Monitoring Spatio-temporal Dynamics of land cover changes for Bolivian land tenure reform using MODIS remote sensing images

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February 2010

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by
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Thesis submitted to the International Institute for Geo-information Science and Earth Observation in partial fulfillment of the requirements for the degree of Master of Science in Geo-information Science and Earth Observation, Specialization: Natural Resources Management

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Abstract

Land cover and land use changes have a direct influence over ecosystems and socioeconomic structures of regions. Some of these changes are decided and administered by local governments in a planned and controlled manner. However many of the changes is the result of one-sided and improper decision making, which directly affects local people, who start to notice important changes in land use types in their communities. In due course, various natural and cultural assets become disturbed in a non-sustainable manner.

Many developing countries are grappling with how to reconcile the three objectives of increasing agricultural production, reducing poverty and using natural resources sustainably. In this context, the Bolivian government is implementing a reform of the agrarian system in Bolivia, based on the principle that everyone has the right to private property, as long as it is a “productive land” (LeyN°3545 2006).

The general objective of this study is to monitor land cover patterns in Alto Parapeti by analyzing time series of MODIS imagery to determine productive and unproductive lands from the Bolivian land tenure reform perspective.

The spatial and temporal MODIS NDVI patterns, in a remote sensing perspective, have been analyzed in the area of Alto Parapeti, part of the Chaco region in Bolivia. The patterns have been explored by applying a decision tree classification for land cover mapping. The land cover classes identified in the study area are dense forest, crop land, dense shrub land, mixed vegetation/shrub dominant and water bodies. The performance of the classification method was evaluated in terms of accuracy for the land cover map of 2009.

Land cover maps from 2001 to 2009 were generated using the decision tree classification, but further work is needed to validate this method with more dates, and later test this approach to determine the sensitivity to inter- annual variability over the classification results of multiple years.

The accuracy assessment of the land cover map 2009 was 76% overall accuracy. The performance of the decision tree classification was successfully at mapping extensive cover lands such as dense forest and mixed vegetation /shrub dominant, although was some miss-classification of dense shrub land in the transition to dense forest. The approach was far less effective at mapping smaller cover types as the small as fragmented cropland areas. The decision tree approach was compared in terms of accuracy with maximum likelihood supervised classification and isodata classification methods. The approach by decision tree provided the highest overall accuracy of three methods.

The land cover classes were allocated to the “productive land” categories producing a “productive land” map Alto Parapeti from 2009. The map showed a large extension of unproductive land. This approach and can be used as a reference to prioritize the efforts of the Bolivian Agrarian Reform finding extensive unproductive land to start field verification.

Acknowledgements

First I would like to express my gratitude to both International Institute for Geo-information Science and Earth Observation (ITC) for providing me this precious opportunity to take this course.

My deepest appreciation goes to my supervisors Ir. B.G.C.M. Krol and Dr. A. Vrieling

To Ir. B.G.C.M. Krol, thank you for being such a patient and caring supervisor and for always being so kind to me and willing to help me out whenever I encountered difficulties in my research.

To Dr. A. Vrieling, I would like to thank you for all the advices for improving my research.

To Dr. Michael Weir who always came by to help resolve questions and provide critical advises.

I'm grateful to all my friends, NRM classmates and all the staff working in ITC, I had a wonderful time with you in the Netherlands.

Last not least, thanks to the most important people in my life – my dear father and brother for supporting me and having faith in me. Words can't say enough, I sincerely thank all those who helped me, encouraged me and stood by me during this special, challenging yet unforgettable phase in my life.

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1 Introduction

Land cover and land use changes have a direct influence over ecosystems and socioeconomic structures of regions. Some of these changes are decided and administered by local governments in a planned and controlled manner, supporting tourism, industry and/or agriculture. However many of the changes is the result of one-sided and improper decision making, which directly affects local people, who start to notice important changes in land use types in their communities. In due course, various natural and cultural assets become disturbed in a non-sustainable manner (Sonmez et al. 2009)

(FAO 2009) stated that "Secure access to land and other natural resources is a direct factor in the alleviation of hunger and rural poverty. Rural landlessness is often the best predictor of poverty and hunger: the poorest are usually landless or land-poor. Inadequate rights of access to land and other natural resources, and insecure tenure of those rights, often result in extreme poverty and hunger. In most societies access to land has favored certain individuals and groups at the expense of others".

The ability to perform analyses as a function of time using past land cover and land use data is important for planning purposes. Various remote sensing tools are available for detecting and monitoring land cover and land use changes and transformations, such as multi temporal classification, image differencing and ratio measurements, vegetation indices differences, image enhancement and visual interpretation (Singh 1989). In addition, GIS enables convenient utilization of the information and results that are obtained from remote sensing techniques for structuring databases, and easy querying of the data.

Especially in areas of conflict, where fieldwork on the ground is dangerous, remote sensing and GIS technology offer an alternative method of obtaining some of the required data. These technologies allow relatively accurate, fast and easy acquisition, analysis, and production of data on land cover and land use. The combination of remote sensing and GIS facilitate the analysis of land cover over time (Sonmez et al. 2009).

Even though the terms, land use and land cover, are in practice often used interchangeably, in change detection studies they are quite distinct (Seto et al. 2002). Land cover is the observed biophysical cover on the earth's surface. Land use is characterized by the arrangements, activities and inputs people undertake in a certain land cover type to produce, change or maintain it. Definition of land use in this way establishes a direct link between land cover and the actions of people in their environment (Di Gregorio et al. 1998). Therefore, conceptual models that identify land-use change based on the idea that land-use classes are composed of component land-covers, provide a good framework with which to infer land-use change from land-cover characteristics (Seto et al. 2002).

Monitoring the locations and distributions of land-cover changes is important for establishing links between policy decisions, regulatory actions and subsequent land-use activities (Lunetta et al. 2006). The MODIS remote sensing instrument (Moderate Resolution Imaging Spectro-radiometer) combines moderate spatial resolution (250, 500 and 1000 meters) with spectral resolution, high temporal resolution and accurate geolocation. It is frequently used for farmland detection, vegetation indices analysis and land cover dynamics monitoring (Galford et al. 2008).

The availability of no-cost MODIS NDVI data and processing techniques that provide high-quality continuous time series data represent a major advancement for monitoring annual land-cover change and vegetation condition over large geographic regions (Sedano et al. 2005; Lunetta et al. 2006; Perera et al. 2009). The main advantage of utilizing MODIS data lies with its unique character, which combines both spatial and spectral resolution of several satellites on a single platform, yet with no cost for data (Lunetta et al. 2006; Perera et al. 2009). These advantages are in sharp contrast to the traditional Landsat data based approaches that are comparatively data and computationally expensive (Lunetta et al. 2006). The increased temporal resolution of the MODIS NDVI 250m data has a significant advantage over traditional Landsat data for both capturing the actual timing of the change event and the subsequent monitoring of the recovery to the next steady state (Lunetta et al. 2006).

The correlation of photosynthetic activity and vegetation indices patterns is one of the cornerstones of remote sensing observation of the environment and has been extensively studied and documented (Tucker et al. 1991; Huete et al. 1997; Jiang et al. 2006). The normalized difference vegetation index (NDVI) is one of the most widely used vegetation indexes and its utility in satellite assessment and monitoring of global vegetation cover has been well demonstrated over the past two decades(Huete et al. 1997; Jiang et al. 2006). Major advantages of the NDVI-based change detection approach include robust results, nominal computational requirements, automated data processing protocols, annual change alarm product capability, and rapid product delivery (Lunetta et al. 2006).

NDVI is commonly used with various sensors to study vegetation phenology, monitor spatial-temporal vegetation dynamic, generate vegetation maps, etc. Various scientific researches have extracted vegetation information using NDVI concerned methods: (Wardlow et al. 2008) demonstrated that time-series MODIS NDVI data provide a viable option for regional-scale crop mapping in the U.S. Central Great Plains.

1.1 Problem Statement

Many developing countries are grappling with how to reconcile the three objectives of increasing agricultural production, reducing poverty and using natural resources sustainably. In this context, the Bolivian government is implementing a reform of the agrarian system in Bolivia, based on the principle that everyone has the right to private property, as long as it is a “productive land” (LeyN°3545 2006).

The Bolivian government stipulates that the agricultural land owned by one individual should not be greater than 5000 hectares. Therefore, The agrarian reform law (LeyN°3545 2006) establishes three classes of agrarian property for subtropical zones: small property of 50 hectares, medium property up to 500 hectares and large agrarian property up to 5000 hectares (Urioste et al. 2001; LeyN°3545 2006).

The Agrarian Reform law recognizes “productive land” as four categories of land: (1) effectively exploited land, (2) fallow land, (3) ecological land and (4) growth projection land. This necessarily will have to be verified and monitored in the field by land use land cover surveys. For this reason, it is important to determine the land cover and use types, as well as to detect their change in time.

It is impractical to implement the process of agrarian reform over lands where conflicts occur. One such area is Alto Parapeti which has become a very sensitive part of the agrarian process because it is the geographic point, and also the social space, where resistance of the agricultural sector prevented the consolidation of the agrarian process. Ranchers and landholders have joined small and medium producers to stop the agrarian reform, although their interests are not the same, because some small and medium producers will accept the reorganization in order to consolidate their property rights over their land.

The agrarian process has reverted 40000 hectares of unproductive lands in Alto Parapeti, in the province of Cordillera (Santa Cruz-Bolivia). There are a total of 10,000 families, including Guaraní Indians and (mixed race or non-indigenous) small farmers and peasants. All of them will benefit from the land reform process, which involves surveying and measuring properties and identifying unused land, to be distributed to the indigenous communities as collectively-owned property. But much of that land is currently occupied by ranchers and medium and large landholders. According to Government preliminary data, 14 large producers own 52 percent of the land in Alto Parapeti, 28 medium producers own 34.6 percent, and 40 small producers own 7.8 percent.

The conflictive situation in Alto Parapeti has highlighted a disturbing trend that is becoming increasingly common in Santa Cruz: the willingness of the land owning elite to use violence to halt land reform and the central government's inability to protect their supporters in the indigenous community as well as their own employees from such violence.

1.2 Research Objectives and Questions

1.2.1 Main Objective

The general objective of this study is to monitor land cover patterns in Alto Parapeti by analyzing time series of MODIS imagery to determine productive and unproductive lands from the Bolivian land tenure reform perspective.

1.2.2 Specific Objectives and Questions

a) To determine the actual spatial distribution of land cover types in Alto Parapeti

   i. **Which land cover classes can be effectively discriminate using MODIS NDVI imagery?**

b) To determine the land cover temporal dynamics during the period from 2000 to 2009

   i. **What land cover changes can be derived from 2000 to 2009?**

c) To validate the actual land cover map.

   i. **What is the accuracy assessment of the land cover map of 2009?**

d) To predict the actual spatial distribution of both "productive land" and "unproductive land" from land cover change dynamics in Alto Parapeti.

   i. **What are the land cover temporal profiles that belong to the different "productive lands" categories?**

2 Methods and Materials

This chapter describes the study area, methods and materials that were applied in the collection, processing, analysis and presentation of data with a view to fulfilling the set objectives and answering the research questions.

2.1 Study Area

The study area is located in the Alto Parapeti area shown in Figure2-1, in the southern part of Cordillera Province in Santa Cruz, Bolivia. It is located between 20° 14' 05" S and 20° 29' 11"S latitude and 63° 46' 56" W and 63° 20' 46" W Longitude. The study area spans approximately 850 Km^2.

