatic conditions are similar to those at my study site, allowing the extrapolation of these results to other regions, and the estimation of landscape transformation at a national and continental scale. The WWF South American Ecoregional Map was not appropriate for this purpose, as it was developed to determine areas of distinct biological diversity. The clustering technique described in this paper permits not only the empirical delineation of similar units based on basic environmental drivers, but also allows non-subjective comparison between the units. The dendrogram provided a useful tool to determine the different ecoregional units that are most likely to respond similarly to disturbance and management activities.

The ecoregional analysis showed that the study area is part of a broad region of the South American Andes extending from northern Colombia to southern Argentina. Large areas of Bolivia, Peru, Chile, and Argentina have similar environmental conditions, indicating that managers working throughout the Andean mountains could 1) appropriately refer to the results of the current study and 2) successfully use the same research methodology. The ecoregional analysis also suggests that alarming rates of deforestation and desertification may be occurring throughout a large extent of the Andean mountains. Additional research at a few sites within the ecoregional cluster is needed to verify these extrapolations.

The study of other sites within the ecoregion would also facilitate the improvement of the research methodology. Separation of physiographic regions prior to image analysis should improve classification efficiency and accuracy. Satellite data with higher spatial resolution would diminish the “mixed pixel” problem. RS data with finer spectral resolution would improve the separation of agriculture, intensive pasture, and forest. Experimentation with alternative classification techniques (e.g. discriminant functions) would likely improve classification ability (Cingolani *et al.* 2004). Increasing the field data set would reduce error by enhancing both the density and the spatial coverage of the field data.

6.0 CONCLUSIONS AND MANAGEMENT IMPLICATIONS

The Sama Reserve and the surrounding area have been under increased pressure from development and population growth in the past several decades. Local environmental managers in the region target deforestation, agricultural conversion, and rangeland degradation as main threats to the region (Ayala Bluske 1998). However, a formal assessment of the patterns of land cover change at the regional scale had not been performed. This study was conducted to determine 1) if traditional remote sensing techniques, readily available data sources (e.g. Landsat images and the SRTM DEM), and very limited field data could be used to effectively characterize LULCC in the region and 2) if the LULCC characterization could provide information relevant for management.

Certain aspects of the study region make it a unique and challenging area to study. The collection of field data was severely restricted by limited financial resources and the remoteness of the study area. Historical field data for interpretation of the 1985 image were completely absent. The geomorphologic heterogeneity, mountainous terrain, and subpixel mixed land cover patterns of the region presented additional challenges in the application of traditional RS methods. Results of this study show that, despite these challenges, LULCC in the study region cover can be effectively characterized using established techniques and limited field data.

Land cover in 2003 was mapped into 9 classes with an overall accuracy of 89%. This classification can be used by managers as 1) a reliable base map for the development of land management plans, 2) a foundation for future land use change monitoring, and 3) the basis for a stream survey designed to examine the relationship between streams and their watersheds. Results of the secondary classifications demonstrate that past land cover can also be effectively characterized. Although classification without field data could not be performed with the same degree of detail and accuracy as the primary classification, it did allow a valuable analysis of change that would have otherwise been impossible.

The LULCC analysis showed that extensive deforestation and desertification at a regional scale has occurred in the last 20 years. If current trends persist, forest in the mountain region will disappear by 2020 and complete desertification of the communal rangelands will occur in less than 300 years. The land cover conversion analysis detected little change in the Altiplano region, but the SMA results indicated that large areas of the Altiplano are in the process of desertification. Such dramatic landscape transformations have disastrous consequences for both landscape productivity and the hydrologic cycle, decreasing both the quantity of base flows and the quality of surface water.

Management to protect remaining forest and control degradation of communal rangeland is necessary to avoid severe landscape deterioration in the near future. This research demonstrated that local management activities have greatly influenced landscape dynamics in the study area. Conversion to agriculture land since 1985 was very much a result of reservoir construction and irrigation development. The protection of the Victoria watershed has been a huge success, as seen by the large area of green vegetation regeneration in the protected area. Actions of the local government, communities, and environmental managers could potentially moderate the severe future changes implied by the results of this study.

Conducting similar research for all of South America would be prohibitively resource-intensive. The ecoregional analysis identified large areas of Bolivia, Peru, Chile, and Argentina that have similar environmental conditions, indicating that managers working throughout the Andes could refer to the results of this study. The ecoregional analysis also suggested that alarming rates of deforestation and desertification may be occurring throughout large areas of the Andean region. The selection of additional sites for similar research within the ecoregional cluster will allow validation of these extrapolations and improve the research methodology.