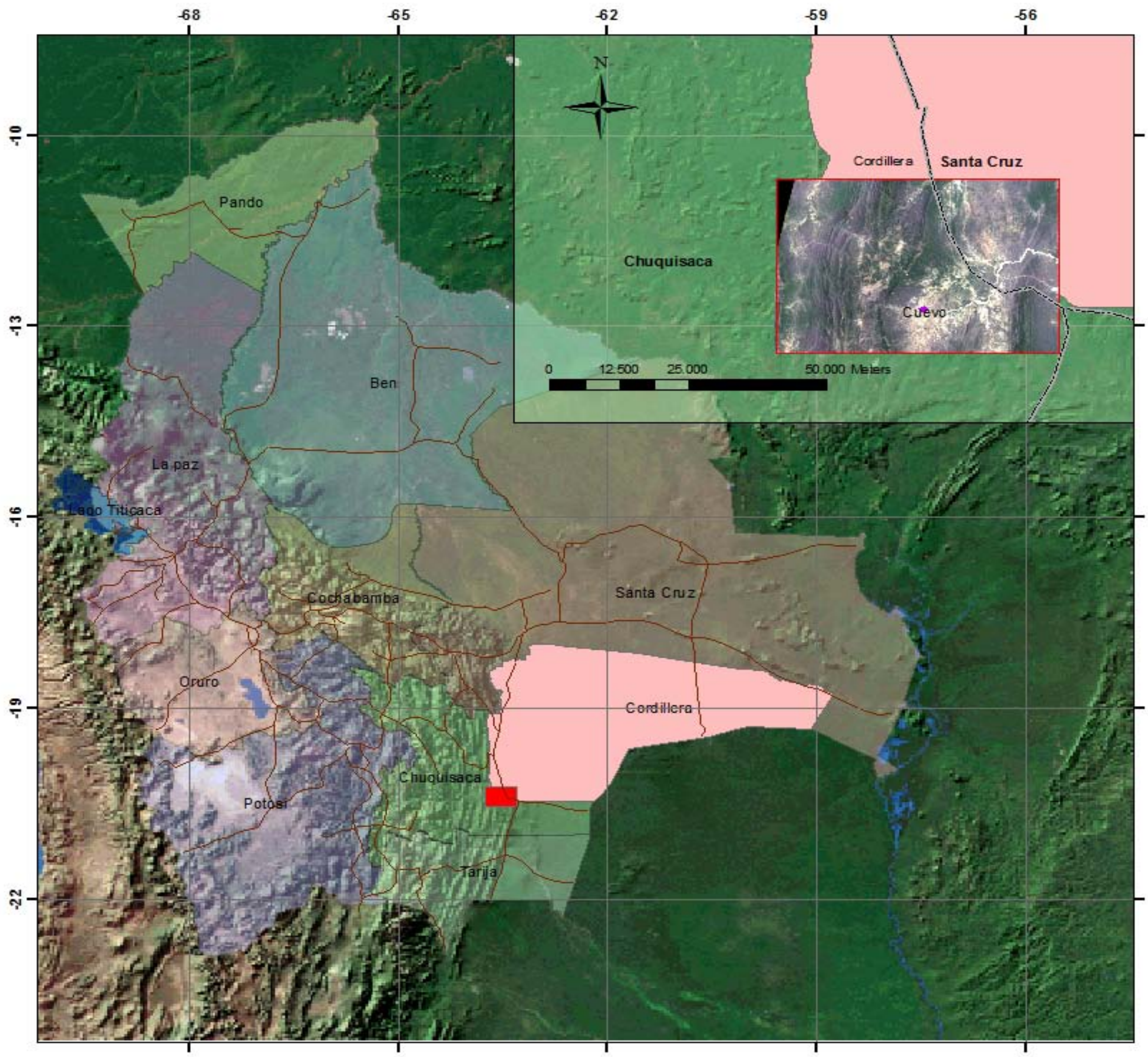

Figure2-1 Location map of Alto Parapeti

Alto Parapeti is part of the Gran Chaco geological system. The landscape is generally flat with a few low undulating hills. The main river is the Parapeti, which has its origins in the locality of Irenda (Choreti) and flows into a vast area of wetlands named Izozog Swamps (Urioste et al. 2001).

The climate of the Bolivian Chaco is characterized by dry and hot weather in the summer period, between November and March, while the months of June and July are the coldest of the year. The climate ranges from hot and arid to sub-humid with an average annual rainfall of 400 mm in the easternmost part (border with Paraguay) to 900 - 1000 mm near the Sub-Andin part (Aguaragüe Mountains). The dry season lasts from 7 to 9 months with some winter rains (Argollo 2006).

The Bolivian Chaco presents the following five major ecoregion types (Urioste et al. 2001):

- Lowland sand-flats;
- Lowland sub-humid forests;
- Deciduous dry Chaco forests
- Scrublands:
- Chaco xeric grasslands.

(Riveros 2004) described the vegetation of Chaco as fallow "Dry Chaco woodland is the dominant formation and covers large tracts to the west, south and southwest of Los Bañados del Izozog. It is low woodland with a sparse tree layer, which is almost entirely *caha* in the form of scattered trees, and candelabra cacti. Its main characteristic is a nearly impenetrable shrub layer, 4 to 6 m high, of *chorquetta* which also occurs in the forests of the sub-humid Chaco.

The population of Alto Parapeti is from Guarani origin approximately 3500 to 4000 habitants. Social organizations are the peasant unions of small and medium farmers, farm women's organizations and mothers' clubs (PIT 2007).

Originally, the Guarani relied upon slash-and-burn agriculture. Their main crops were cassava, maize, sweet potatoes, beans, squash, peanuts, cara (*Dioscorea* sp.), mangara (*Aroidea* sp.), bananas and papaya. This diet was supplemented by hunting, limited 32 fishing and gathering. Men did the hunting and fishing and were responsible for the initial clearing for agriculture; cultivation was left to the women (Beltran et al. 2000).

Agriculture is the main activity of the indigenous and peasant families in Alto parapeti, while for the landowners is a complementary activity to livestock. Maize is the most important crop for both farmers and community members of families, though other varieties are still grown with low yielding and low productivity. The bean crop is second in importance, followed by pumpkin, sweet potato, cassava and groundnuts. A small part of the production is destined for the market and the rest is for human consumption, animal breeding and seed production (PIT 2007).

Water availability in the soil determines the planting date of the maize, coinciding with the start of the rainy season in November or December (depending on year). The temperatures most suitable for germination of maize are between 25 ° and 30 ° C. If temperatures occur outside of these ranges for extended periods may affect plant (Jungwirth 2009).

The periods of work in the Maize during the annual agricultural crop management, has the following activities showed in Table 2-1 (Jungwirth 2009):

Table 2-1 Agricultural calendar of Maize in the Chaco Region

Agricultural calendar of Maize												
Activities	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Soil preparation												
Seed												
Harvest												

There is no rotation of crops in the communities, after 10 or 20 years of production is left as fallow land, letting the natural vegetation to grow up again, until a new clearing and burning of bushes and trees starts (if the fallow is very long, it gives time to recover a little of natural forest)(Jungwirth 2009).

Often, the products obtained are not sufficient to satisfy the nutritional needs of the family throughout the year. Likewise, lack of water prevents fruit production. 90 of agricultural and livestock output is used for local consumption, while the remaining 10 per cent is swapped for provisions. In other words, it is not a modern, commercial agricultural and livestock economy, but, rather, an inefficient economy(Urioste et al. 2001).

There are no recent land tenure data of Alto Parapeti in Bolivia, as the last agricultural and livestock census was carried out in 1984. That is why the INRA is beginning to investigate the reorganization of land. This process has been and still is slow, given the natural resistance of the Land owners. According to INRA, in December 2008, 52 per cent of the lands still have to be reorganized and in 12 per cent the process is under way. In other words, only 35 per cent had been examined as part of the titling process. The result of this long bureaucratic process has been a severe worsening of living conditions for the Guaraníes. The disputed lands remain intact, despite the handing over of titles. Many Guaraníes were expelled from Alto Parapeti and have no access to land; and those that do have access to a small amount of land lack seeds and materials (PIT 2007).

2.2 Research Materials

MODIS data acquisition

MODIS satellite data was selected for studying land cover variation. MODIS imageries have coarse spatial resolution of 250m, 500m, 1000m, which is a shortage in accurately identifying small land covers. However, the area of Alto Parapeti is up to 850 Km^2, corresponding to 13600 pixels on the 250 m image data and the minimum area of agrarian land is 0.5 Km^2. The resolution is good enough to display the study area.

- MODIS NDVI 16-day composite grid data 250 m x 250 m (MOD13Q1 version 5 obtain from the Terra spacecraft) in HDF format were acquired between March 2000 and December 2009. The study area was covered the h12v11 tile. A total of 223 images were downloaded from the Land Processes DAAC (LP DAAC) USGS Earth resources Observation and Science (EROS).

Ancillary data acquisition

- Landsat ETM+ imageries from 01/08/2000 with 30 m x 30 m grid cell size, which consists of bands 1, 2, 3, 4, 5 and 7 in WGS-1984 UTM zone 20 south coordinate system, were acquired from Earth Science Data Interface (ESDI) at the Global Land Cover Facility.

- Aerial Photography 2008 true color film, 1:30000 scale, flight altitude 15000 feet, consisting of 49 digital images which are 41 stereoscopic pairs in WGS-1984 UTM zone 20 south coordinate system, were acquired from Geomatica Ingenieria y Proyectos (GEOINPRO) from Bolivia.

- Topographic map 1:250000 in Microstation digital format from Alto Parapeti Bolivia, map sheet SF-20-02 WGS-1984 UTM zone 20 south coordinate system was acquired from the Bolivian Geographic Military Institute (IGM).

- The ASTER Global DEM (GDEM) in GeoTIFF format with geographic lat/long coordinates and a 1 arcsecond (approximately 30 m) grid, referenced to the WGS84/EGM96 geoid. S20W064 tile was downloaded from the Earth Remote Sensing Data Analysis Center (ERSDAC) of Japan and NASA's Land Processes Distributed Active Archive Center (LP DAAC).

2.2.1 MODIS Application

Moderate Resolution Imaging Spectroradiometer (MODIS) is the most comprehensive sensor carried one Terra (EOS AM), launched in December 18 1999. Terra's orbit around the Earth passes from north to south across the equator in the morning. Terra MODIS is viewing the entire Earth's surface every 1 to 2 days, with a 2330 km wide viewing swatch(Justice et al. 2002).

The MODIS instrument has 36 spectral bands from 0.4 µm to 14.4 µm. and measures data at three different spatial resolutions: 250m (Bands 1-2), 500m (Bands 3-7) and 1000m (Bands 8-36). The MODIS science team of NASA has developed 44 MODIS data products (MOD01-MOD44) of four categories: calibration, atmosphere, land and ocean with different specific usage(Justice et al. 2002).

2.2.2 MODIS vegetation index (MOD 13)

Global MODIS vegetation indices are determined using spectral bands blue centered at 469 nanometers, red centered at 645 nanometers and near infrared centered at 858 nanometers, providing consistent spatial and temporal comparisons of vegetation conditions (NASA 2010).

(NASA 2010) stated that "Version-5 MODIS/Terra Vegetation Indices products are Validated Stage 2, meaning that accuracy has been assessed over a widely distributed set of locations and time periods via several ground-truth and validation efforts. Although there may be later improved versions, these data are ready for use in scientific publications".

2.3 General Methods

This chapter describes the study area, methods and materials that were applied in the collection, processing, analysis and presentation of data with a view to fulfilling the set objectives and answering the research questions.

2.3.1 Research approach

The approach that was adopted in the implementation of this research is summarized in Figure 2-2:

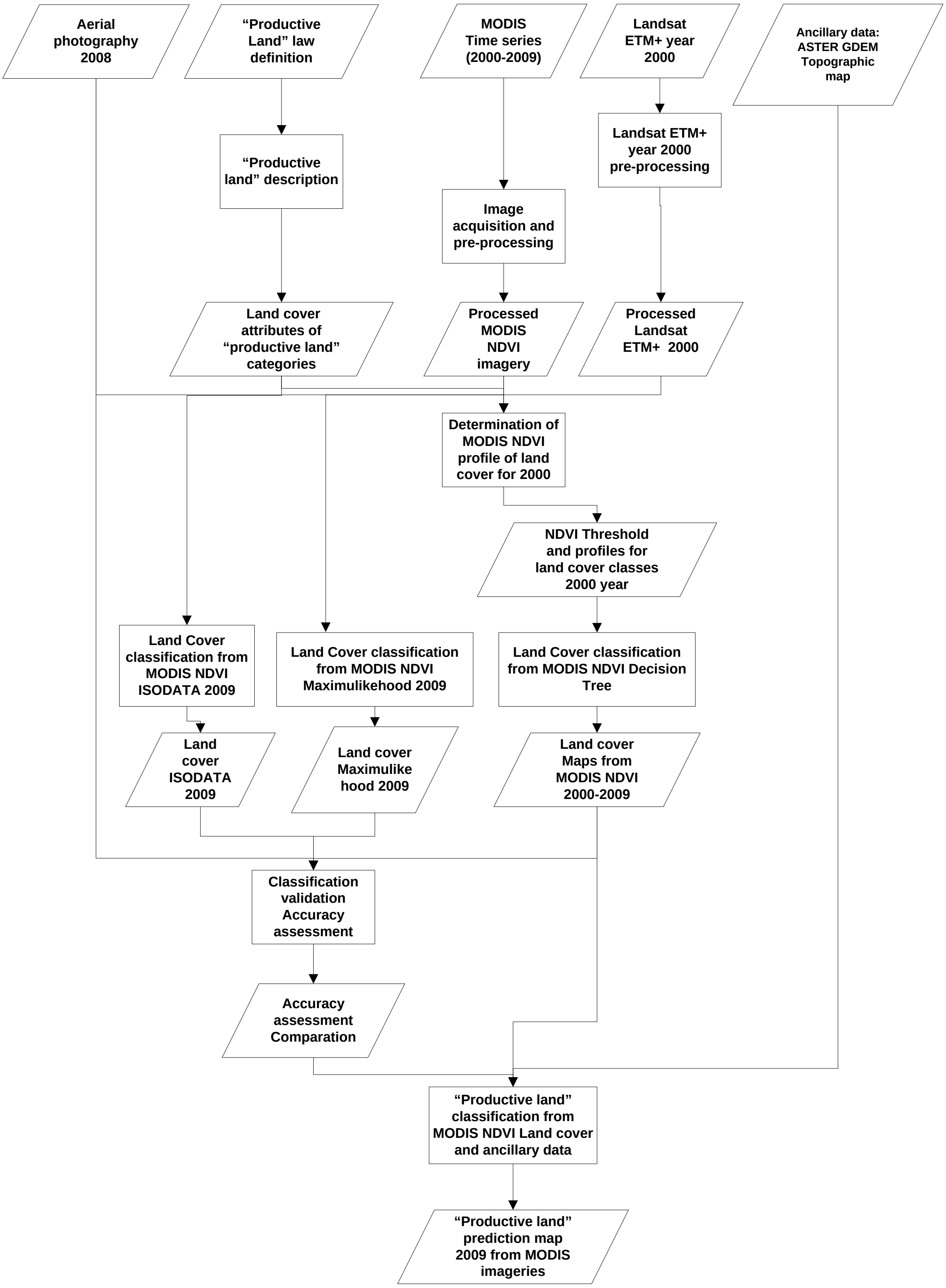

Figure 2-2 Flowchart for research methodology

2.3.2 "Productive land" description

Attributes of land covers belonging to the five categories of *productive land* were determined based on the interpretation of (LeyN°3545 2006) and "The Verification of Productive Land Guide" with help of an expert analyst of Bolivian National Institute of Agrarian Reformation (INRA).

"Productive Land" established by Article 169 of the Constitution of the State Policy is the sustainable land use in the development of farming, forestry and other productive nature, and in the conservation and protection biodiversity, research and ecotourism, according to its use capacity for the benefit of society, the collective interest and that of its owner(LeyN°3545 2006).

The "Productive land" of a property necessarily has to be verified in field, being the primary means of verification (LeyN°3545 2006). The use of remote sensing should only be used as a reference, to help to identify the priority zones for the agrarian reform, since field verification is very costly and cause of social conflict. The Bolivian Agrarian reform law is not very clear in the description and verification of what is "Productive land". In fact, it still is in a process of improvements as it was stated by the Bolivian National Institute of Agrarian Reform (INRA):

The Agrarian Reform law (LeyN°3545 2006) recognizes "productive land" as five categories of land:

Effectively exploited land in agricultural areas is land that is in production, while in cattle properties is the surface corresponding to the amount of existing livestock.

Fallow lands are lands under crop rotating, but currently not used, while productive investment improvements clearly identifiable. They are recognized only on farms.

Ecological lands are lands under forestry, conservation and biodiversity protection, research and ecotourism. These will be checked regularly granting of authorizations, current and effective enforcement, according to special rules.

- Conservation and protection of biodiversity: Water bodies (lakes, rivers), conservation area
- Slope land, lands with slope > 45 degrees
- Wetland
- areas of natural water upwelling with 50 m buffer
- windbreaks not less than 50 m wide
- reserves of natural heritage
- natural forest (biodiversity)

Growth projection land is defined as Land surface allocated to the expansion of productive activity". Growth projection land is calculated from 30% of effectively exploited land and fallow land for properties greater than 500 Ha and 50% for properties below 500 Ha. There are 3 classes of agrarian property for subtropical zones to calculate growth projection land: small property of 50 hectares, medium property up to 500 hectares and large agrarian property up to 5000 hectares.

Unproductive lands are lands that don't have any productive activity or development activities such as Conservation and Biodiversity Protection, Natural Heritage Reserve, Ecotourism or research on the property.

- Shrub land (These are areas characterized by a high percentage of shrub cover (2 – 5m high))
- Bare land (These are either completely non-vegetated areas or lands with very low percent of vegetation cover)

Not all land classes described in the Bolivian Agrarian reform can be identified by remote sensing, such as growth projection land, which is an attribute of the properties. Based in visual interpretation of orthorectified aerial photography of 2008 and field survey during September of 2009, the fallowing land classes were identified in the study area: natural forest, agricultural land, shrub land, bare land water bodies and slope land. These Land classes of the study area were separated into:

- Land cover classes: Dense forest (natural forest), crop land (agricultural land), dense shrub land, mixed vegetation/shrub dominant, bare land and water bodies.
- Other Land classes: Slope land (slope > 45 degrees)

2.3.3 MODIS image pre-processing

The MODIS land products are distributed by USGS in so called Hierarchical Data Format (HDF) and projected in Sinusoidal (SIN) projection. Neither the projection nor the storing format is well supported in conventional data-processing software. Thus for convenient usage, each image was subsetted to the study area boundary shown in Figure 2-4 and re-projected from a Sinusoidal to WGS-1984 UTM zone 20 south coordinate system and Transverse Mercator projection since the majority of the data used in this research is in WGS-1984 coordinate system, using a nearest neighbor re-sampling routine and entered into a 250 m×250 m grid cell multilayer image stack. Nearest neighbor interpolation is preferred if subtle variations in the value need to be retained since it does not alter the NDVI value. Excluding the cloudy and noisy images, 178 images MOD13Q1 were acquired in this 10 year period.

MODIS re-projection tool developed by U.S. Geological survey (http://igskmncnwb001.cr.usgs.gov/landdaac/tools/modis/index.asp) was used to carry out this preprocessing. This software allows the user to read HDF metadata, resize, resample and re-project the data.

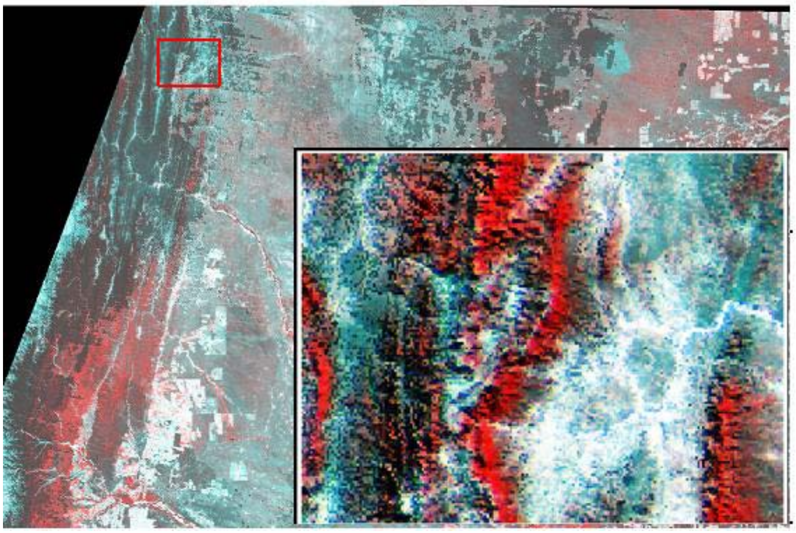

Figure 2-3: MODIS terra MOD13Q1 raw and subseting image of the study area, using a color composites with band 3 (NIR), 4 (MIR) and 2 (Red).

2.3.4 Training points

The MODIS images are too coarse to precisely recognize the different land covers. Therefore medium resolution Landsat image data of 1 of August 2000 and high resolution orthorectified aerial photography September 2008 was used to provide more accurate land cover details and clearer spatial pattern of vegetation and to locate sample points of the different land covers.

We used a grid of 250 m x 250 m corresponding to MODIS pixel size over the selected Landsat image and aerial photography in order to find representative sample points of the same land cover for the years 2000 an 2008, therefore they can be used for all years of the study, assuming there are no changes in the land cover during the different years.

Figure 2-5 shows sample points carefully selected by visual interpretation to find pure MODIS pixel of the different land cover classes. The visual interpretation was carried on the selected aerial photography and Landsat ETM+ image using a color composites with band 4 (NIR), 5 (MIR), 3(Red).

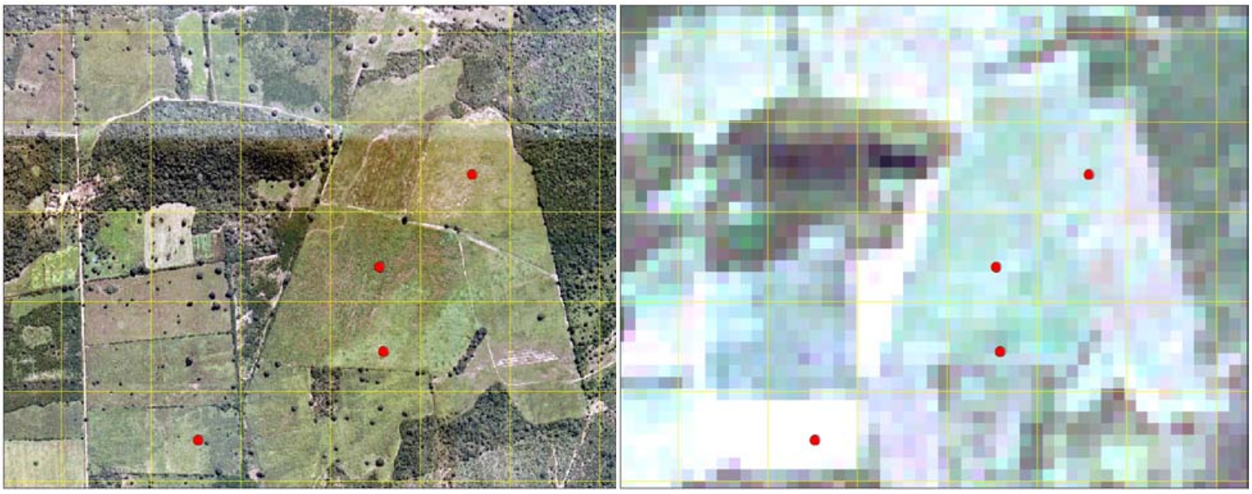

Figure 2-4: Sample points for land cover classes over ortho-photography of September 2008 (left) and associated with Lantsat TM+ image of 1th Aug, 2000 using a color composites with band 4 (NIR), 5 (MIR), 3(Red) (right)

Healthy vegetation appears in shades of reds, browns, oranges and yellows. Soils may be in greens and browns, urban features are white, cyan and gray, bright blue areas represent recently clear cut areas and reddish areas show new vegetation growth, probably sparse grasslands. Clear, deep water will be very dark in this combination, if the water is shallow or contains sediments it would appear as shades of lighter blue. For vegetation studies, the addition of the Mid-IR band increases sensitivity of detecting various stages of plant growth or stress. The date of the images was selected in the dry season since with this combination care must be taken in interpretation when acquisition closely follows precipitation. Use of NIR and MIR band shows high reflectance in healthy vegetated areas.

48 sample points were carefully selected, by visual image interpretation of the selected Landsat TM+ and aerial photography, within the crop land area and digitized using ArcGIS 9.31. The sample points were saved in a point type geodatabase. 72, 70, 42 and 31 sample points were selected within the dense forest, dense shrub land, mixed veg/ shrub dominant and bare land.

2.3.5 Temporal NDVI profile

Sample points were used to understand the distributions of NDVI values of the different land cover classes on the selected MODIS image. Descriptive Statistics were calculated for each land cover, shown in Table 2-2: Maximum, Minimum, Mean and Standard deviation of the sample points to understand the distributions of NDVI value of the land covers classes on MODIS image.

Table 2-2 Statistics of MODIS NDVI values of the land cover classes July 2000

MODIS NDVI July 2000				
	MAX	MIN	MEAN	STD
Dense forest	0.75	0.56	0.70	0.04
Crop land	0.44	0.25	0.34	0.05
Dense shrub land	0.52	0.34	0.42	0.03
Mix veg./shrub dominant	0.46	0.31	0.37	0.05
Bare land	0.28	0.14	0.22	0.05

The MODIS NDVI subset of 2001 (since 2000 is incomplete series) and the sample points were used to extract NDVI temporal profile using ArcGis 9.31 spatial analyst sample tool. The temporal NDVI profile were use to plot the pattern of average NDVI values over time of the land cover classes and descriptive statistics were calculated, to understand annual NDVI distribution of the different land covers.

The same process was done for all years from 2000 to 2009 to compare the behavior of the temporal NDVI profile between years. An Average annual NDVI profile of 2000 to 2009 was calculated to determine a representative profile for all years. The range of NDVI values of crop lands goes between grass lands and shrub lands. Total annual NDVI values and standard deviation was calculate to analyze NDVI profile of crop lands forest, shrub land and bare land for every year using the average NDVI profiles from 2000-2009.