7.0 CITED REFERENCES

Abell, R. A., D. M. Olson, et al. (2000). Freshwater Ecoregions of North America. Washington, D.C., Island Press.

Adams, J., D. Sabol, et al. (1995). "Classification of Multispectral Images Based on Fractions of Endmembers: Application to Land-Cover Change in the Brazilian Amazon." Remote Sensing of the Environment **52**: 137-154.

Allan, J. D., A. J. Brenner, et al. (2002). "Land use in watersheds of the Venezuelan Andes: a comparative analysis." Conservation Biology **16**(2): 527-538.

Allan, J. D., D. L. Erickson, et al. (1997). "The influence of catchment land use on stream integrity across multiple spatial scales." Freshwater Biology **37**(1): 149-161.

Ayala Bluske, R. (1998). Areas Protegidas de Departamento de Tarija, PROMETA, IYA, Grupo DRU.

Baatz, M., U. Benz, et al. (2003). eCognition. Germany, Definiens Imaging.

Baied, C. A. and J. C. Wheeler (1993). "Evolution of High Andean Puna Ecosystems - Environment, Climate, and Culture Change over the Last 12,000 Years in the Central Andes." Mountain Research and Development **13**(2): 145-156.

Bailey, R. G. (1983). "Delineation of Ecosystem Regions." Environmental Management **7**(4): 365-373.

Baker, W. (1989). "A review of models of landscape change." Landscape Ecology **2**(2): 111-133.

Ballester, M., D. d. C. Victoria, et al. (2003). "A remote sensing/GIS-based physical template to understand the biogeochemistry of the Ji-Parana' river basin (Western Amazonia)." Remote Sensing of the Environment **87**: 429-445.

Barry, R. G. and A. Seimon (2000). "Research for Mountain Area Development: Climatic Fluctuations in the Mountains of the Americas and Their Significance." Ambio **29**(7).

Bernert, J. A., J. M. Eilers, et al. (1997). "A quantitative method for delineating regions: An example for the western Corn Belt plains ecoregion of the USA." Environmental Management **21**(3): 405-420.

Beven, K. J. and M. J. Kirkby (1979). "A physically based, variable contribution area model of basin hydrology." Hydrological Sciences Bulletin **24**(43-69).

Brooks, K. N., P. F. Ffolliott, et al. (1991). Hydrology and the Management of Watersheds, Iowa State University Press.

Brush, S. B. (1982). "The Natural and Human Environment of the Central Andes." Mountain Research and Development **2**(1): 19-38.

Buytaert, W., J. Deckers, et al. (2002). "Impact of land use changes on the hydrological properties of volcanic ash soils in South Ecuador." Soil Use and Management **18**(2): 94-100.

Carney, H. J., M. W. Binford, et al. (1993). "Nutrient and Sediment Retention in Andean Raised-Field Agriculture." Nature **364**(6433): 131-133.

Carney, H. J., M. W. Binford, et al. (1993). "Nitrogen and Phosphorus Dynamics and Retention in Ecotones of Lake Titicaca, Bolivia Peru." Hydrobiologia **251**(1-3): 39-47.

Carpio, J., C. Camacho, et al. (2002). Valoracion Hidrologica de las Cuencas de los Rios Tolomosa y La Victoria. La Paz, Bolivia, Instituto de Hidraulica e Hidrologia, Universidad Mayor de San Andres.

Carril, A. F., M. E. Doyle, et al. (1997). "Impacts of climate change on the oases of the Argentinean cordillera." Climate Research **9**(121-129).

Cingolani, A., D. Renison, et al. (2004). "Mapping vegetation in a heterogeneous mountain rangeland using landsat data: an alternative method to define and classify land-cover units." Remote Sensing of Environment **92**: 84-97.

Clinebell, R. R., O. L. Phillips, et al. (1995). "Prediction of Neotropical Tree and Liana Species Richness from Soil and Climatic Data." Biodiversity and Conservation **4**(1): 56-90.