2.4 Land cover classification and time series analysis

This research was based on a decision tree classification technique of MODIS NDVI images and it will be compared with maximum likelihood supervised classification and an isodata unsupervised classification method.

Based on the land classes identified in section 2.3.2, the fallowing land cover classes: Dense forest, crop land, dense shrub land, mixed vegetation/shrub dominant and bare land were classified using MODIS NDVI images. Water bodies class was masked using Landsat ETM+ image of 1 August 2000, and Slope land was classified using ASTER GDEM.

2.4.1 Water bodies and slope land classification

To prevent that the variable nature of water bodies (i.e., turbidity and water level fluctuations) confuses change analyses, a water mask was developed using Landsat Enhanced Thematic Mapper plus (ETM+) image dated 1 of August year 2000 with the help topographic map at 1:250000 scale from the Bolivian Geographic Military Institute (IGM) to find more easily the different rivers o the study area. These were used to delineate rivers using ArcGIS 9.3 editor, as well the town of Cuevo was delineated and masked for exclusion from further change analysis.

The study area present dry rivers for most part of the year, once we masked the water bodies, we observed that most of the sampling points of bare land fallow inside the mask. Since complete MODIS pixels of bare land can only be identified along the river, we decided to exclude bare land from the classification and maintain water bodies. From the "productive land" perspective the rivers should fallow in the ecological land category.

For the classification of slope land, a slope map was created using ASTER GDEM of 30 m using ArcGis 9.31 spatial analyst tool to determine lands with slope greater than 45 degrees.

2.4.2 Decision tree classification

A Decision tree classification technique based on the Average NDVI temporal profile shown in Figure 3-7 was selected to determine the land cover spatial distribution for every year in the study area. Large-area mapping has improved with the application of advanced classification techniques such as decision tree (DT) classifiers, which have several advantages over traditional supervised classifiers(Hansen et al. 1996) and have consistently produced higher classification accuracies for this task (Wessels et al. 2004; Matsuoka et al. 2007; Zhang et al. 2008).

We first determined a decision rule to separate croplands from other land covers since this are the smaller cover types in the study area. Lands managed in croplands display a distinctly higher annual standard deviation compared to natural vegetation due to high vegetation density during the growing season and extremely low vegetation density following harvest (Galford et al. 2008). Dense shrub lands present an NDVI standard deviation similar to crop lands; however the NDVI profile and Annual NDVI mean of dense shrub land are higher.

The temporal NDVI profile of crop land is difficult to differentiate from dense shrub land and has an annual NDVI value similar to the land cover class mixed vegetation/ shrub dominant. We propose a normalized in time NDVI (NNDVI) to enhance the seasonal fluctuation of crop land, calculated from the formula:

$$NNDVI = \frac{\text{Max NDVI value} - \text{Min NDVI value}}{\text{Max NDVI value} + \text{Min NDVI value}}$$

The results of Normalized in time NDVI of the land cover classes is shown in Table 2-3

Table 2-3 Normalized in time NDVI of the land covers

Land cover	NNDVI
Dense Forest	0.25
Crop Land	0.42
Dense Shrub Land	0.36
Mixed veg./ Shrub dominant	0.29
Bare Land	0.24

We define the fallowing rules for the decision classification:

- To classify crop land and no-crop land: pixels with NNDVI> 0.39 and annual average NDVI< 0.55 were classified as crop land.
- To classify dense forest: the NDVI value of July 11 of each year was chosen since it's the value that shows more difference between dense forest and the rest of classes. All the pixels that were not classified as crops and had a NDVI value greater than 0.63 on July 11 were classified as dense forest.
- To classify dense shrub land: the NDVI value of February 18, March 05 and March 21 were selected to differentiate dense shrub land from mixed vegetation an average of the three dates was calculated and NDVI greater than 0.67 was classified as dense shrub land, the remaining unclassified pixels were classified as mixed vegetation.

2.4.3 Maximum likelihood supervised classification

Supervised classification requires a priori knowledge of the number of classes, as well as knowledge concerning statistical aspects of the classes. The method start with establishing training samples, which are areas that are assumed or verified to be of a particular type. The maximum likelihood decision rule is based on the probability that a pixel belongs to a particular class. The basic equation assumes that these probabilities are equal for all classes, and that the input bands have normal distributions.

The study area was classified with maximum likelihood technique to compare with decision tree classification. Supervised classifications were carried out using ERDAS imagine 9.3 classifier. A stack of 20 MODIS NDVI images from 2009 was used for the supervised classification, the water bodies and built up class were masked and taken out from the classification. The images were classified in 4 classes: dense forest, crop land, dense shrub land and mixed vegetation, each signature was selected base on training points of the NDVI profiles.

2.4.4 ISODATA classification

For the Unsupervised Classification the research adopted an approach that had been successfully applied for small-scale land use mapping on the basis of temporal Normalized Difference Vegetation Index (NDVI) characteristics (de Bie et al. 2008) to objectively derive these mapping units. Geo-referenced hyper-temporal MODIS NDVI data (20 MODIS NDVI images from 2009) was classified repeatedly by unsupervised ISODATA (iterative self-organizing data analysis) clustering in ERDAS imagine 9.3 software.

Each run had a specified number of classes from 10, 11, 12, 13 to 20, a convergence threshold of 1 and a maximum of 30 iterations. A convergence threshold of 1 ensured attainment of maximum iteration in each run for better accuracy. Statistical divergence tests, that measure the distances between the generated signatures, were then conducted for each classification to establish the maximum signature separability among the classes. From the signature separability listings of each statistical divergence test, the minimum and the average values were entered in spreadsheet and a graph plotted. The classification with 14 classes were selected for further analyses as it depicted a peak in average divergence statistical measure, hence, the one with the most distinct classes.

The last step in derivation of the mapping units was grouping together the classes that depicted somewhat similar temporal NDVI profiles. The average temporal NDVI profile of the 14 classes were plotted and compared with the NDVI profile of the land cove classes shown in Figure 3-7, reducing the classes to five 4 land covers in the study area.

2.5 Classification validation

2.5.1 Sampling

Stratified random sampling scheme based on the land cover classes was used for validation for the decision tree, the maximum likelihood and ISODATA classification of 2009. 1 pixel plots were chosen using ERDAS 9.3 accuracy assessment module. A stratified random sampling scheme was used to select the sites because the class sizes may vary significantly, and a random sampling scheme may not have selected sites from all map classes in a well distributed manner.

The training points used for the classification, water bodies class and built up class were reclassified as no data and excluded for the sampling scheme. The number of samples plots were 50 per stratum, since 25 pixels per stratum is the recommended minimum to assure adequate confidence interval coverage, and increasing the sample size to 50 pixels per stratum produces even better coverage and a meaningful reduction in the standard error of the estimator of KAPPA. A further increase in sample size from 50 to 75 pixels per stratum does not appear warranted (Stehman 1996).

For each assessment point, visual interpretations of orthorectified aerial photography of 2008 of 0.5 meters resolution was conducted by first delineating the cell boundary on the digital images, then the cover types and percent coverage within the cell was determined. Each site was viewed independently to determine the land cover class based on the land cover percentage.

2.5.2 Accuracy assessment

An accuracy assessment was conducted using orthorectidied aerial photography visual interpretation and to document the occurrence or non-occurrence of the different land covers to generate an overall accuracy and quantify both commission and omission errors. The map quality was measured in terms of kappa statistic, overall, producer and user accuracy using the conventional error confusion matrix. The confusion matrix was used to provide a site-specific assessment of the correspondence between the image classification and ground conditions (Foody 2002).

The kappa statistic is a measure of agreement or accuracy. Land use and land cover classifications are usually evaluated by kappa statistic. Empirical results demonstrate that these estimators have little bias, and confidence intervals perform well, often even at relatively small sample sizes (Stehman 1996).

2.6 Post classification labeling

Fallowing the criteria of the Agrarian reform law, the land classes were allocated to their corresponding “productive land” categories:

Effectively exploited land: pixels of crop land in 2009 were classified in this category.

Fallow land: pixels of mixed vegetation/ shrub dominant in 2009 and were crop land in the period of 2001 and 2008 were classified in this category

Ecological land pixels of dense forest, water bodies and slope land in 2009 were classified in this category.

Unproductive land: pixels of dense shrub land or mixed vegetation / shrub dominant, which were not classified as fallow land, were classified in this category.

3 Results and discussions

3.1.1 Determination of Temporal NDVI profile for land cover classification

The result of temporal NDVI profile for the land cover classes for 2001 is shown in Figure 3-1. To generate this graph and average NDVI value was calculated based on the number of sample points for each class, 48 sample points for dense forest, 72 crop land , 70 shrub land, 42 mixed vegetation / shrub dominant and 31 bare land.

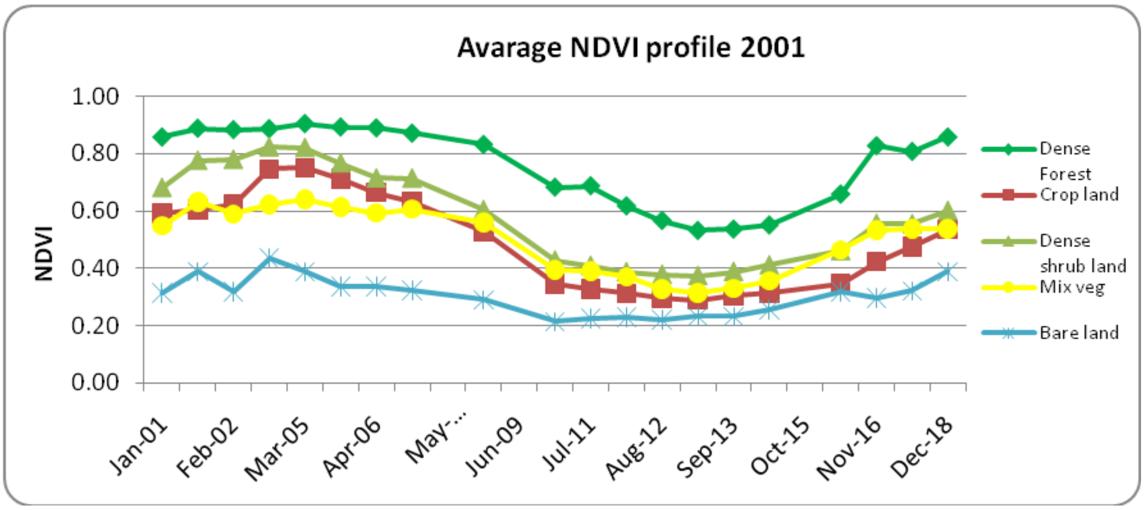

Figure 3-1 Temporal NDVI profile 2001

The graph shows major differences in the temporal profile of dense forest and bare land with the rest of the classes. Dense forest indicates clearly higher NDVI through the year than the rest of land covers showing an increase of NDVI during the rainy season in the months of October, November and December, and a NDVI decrease during the months of June July and August, the driest months of the year. Bare land indicates low NDVI values over the year with minor seasonal fluctuations.

Dense shrub land presents a temporal NDVI patter with very clear seasonal fluctuation, with an increase of NDVI during the rainy season and a decrease during the driest months. Research made by (Sedano et al. 2005) showed that herbaceous and shrubs presents NDVI patterns decreasing more rapidly along the dry season than forest stands. Dense Shrub land presents higher NDVI values along the year than crop land and mixed vegetation / shrub dominant.

The NDVI pattern of crop land presents a good agreement with the crop calendar of maize, described in Table 2-1, which shows a rapidly increase of NDVI during the crop seed at the beginning of the rainy season in the months of November and December. The NDVI pattern starts to decrease after the harvest, in the months of April or May when the plants are left to dry and shows minimum values September where the soil preparation begins.

Mixed vegetation/ shrub dominant have similar NDVI values as crop land during the year but the temporal NDVI pattern show less seasonal fluctuations, because mixed vegetation present more opens spaces without vegetation and crop land is also influence by the seeding and harvesting of the crop calendar.

In order to define the decision rules for classify the different land covers; we extract the temporal NDVI profile of the sample points for all years from 2000 to 2009. The temporal NDVI profile of all years were plotted for each of the five identified land covers classes, showing the different behavior of temporal NDVI profiles between years and an average profile of all years.

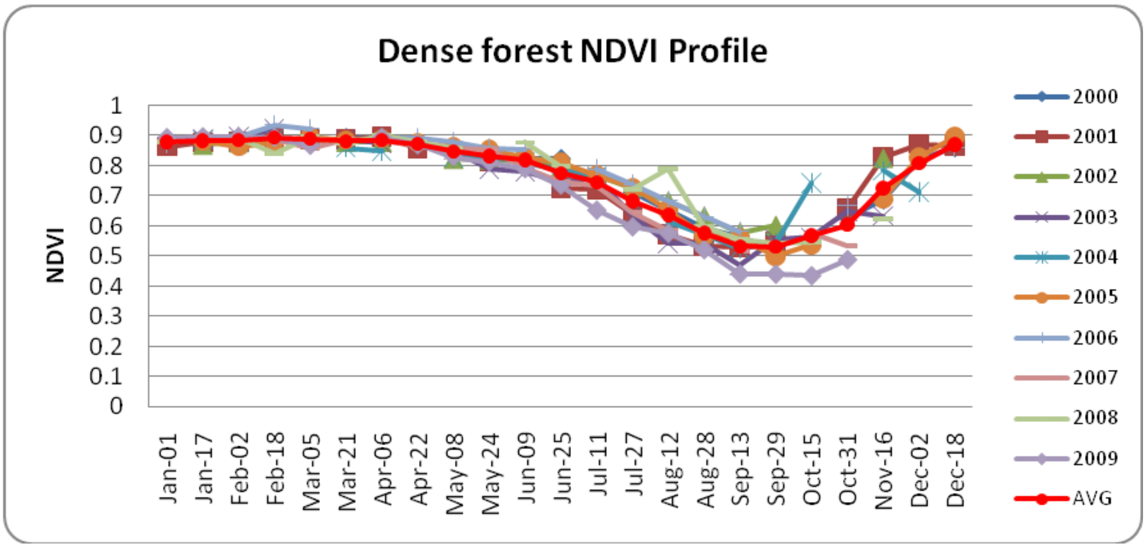

Figure 3-2 Temporal NDVI profile for dense forest 2000-2009

Dense forest shows in Figure 3-2 a very similar temporal NDVI profile over the years fallowing seasonal fluctuations. High NDVI values in the months of February, March and April with a NDVI value around 0.9 after the rainy season, and low NDVI values during September with a NDVI value around 0.5 after the dry season of June, July and August.

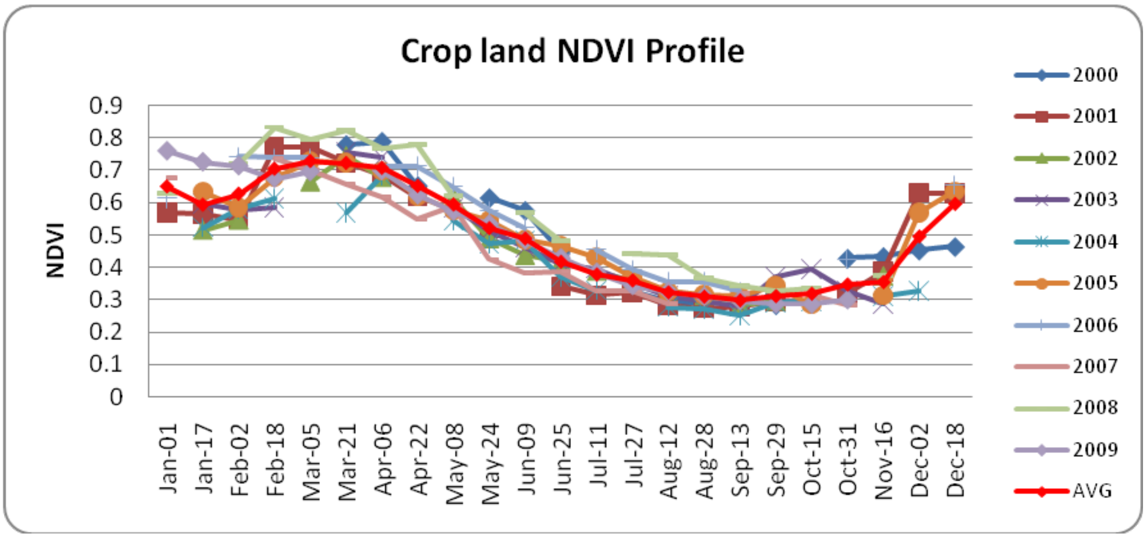

Figure 3-3 Temporal NDVI profile for crop land 2000-2009

Crop land shows in Figure 3-3 a similar Temporal NDVI pattern with some variation in deeps and peaks over the years. High NDVI values in the months of February, March and April with a NDVI value around 0.7 after the rainy season, and low NDVI values during September with a NDVI value around 0.3 after the dry season of June, July and August.

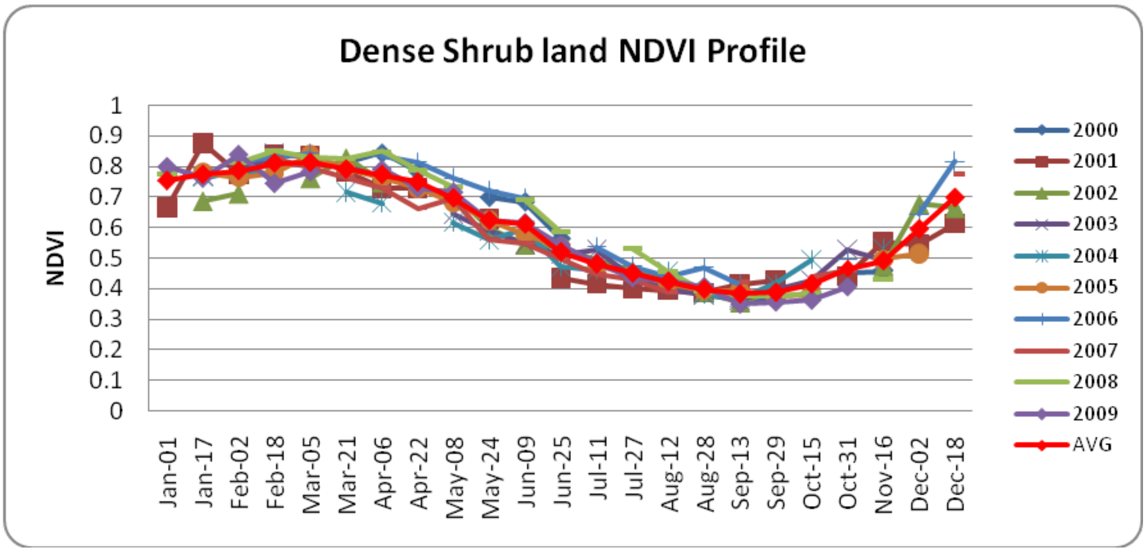

Figure 3-4 Temporal NDVI profile for dense shrub land 2000-2009

Dense shrub land shows in Figure 3-4 a very similar temporal NDVI profile over the years, with high NDVI values in the months of February and March with a NDVI value around 0.8 after the rainy season, and low NDVI values during September with a NDVI value around 0.4 after the dry season of June, July and August, with some anomalous values on January of 2001.

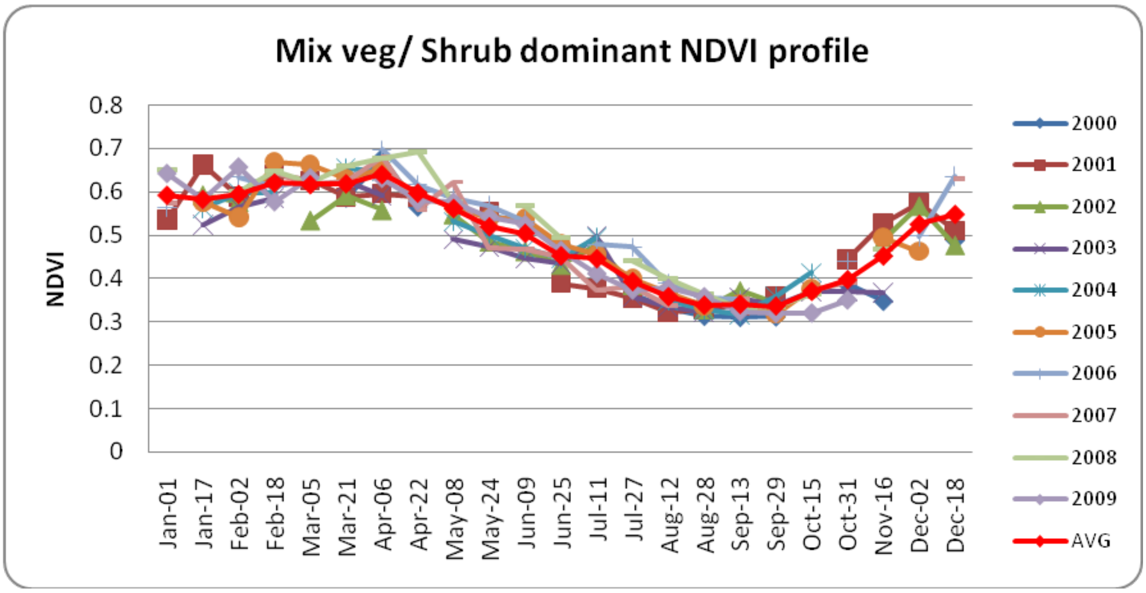

Figure 3-5 Temporal NDVI profile for mixed vegetation/ shrub dominant 2000-2009

Mixed vegetation /shrub dominant shows in Figure 3-5 a similar Temporal NDVI pattern with some variation in deeps and peaks over the years. High NDVI values in the months of

February, March and April with a NDVI value around 0.7 after the rainy season, and low NDVI values during September with a NDVI value around 0.3 after the dry season of June, July and August.

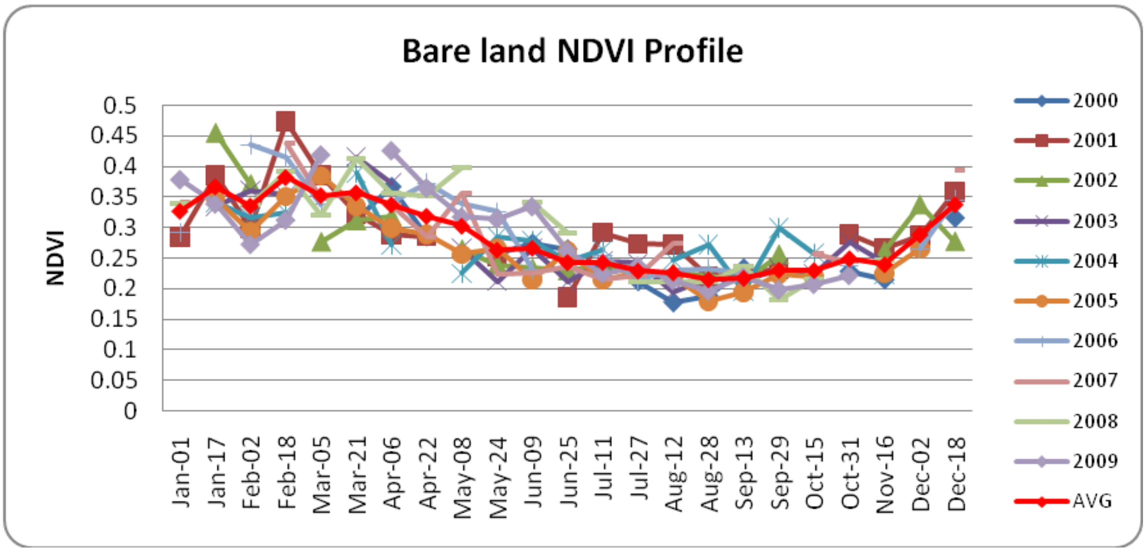

Figure 3-6 Temporal NDVI profile for bare land 2000-2009

Bare land shows Figure 3-6 in a different Temporal NDVI pattern over the years with deeps an peak in different months. Pure bare land pixels of MODIS are only distributed near the river and the NDVI values are affected by the variable nature of the water during the year. It is not possible to difference months with high a low values because of the variable NDVI pattern.