Collins, J. and C. Woodcock (1996). "An assessment of several linear change detection techniques for mapping forest mortality using multitemporal Landsat TM data." Remote Sensing of Environment **56**: 66-77.
Crist, E. and R. Cicone (1984). "Application of the Tasseled Cap Concept to Simulated Thematic Mapper Data." Photogrammetric Engineering and Remote Sensing **50**(3): 343-352.
Davis, M. B. (1989). "Insights from Paleoecology on Global Change." Ecological Society of America Bulletin **70**(4): 222-228.
Delcourt, P. A. and H. R. Delcourt (1998). "Paleoecological insights on conservation of biodiversity: A focus on species, ecosystems, and landscapes." Ecological Applications **8**(4): 921-934.
Depetris, P. J. and J. E. Paolini (1991). Ch. 5 Biogeochemical aspects of South American Rivers: The Parana and the Orinoco. Biogeochemistry of Major World Rivers. S. K. a. J. E. R. E.T. Degens.
Dinerstein, E., D. M. Olson, et al. (1995). Una Evaluacion del Estado de Conservacion de las Ecoregiones Terrestres de America Latina y el Caribe, World Wildlife Fund and World Bank.
Ellenberg, H. (1979). "Mans Influence on Tropical Mountain Ecosystems in South-America - 2nd Tansley Lecture." Journal of Ecology **67**(2): 401-&.
Elmore, A., J. Mustard, et al. (2000). "Quantifying Vegetation Change in Semiarid Environments: Precision and Accuracy of Spectral Mixture Analysis and the Normalized Difference Vegetation Index." Remote Sensing of the Environment **73**: 87-102.
Erdas (2002). Erdas Imagine.
ESRI (2002). ARC. Redlands, CA, ESRI, Inc.
Etter, A. and W. van Wyngaarden (2000). "Patterns of landscape transformation in Colombia, with emphasis in the Andean region." Ambio **29**(7): 432-439.
FAO (1978). Soil map of the world, scale 1:5,000,000. Paris, United Nations Educational, Scientific, and Cultural Organization. **I- X**.
Flecker, A. S. and B. Feifarek (1994). "Disturbance and the Temporal Variability of Invertebrate Assemblages in 2 Andean Streams." Freshwater Biology **31**(2): 131-142.
Fossati, O., J. G. Wasson, et al. (2001). "Impact of sediment releases on water chemistry and macroinvertebrate communities in clear water Andean streams (Bolivia)." Archiv Fur Hydrobiologie **151**(1): 33-50.
Gerritsen, J., M. T. Barbour, et al. (2000). "Apples, oranges, and ecoregions: on determining pattern in aquatic assemblages." Journal of the North American Benthological Society **19**(3): 487-496.
Gopal, S. and C. Woodcock (1994). "Theory and methods for accuracy assessment of thematic maps using fuzzy sets." Photogrammetric Engineering and Remote Sensing **60**: 181-188.
Grace, J., F. Berninger, et al. (2002). "Impacts of Climate Change on the Tree Line." Annals of Botany **90**: 537-544.
Grau, A. and A. D. Brown (2000). "Development threats to biodiversity and opportunities for conservation in the mountain ranges of the Upper Bermejo River Basin, NW Argentina and SW Bolivia." Ambio **29**(7): 445-450.
Guyot, J. L., J. G. Wasson, et al. (1992). Dissolved matter and suspended sediment loads in some inflow rivers and in the Rio Desaguedero. Lake Titicaca. C. D. a. A. Iltis. The Netherlands, Kluwer Academic Publishers**:** 113-119.
Hall, C. A. S., H. Tian, et al. (1995). "Modelling spatial and temporal patterns of tropical land use change." Journal of Biogeography **22**: 753-757.
Hamilton, L. S. and L. A. Bruijnzeel (1997). Ch. 15. Mountain watersheds - integrating water, soils, gravity, vegetation, and people. Mountains of the world: a global priority. a. J. D. I. B. Messerli.

Hamilton, L. S. and P. N. King (1983). Tropical Forested Watersheds: Hydrologic and Soils Response to Major Uses or Conversions, Westview Press.
Harding, J. S. and M. J. Winterbourn (1997). "An ecoregion classification of the South Island, New Zealand." Journal of Environmental Management **51**(3): 275-287.
Harding, J. S., M. J. Winterbourn, et al. (1997). "Stream faunas and ecoregions in South Island, New Zealand: do they correspond?" Archiv Fur Hydrobiologie **140**(3): 289-307.
Hargrove, W. W. and F. M. Hoffman (1999). "Using multivariate clustering to characterize ecoregion borders." Computing in Science & Engineering **1**(4): 18-25.
Hargrove, W. W. and R. J. Luxmoore (1997). "Spatial Clustering Technique for the Identification of Customizable Ecoregions." Web-based Publication.
Hawkins, C. P., R. H. Norris, et al. (2000). "Evaluation of the use of landscape classifications for the prediction of freshwater biota: synthesis and recommendations." Journal of the North American Benthological Society **19**(3): 541-556.
Hearn, P., T. Hare, et al. (2000). Global GIS Database: Digital Atlas of Central and South America. USGS Digital Data Series DDS-62-A.
Host, G. E., P. L. Polzer, et al. (1996). "A quantitative approach to developing regional ecosystem classifications." Ecological Applications **6**(2): 608-618.
Huete, A. R. (1989). Soil Influences in Remotely Sensed Vegetation-Canopy Spectra. Theory and Applications of Optical Remote Sensing. G. Asrar**:** 107-140.
Jenerette, G. D., J. Lee, et al. (2002). "Multivariate analysis of the ecoregion delineation for aquatic systems." Environmental Management **29**(1): 67-75.
Jenerette, G. D. and J. G. Wu (2001). "Analysis and simulation of land-use change in the central Arizona-Phoenix region, USA." Landscape Ecology **16**(7): 611-626.
Johnson, L. B., C. Richards, et al. (1997). "Landscape influences on water chemistry in Midwestern stream ecosystems." Freshwater Biology **37**(1): 193-&.
Jones, K. B., K. H. Riitters, et al. (1997). An Ecological Assessment of the United States Mid-Atlantic Region: A Landscape Atlas, EPA/600/R-97/130.
Justice, C. and J. Townshend (1981). Integrating ground data with remote sensing. Terrain Analysis and Remote Sensing. J. Townshend. Boston, Allen and Unwin**:** 38-58.
Karwan, D. L., J. D. Allan, et al. (2001). "Changing near-stream land use and river channel morphology in the Venezuelan Andes." Journal of the American Water Resources Association **37**(6): 1579-1587.
Kessler, M. (1995). Present and Potential Distribution of Polylepis (Rosaceae) Forests in Bolivia. Biodiversity and Conservation of Neotropical Montane Forests. S. P. C. e. al., The New York Botanical Garden**:** 281-294.
Kok, K., A. Farrow, et al. (2001). "A method and applicataion of multi-scale validation in spatial land use models." Agriculture, Ecosystems and Environment **85**: 223-238.
Kok, K., P. A. Verweij, et al. (1995). Effects of Cutting and Grazing on Andean Treeline Vegetation. Biodiversity and Conservation of Neotropical Montane Forests. S. P. Churchill, The New York Botanical Garden**:** 527-539.
Laegaard, S. (1992). Influence of fire in the grass paramo vegetation of Ecuador. Paramo: An Andean Ecosystem under Human Influence. H. B. a. J. L. Luteym.
Leemans, R. and W. Cramer (1991). The IIASA database for mean monthly values of temperature, precipitation and cloudiness on a global terrestrial grid, IIASA Research Report RR-91-18.
Likens, G. E., F. H. Bormann, et al. (1970). "Effects of Forest Cutting and Herbicide Treatment on Nutrient Budgets in Hubbard Brook Watershed-Ecosystem." Ecological Monographs **40**(1): 23-&.
Lillesand, T. and R. Kiefer (1994). Remote Sensing and Image Interpretation, John Wiley & Sons, Inc.