Figure 4-7 shows the average temporal NDVI profile for all land cover classes plotted in order to establish decision rules for classification based on differences in the NDVI profile

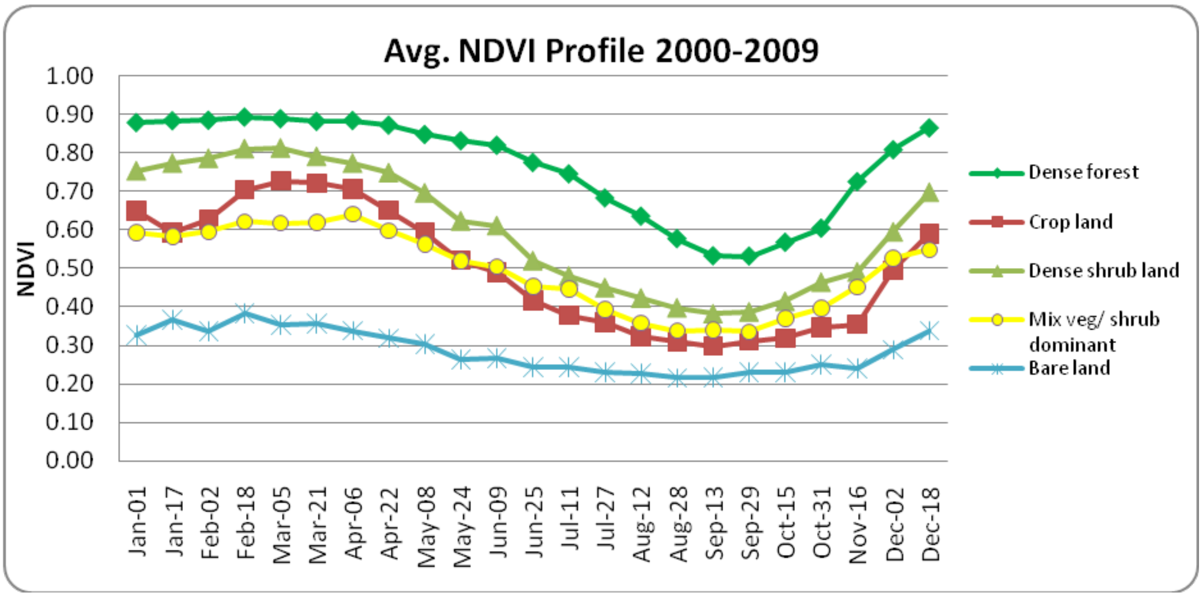

Figure 3-7 Average Temporal NDVI Profile of land cover classes from 2000 - 2009

The average temporal NDVI profiles of dense forest and bare land have significant differences from the other classes; the behavior of crop land, mixed vegetation and dense shrub land in terms of NDVI profile performs relatively similar.

Table 4-2 shows the maximum NDVI value, minimum NDVI value, mean value and standard deviation of the average NDVI profile for the land cover classes. Dense forest present high NDVI values with a mean NDVI value of 0.77 and a low STD (standard deviation) of 0.13, bare land low NDVI values with a mean value of 0.29 and very los STD of 0.06. Crop land and mixed vegetation / shrub dominant present the same mean NDVI value of 0.5 but different STD, 0.16 for crop land and 0.11 for mixed vegetation. Crop land and dense shrub land present the same NDVI STD of 0.17 but different mean NDVI value as dense shrub land shows a 0.6 mean NDVI.

Table 3-1 NDVI statistics of the land covers from 2000-2009

NDVI 2000-2009 statistics				
Land cover	Maximum	Minimum	Mean	STD
Dense forest	0,89	0,53	0,77	0,13
Crop land	0,73	0,30	0,50	0,16
Dense Shrub land	0,81	0,38	0,60	0,16
Mix veg. / shrub dominant	0,64	0,34	0,50	0,11
Bare land	0,38	0,22	0,29	0,06

3.2 Land cover classification

3.2.1 Decision tree classification

Figure 3-8 and Figure 3-9 show land cover maps from 2001 to 2009. A zonal distribution of dense forest, crop lands, dense shrub land, mixed vegetation/ shrub dominant, water bodies and built up class from Alto Parapeti.

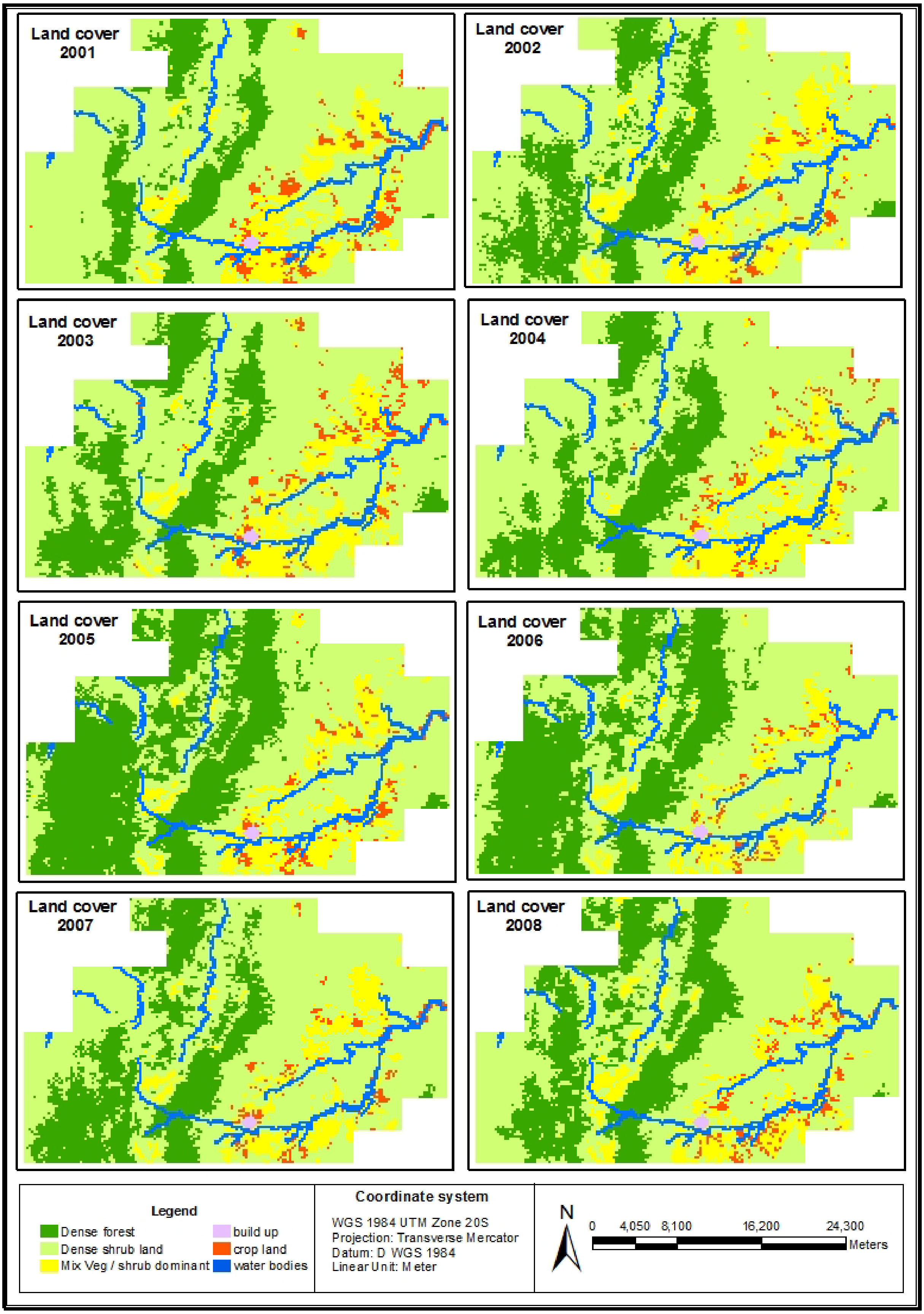

Figure 3-8 Land cover classes of Alto Parapeti 2001-2008 using decision tree classification

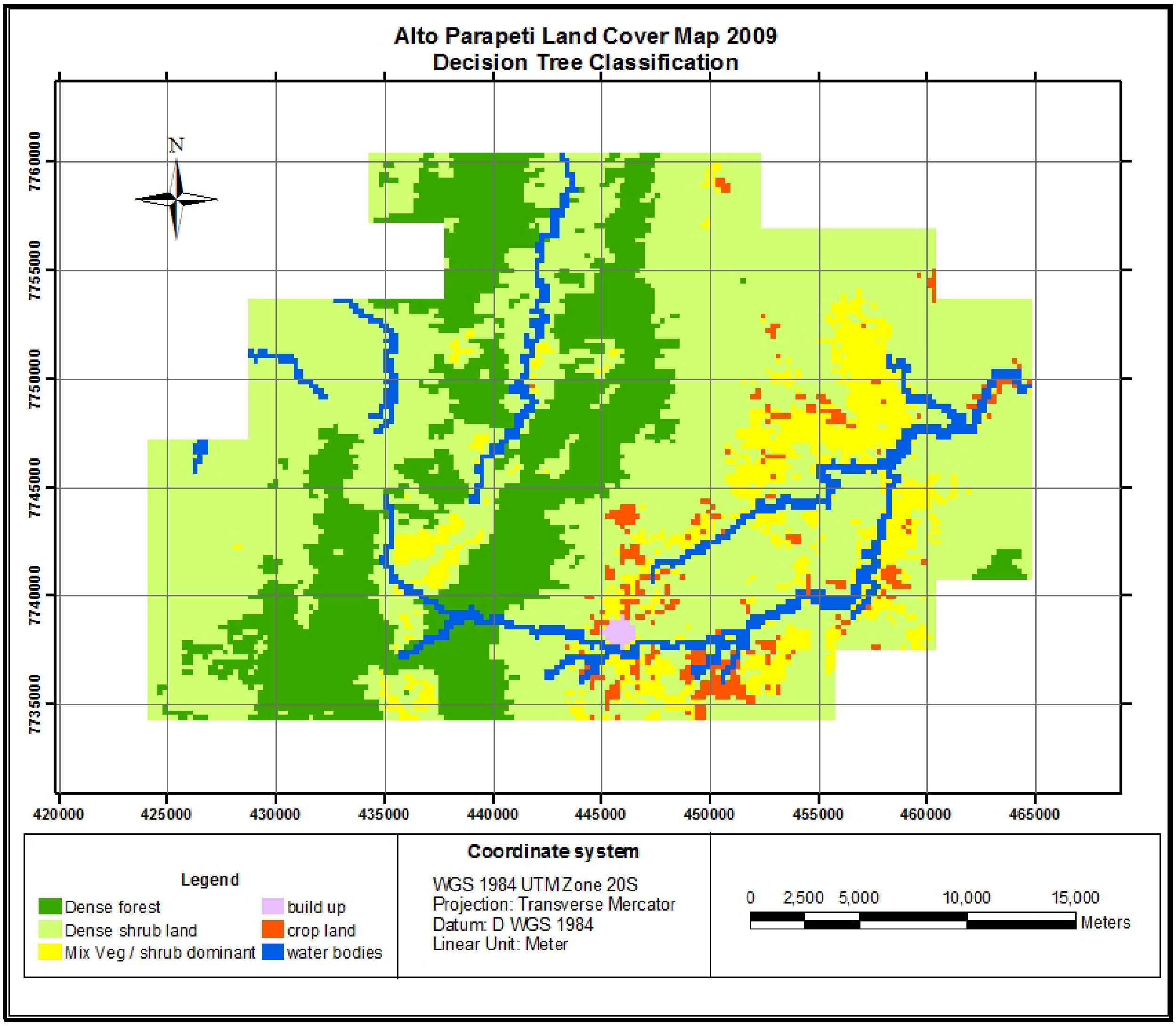

Figure 3-9 Land cover classes of Alto Parapeti 2009 using decision tree classification

Dense forest are mainly in the mountain region, this class was sensitive to the NDVI threshold, and the boundary changed significantly as the threshold value changed between dense forest and dense shrub land. Dense forest consists of low woodland, and main characteristic of dense shrub land is an impenetrable layer of shrubs. The transition zone between them was very narrow to distinguish effetely. Interannual variations are inferred to be large in this region because in semi-arid regions is sensitive to climatic variability. The study area suffers of severe droughts as the Chaco is one of the driest regions of Bolivia.

The land cover map from 2001 to 2009 shows an increase of dense forest during 2001 until 2005, a reduction from 2006 and 2007 and an increment in 2008 and 2009. This drastic change in the extension of dense forest could be caused by selecting a decision rule that it is to sensitive to climatic inter annual variations, showing during rainy years more extension of dense forest and less extension in dry years. We cannot fully answer the dense forest inter annual change, validation of more years are needed to further analyze changes in land cover.

Crop land is distributed near the town of Cuevo and along the river, widespread between dense shrub land and mixed vegetation/ shrub dominant. The variability of crop land is inferred to be caused by the agricultural practices of the region, being maize the principal crop destined mainly for local consumption, they only produce in part of the parcel land letting the rest as a fallow land changing from year to year the crop area.