Lu, D. S., E. Moran, et al. (2003). "Linear mixture model applied to Amazonian vegetation classification." Remote Sensing of Environment **87**(4): 456-469.
Messerli, B., M. Grosjean, et al. (1997). "Water availability, protected areas, and natural resources in the Andean desert altiplano." Mountain Research and Development **17**(3): 229-238.
Meyer, P., K. Itten, et al. (1993). "Radiometric corrections of topographicall induced effects on Landsat TM data in an Alpine environment." Isprs Journal of Photogrammetry and Remote Sensing **48**: 17-28.
Miller, S. N., W. G. Kepner, et al. (2002). "Integrating landscape assessment and hydrologic modeling for land cover change analysis." Journal of the American Water Resources Association **38**(4): 915-929.
Millette, T. L., A. R. Tuladhar, et al. (1995). "The Use and Limits of Remote-Sensing for Analyzing Environmental and Social-Change in the Himalayan-Middle-Mountains-of-Nepal." Global Environmental Change-Human and Policy Dimensions **5**(4): 367-380.
Monaghan, K. A., M. R. Peck, et al. (2000). "Macroinvertebrate distribution in Ecuadorian hill streams: the effects of altitude and land use." Archiv Fur Hydrobiologie **149**(3): 421-440.
Moore, I. D., R. B. Grayson, et al. (1991). "Digital terrain modelling: a review of hydrological, geomorphological, and biological applications." Hydrological Processes **5**: 3-30.
Numata, I., J. V. Soares, et al. (2003). "Relationships among soil fertility dynamics and remotely sensed measures across pasture chronosequences in Rondonia, Brazil." Remote Sensing of Environment **87**(4): 446-455.
Okin, G. S., D. A. Roberts, et al. (2001). "Practical limits on hyperspectral vegetation discrimination in arid and semiarid environments." Remote Sensing of Environment **77**(2): 212-225.
Olson, D. M., E. Dinerstein, et al. (2001). "Terrestrial ecoregions of the worlds: A new map of life on Earth." Bioscience **51**(11): 933-938.
Omernik, J. M. (1987). "Ecoregions of the Conterminous United-States." Annals of the Association of American Geographers **77**(1): 118-125.
Omi, P. N., L. C. Wensel, et al. (1979). "Application of Multivariate Statistics to Land-Use Planning - Classifying Land Units into Homogeneous Zones." Forest Science **25**(3): 399-414.
Parker, D. C., T. Berger, et al., Eds. (2002). Agent-Based Models of Land-Use and Land-Cover Change. LUCC Report Series No. 6. Indiana University, LUCC Focus 1 Office.
Peterson, B. J., W. M. Wollheim, et al. (2001). "Control of nitrogen export from watersheds by headwater streams." Science **292**(5514): 86-90.
Peterson, G. D. (2002). Ch. 12 Alternative Stable States. Learning Landscape Ecology, S. Gergel and M.G. Turner, eds.
Preston, D., J. Fairbairn, et al. (2003). "Grazing and environmental change on the Tarija altiplano, Bolivia." Mountain Research and Development **23**(2): 141-148.
Roberts, D., G. Batista, et al. (1998). Change Identification Using Multitemporal Spectral Mixture Analysis: Applications in Eastern Amazonia. Remote Sensing Change Detection: environmental monitoring methods and applications. R. Lunetta. Chelsea, MI, Sleeping Bear Press**:** 137-161.
Roberts, D. A., M. Keller, et al. (2003). "Studies of land-cover, land-use, and biophysical properties of vegetation in the Large Scale Biosphere Atmosphere experiment in Amazonia." Remote Sensing of Environment **87**(4): 377-388.
Rohm, C. M., J. W. Giese, et al. (1987). "Evaluation of an Aquatic Ecoregion Classification of Streams in Arkansas." Journal of Freshwater Ecology **4**(1): 127-140.
Roth, N. E., J. D. Allan, et al. (1996). "Landscape influences on stream biotic integrity assessed at multiple spatial scales." Landscape Ecology **11**(3): 141-156.
RSI (2000). ENVI User's Guide. Boulder, CO, Research Systems.