3.2.2 Maximum likelihood supervised classification

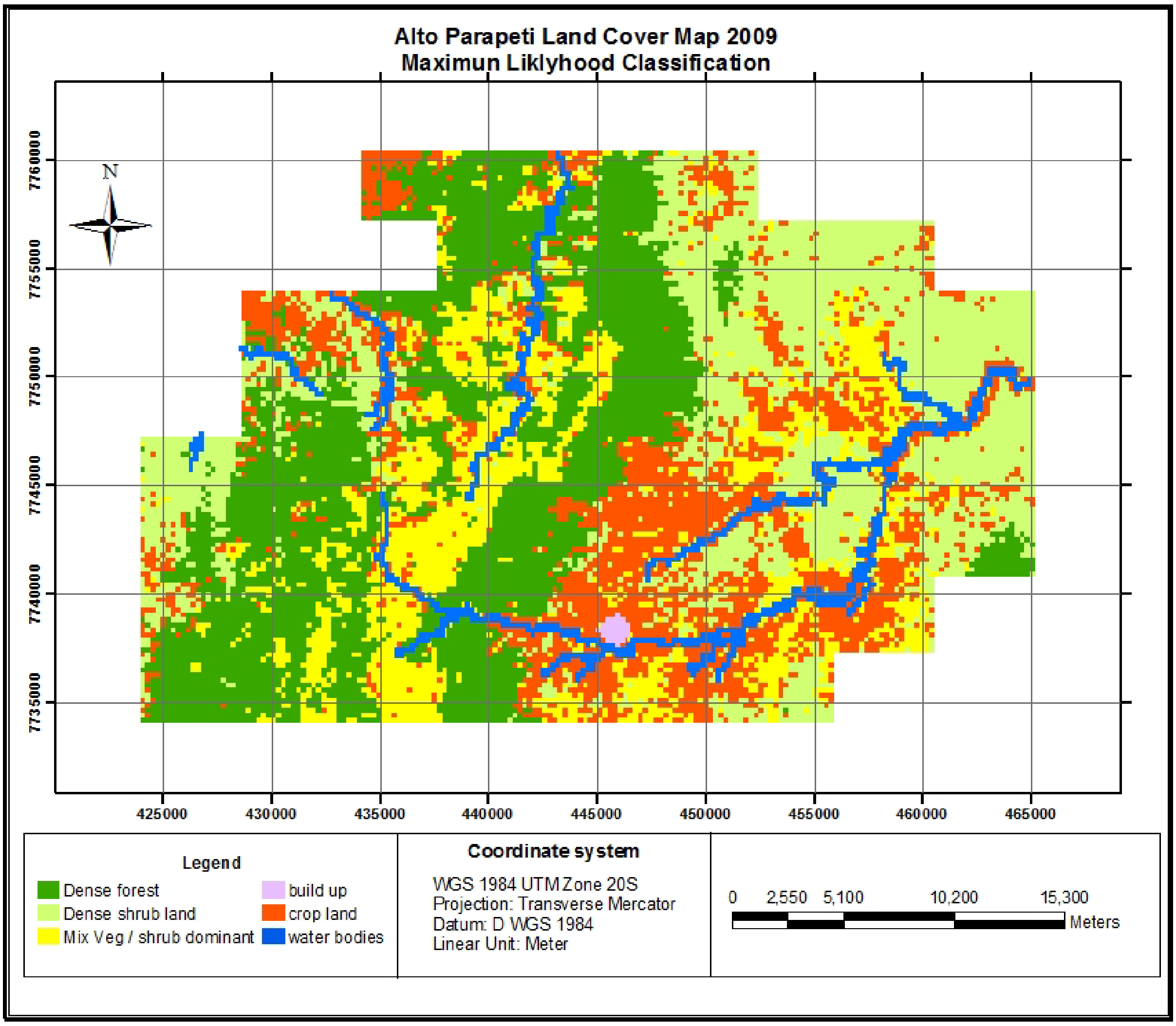

Figure 3-10 Land cover classes of Alto Parapeti 2009 using Maximum likelihood classification

Figure 3-11 shows the classification map of Alto Parapeti of 2009 Maximum likelihood supervised classification (MLC). Dense forest showed similar extension as the decision tree classification (DTC). Many dense shrub lands classified by decision tree were classified as crop land by MLC especially near the dense forest class, the crop land class in MLC is much larger and disperse in all the study area, some in the mountains, the region of mixed vegetation /shrub dominant between the dense forest lands is larger in MLC classification and dense shrub land is smaller in MLC classification.

3.2.3 Unsupervised isodata classification

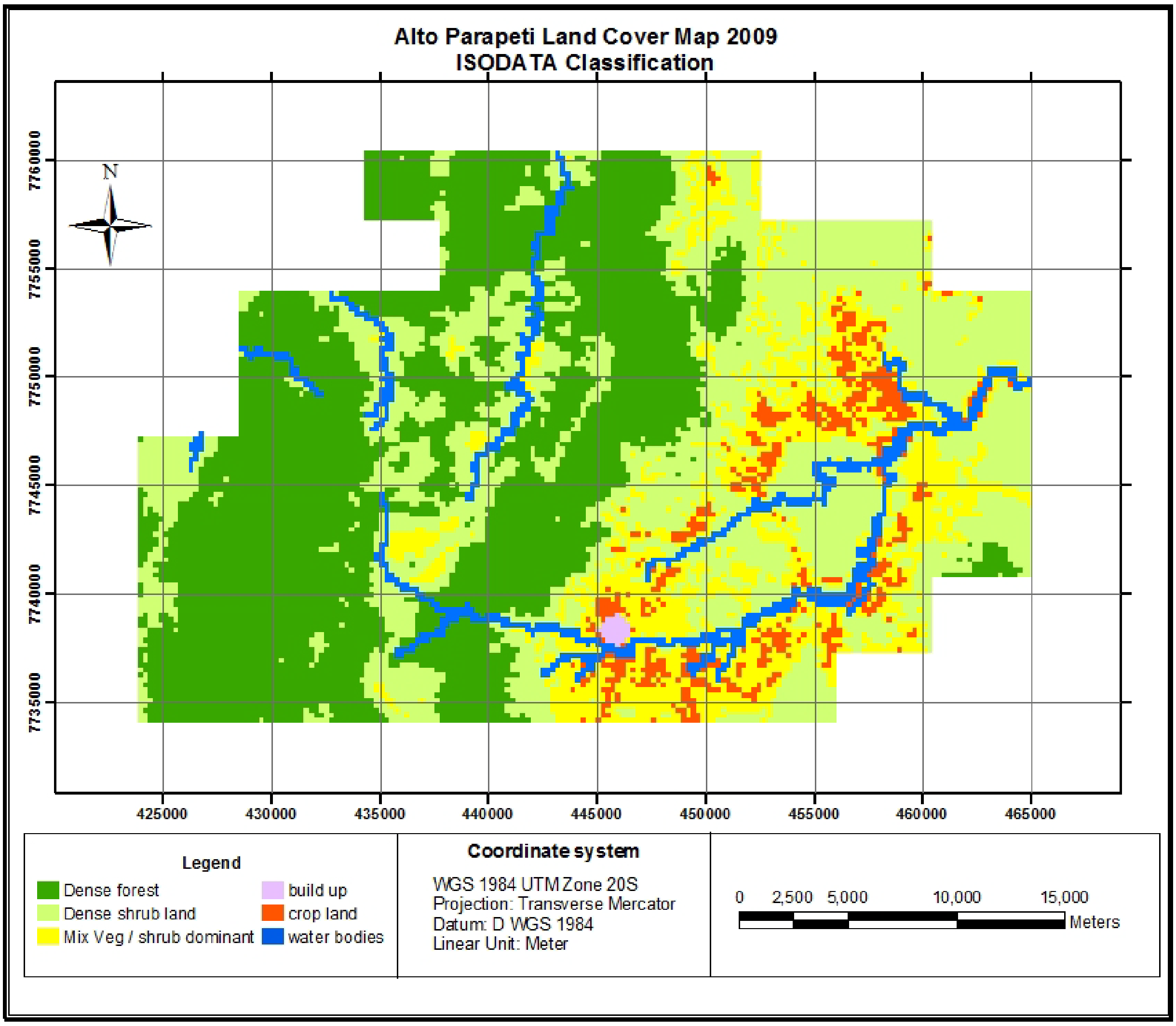

Figure 3-11 Land cover classes of Alto Parapeti 2009 using Isodata classification

Figure 3-12 shows the classification map of Alto Parapeti of 2009 unsupervised isodata classification. Dense forest showed a good agreement with decision tree classification (DTC), except in the west part where DTC shows more shrub land than dense forest. It shows more small and fragmented crops than DTC land cover map, but in the same region.

3.3 Classification Validation

3.3.1 Accuracy assessment decision tree classification

Accuracy assessment of land cover map o 2009 obtained by the decision tree classification was conducted for the land cover classes excluding water bodies and built up class .We use a confusion matrix to compare our classification result to the orthorectified aerial photography of 2008 sample data. 50 sample points per class, a total of 200 sample points. An overall accuracy and kappa statistic were calculated for the land cover classes.

Table 3-2 presents the confusion matrix, showing the class distribution for each sample point class, Table 3-3 shows accuracy totals decision tree classification and Table 3-4 shows the kappa statistic. The land cover map of 2009 had an overall accuracy of 76.50%, which means that a random point on the map has 76.5% of probability to be correctly classified. kappa of 0.69.

Table 3-2 Error Matrix Decision tree classification

Error Matrix Decision tree classification					
Classified Data	Dense forest	Crop land	Dense Shrub land	Mix veg	Row Total
Dense forest	47	0	1	2	50
Crop land	0	26	7	17	50
Dense Shrub land	12	1	36	1	50
Mix veg/ Shrub dominant	0	1	5	44	50
Column Total	59	28	49	64	200

Table 3-3 Accuracy totals decision tree classification

ACCURACY TOTALS DECISION TREE CLASSIFICATION					
Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
Dense forest	59	50	47	79.66%	94.00%
Crop land	28	50	26	92.86%	52.00%
Dense Shrub land	49	50	36	73.47%	72.00%
Mix veg/ Shrub dominant	64	50	44	68.75%	88.00%
Totals	200	200	153		

Table 3-4 Kappa statistics decision tree classification

Class Name	Kappa
Dense forest	0.91
Crop land	0.44
Dense Shrub land	0.62
Mix veg/ Shrub dominant	0.82

Dense forest presents the highest accuracy with a kappa of 0.91.

Crop land presents the lowest accuracy with a kappa 0.44. Seven crop land samples were misclassified as dense shrub land and 17 as mixed vegetation / shrub dominant. This is attributed to small-scale agriculture dominating the study area. Crop fields cannot be well separated at 250 m spatial resolution. Also, due to their similar phenology and structure, shrub lands and crops can be difficult to separate.

The reason for low accuracy classifying crop land class can be explained by the small and fragmented extension of crops in the study area, with only 1991 hectares, 2.33% of the total area. The coarse resolution of MODIS images has difficulties to classify small fragmented areas. This is also shown in others results researches where the MODIS-derived land cover maps were very successful at mapping extensive cover types and less successful at mapping smaller cover types (Wessels et al. 2004). small, fragmented cropland areas could not be resolved at MODIS' 250 m spatial resolution in the crop/noncrop map(Wardlow et al. 2008)

Dense shrub land presented a kappa of 0.63, 12. Dense shrub lands samples were misclassified as a dense forest. The difficulty to classify between these two classes was in the transition zone from dense shrub land to dense forest.

Mixed vegetation/shrub dominant was effectively distinguished from other classes by MODIS data with a kappa statistic of 0.82, although there was some confusion between dense shrub lands.

3.3.2 Accuracy assessment comparison between classification methods

Accuracy assessment of land cover map o 2009 obtained by the supervised maximum likelihood classification was conducted for the land cover classes excluding water bodies and built up class .We use a confusion matrix to compare our classification result to the orthorectified aerial photography of 2008 sample data. We used the same 200 sample points for the 3 classification methods. An overall accuracy and kappa statistic were calculated for the land cover classes.

The land cover map of 2009 had an overall accuracy of 59.50% and a kappa of 0.45. Table 3-6 shows the kappa statistic.

Table 3-5 Kappa Statistic for MLC

Class Name	Kappa
Dense forest	0.78
Crop land	0.19
Dense Shrub land	0.38
Mix veg/ Shrub dominant	0.32

Accuracy assessment of land cover map o 2009 obtained by the unsupervised isodata classification was conducted for the land cover classes excluding water bodies and built up class .We use a confusion matrix to compare our classification result to the orthorectified aerial photography of 2008 sample data. An overall accuracy and kappa statistic were calculated for the land cover classes.

The land cover map of 2009 had an overall accuracy of 65.00% and a kappa of 0.54. Table 3-6 shows the kappa statistic.

Table 3-6 Kappa Statistic for Isodata classification

Class Name	Kappa
Dense forest	0.82
Crop land	0.27
Dense Shrub land	0.69
Mix veg/ Shrub dominant	0.58

The MLC classification produced a lowest overall accuracy of 59.5% of the tree methods and the decision tree classification presented the highest accuracy assessment. Dense forest was the land cover with better accuracy in the 3 classification methods and crop land the presented the lowest accuracy.

Although past researches have showed that decision tree method shows similar accuracy as methods such as maximum likelihood and neural networks (Pal and Mather 2003). The major problem with maximum classification was the overestimation of crop land, presenting a very low accuracy with a kappa statistic o 0.19. Decision tree showed better results with kappa statistic 0.44, still low accuracy.