Rundel, P. W. and B. Palma (2000). "Preserving the unique puna ecosystems of the Andean Altiplano: A descriptive account of Lauca National Park, Chile." Mountain Research and Development **20**(3): 262-271.
Sarmiento, F. O. (2000). "Breaking mountain paradigms: Ecological effects on human impacts in man-aged Tropandean landscapes." Ambio **29**(7): 423-431.
Sarmiento, F. O. and L. M. Frolich (2002). "Andean cloud forest tree lines - Naturalness, agriculture and the human dimension." Mountain Research and Development **22**(3): 278-287.
Seibert, P. (1983). Ch. 19 Human impact on landscape and vegetation in the Central High Andes. Man's Impact on Vegetation. M. J. A. W. a. I. I. W. Holzner. The Netherlands, Dr. W. Junk Publishers.
Smadja, J. (1992). "Studies of climatic and human impacts and their relationship on a mountain slope above Salme in the Himalayan Middle Mountains, Nepal." Mountain Research and Development **12**(1): 1-28.
Souza, C., L. Firestone, et al. (2003). "Mapping forest degradation in the Eastern Amazon from SPOT 4 through spectral mixture models." Remote Sensing of Environment **87**(4): 494-506.
Sturtevant, B. R., S. W. Seagle, et al. (in review). "Interior songbird response to forest productivity and drought in western Maryland." Ecological Applications.
Tou, J. T. and R. C. Gonzalez (1974). Pattern Recognition Principles, Addison-Wesley Publishing Co.
Turner, M. G. (1987). "Spatial simulation of landscape changes in Georgia: A comparison of 3 transition models." Landscape Ecology **1**(1): 29-36.
Urban, D. L. (2000). "Using model analysis to design monitoring programs for landscape management and impact assessment." Ecological Applications **10**: 1820-1832.
Urban, D. L. and D. O. Wallin (2002). Chapter 4 Introduction to Markov Models. Learning Landscape Ecology. e. S.E. Gergel and M.G. Turner.
USGS (2000). HYDRO1k Database for South America, USGS EROS Data Center.
Veldkamp, A. and L. O. Fresco (1996). "CLUE: A conceptual model to study the conversion of land use and its effects." Ecological Modelling **85**(2-3): 253-270.
Veldkamp, A. and L. O. Fresco (1996). "CLUE-CR: An integrated multi-scale model to simulate land use change scenarios in Costa Rica." Ecological Modelling **91**(1-3): 231-248.
Veldkamp, A. and E. Lambin (2001). "Predicting land-use change." Agriculture, Ecosystems and Environment **85**: 1-6.
Veldkamp, A. and P. H. Verburg (2004). "Modelling land use change and environmental impact." Journal of Environmental Management **72**(1-2): 1-3.
Verburg, P., J. van Eck, et al. (2002). "A method to analyse neighbourhood characteristics of land use patterns." Computers, Environment and Urban Systems.
Verburg, P., W. Veldkamp, et al. (2002). "Modeling the Spatial Dynamics of Regional Land Use: The Clue-S Model." Environmental Management **30**(3): 391-405.
Verburg, P. H. and Y. Q. Chen (2000). "Multiscale characterization of land-use patterns in China." Ecosystems **3**(4): 369-385.
Verburg, P. H., G. H. J. de Koning, et al. (1999). "A spatial explicit allocation procedure for modelling the pattern of land use change based upon actual land use." Ecological Modelling **116**(1): 45-61.
Verburg, P. H., W. Soepboer, et al. (2002). "Modeling the spatial dynamics of regional land use: The CLUE-S model." Environmental Management **30**(3): 391-405.
Wang, L. Z., J. Lyons, et al. (1997). "Influences of watershed land use on habitat quality and biotic integrity in Wisconsin streams." Fisheries **22**(6): 6-12.
Wang, X. H. and Z. Y. Yin (1997). "Using GIS to assess the relationship between land use and water quality at a watershed level." Environment International **23**(1): 103-114.

Washington-Allen, R. A., R. D. Ramsey, et al. (1998). "Change detection of the effect of severe drought on subsistence agropastoral communities on the Bolivian Altiplano." International Journal of Remote Sensing **19**(7): 1319-1333.
Wasson, J. G., J. L. Guyot, et al. (1991). "First estimation of organic carbon transport in the Rio Desaguadero (Altiplano, Bolivia)." Revue Des Sciences De L'eau **4**: 363-379.
Wasson, J. G., R. Marin, et al. (1998). "Hydro-morphological variability and benthic community structure in five high altitude Andean streams (Bolivia)." Verh. Internat. Verein. Limnol. **26**: 1169-1173.
Wear, D. N. and P. Bolstad (1998). "Land-use changes in Southern Appalachian landscapes: Spatial analysis and forecast evaluation." Ecosystems **1**(6): 575-594.
Wear, D. N., M. G. Turner, et al. (1998). "Land cover along an urban-rural gradient: Implications for water quality." Ecological Applications **8**(3): 619-630.
Wright, R. G., M. P. Murray, et al. (1998). "Ecoregions as a level of ecological analysis." Biological Conservation **86**(2): 207-213.
Wurtsbaugh, W. A., W. F. Vincent, et al. (1985). "Nutrient Limitation of Algal Growth and Nitrogen-Fixation in a Tropical Alpine Lake, Lake Titicaca (Peru Bolivia)." Freshwater Biology **15**(2): 185-195.