3.4 Land productive classification

Fallowing the criteria of the Agrarian reform law, the land cover classes were allocated to their corresponding “productive land” categories:

Figure 3-13 shows the “productive land” map of 2009, the spatial distribution of ecological land, effectively exploited land, fallow land and unproductive land.

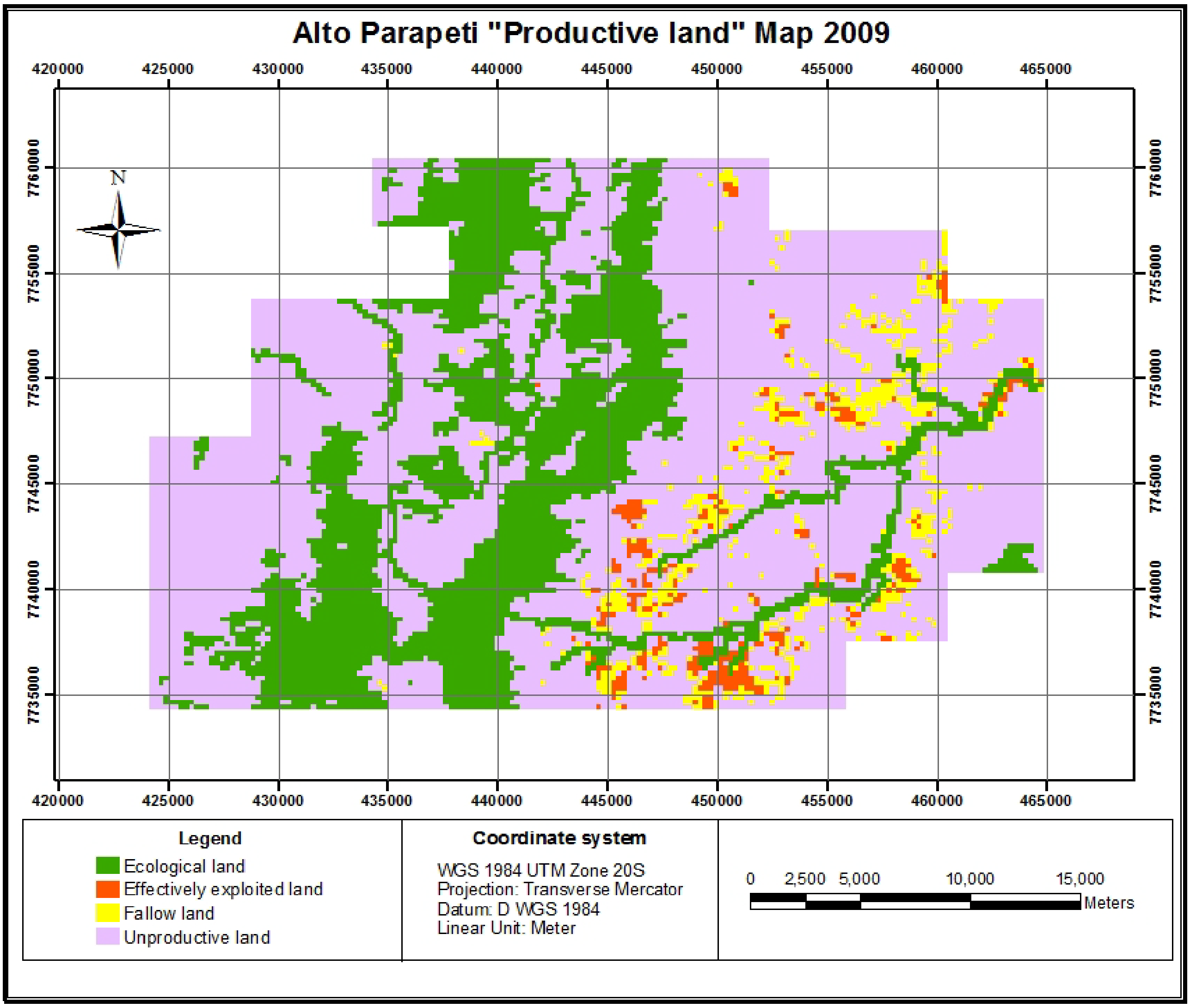

Figure 3-12 Alto Parapeti “productive land” map 2009

The "productive land" map of 2009 shows large extension of ecological land in the mountainous zone, large extension of unproductive land in the flat regions of the study area with small and fragmented effectively exploited land and fallow land. The area in hectares and the percentage for "productive land" the classes were calculated and presented in Table 4-4.

Table 3-7 Productive land Area (Ha) of 2009

Productive land	Area (Ha)	%
Exploited land	1991	2,33
Fallow land	4250	4,97
Ecological land	25094	29,34
Unproductive land	54201	63,37

Ecological land consists of dense forest in the mountain region, and rivers with an area of 25094 hectares. Effectively exploited land consist of crop lands with only 1991 hectares, it covers the 2.33% of the study area. Fallow land showed 4250 hectares of extension. Unproductive land is the dominant class with 54201 hectares, 63.37% of the study area.

In spite of having a relatively low accuracy based in the performance of the land cover classification. The large extension of unproductive land in the study area shows that it can potentially be redistributed to the population, which is a good starting point for field verification of "productive land" by the Bolivian National Agrarian Institute (INRA).

4 Conclusions and Recommendations

4.1 Conclusions

The general objective of this study is to monitor land cover patterns in Alto Parapeti by analyzing time series of MODIS imagery to determine productive and unproductive lands from the Bolivian land tenure reform perspective.

The decision tree classification of MODIS NDVI was successfully at mapping extensive cover lands such as dense forest, dense shrub land and mixed vegetation /shrub dominant. The approach was far less effective at mapping smaller cover types as the small as fragmented cropland areas.

Land cover maps from 2001 to 2009 were generated using the decision tree classification, but further work is needed to validate this method with more dates, and later test this approach to determine the sensitivity to inter annual variability over the classification results of multiple years.

The accuracy assessment of the land cover map 2009 was relative low (76% overall accuracy). The decision tree approach was compared in terms of accuracy with maximum likelihood supervised classification and isodata classification methods. The approach of the decision tree provided the highest overall accuracy of three methods.

The land cover classes were allocated to the “productive land” categories producing a “productive land” map Alto Parapeti from 2009. The map showed a large extension of unproductive land. This approach and can be used as a reference to prioritize the efforts of the Bolivian Agrarian Reform finding extensive unproductive land to start field verification.

The Bolivian agrarian law does not present the specification required for a proper application of remote sensing in the verification of “productive land”.

4.2 Recommendations

The classification approach could be improved by acquiring more additional input data and criteria in discriminating land cover types, and adjusting decision rules and thresholds by finding better phenological differences from MODIS multi temporal images.

Exploration of other classification approaches that might perform better such as object oriented classification; analyze further the unsupervised isodata classification for change detection.

The research could be extended to different study areas to evaluate the performance of MODIS multi temporal images in the complexity of land cover types in the different regions of Bolivia. Select a region of agricultural enterprises an large extensions of crop fields for further studies.

To improve the land cover classification, the Bolivian Agrarian reform law should be adequate in more specific way for the use of remote sensing.

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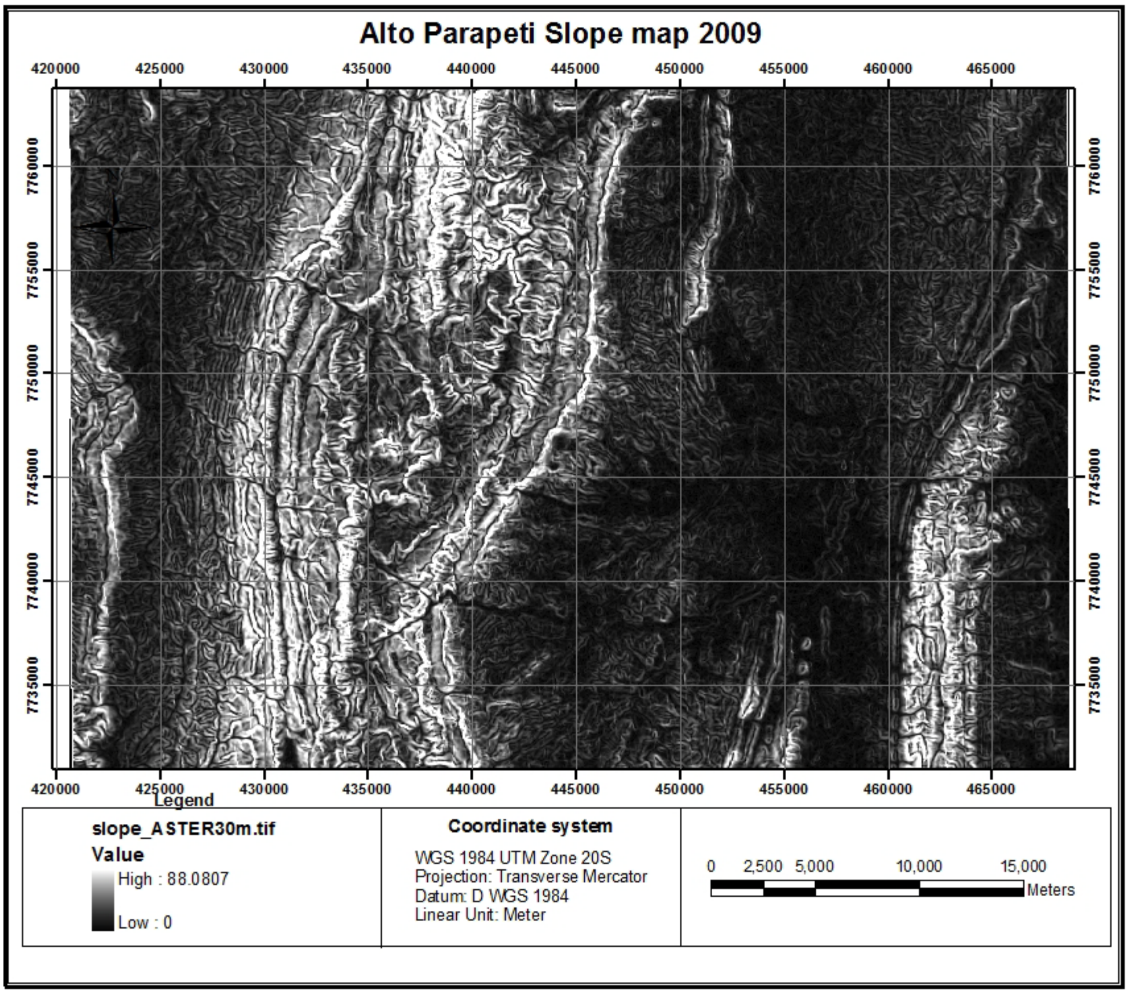
Appendices

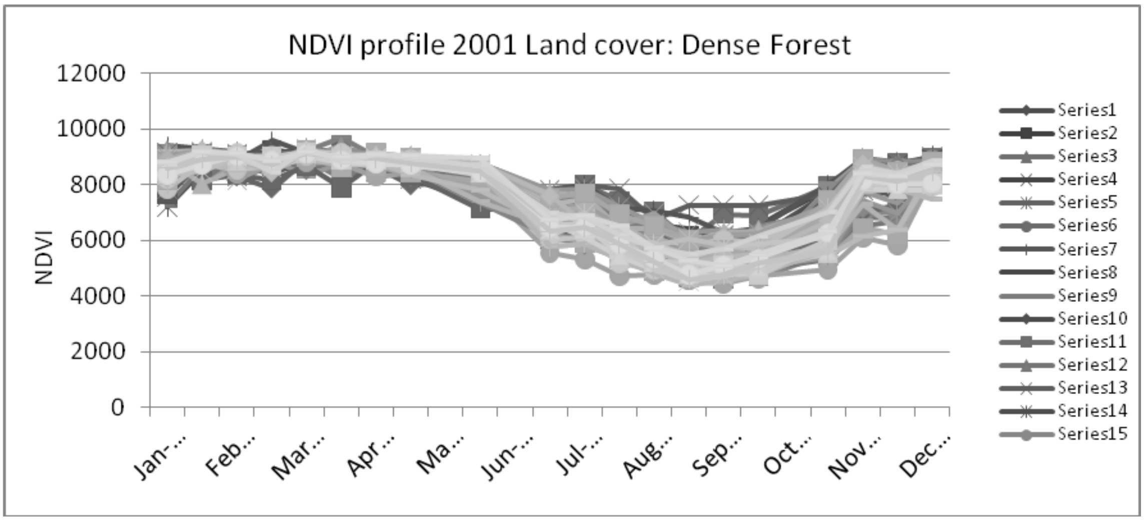
Appendix 1

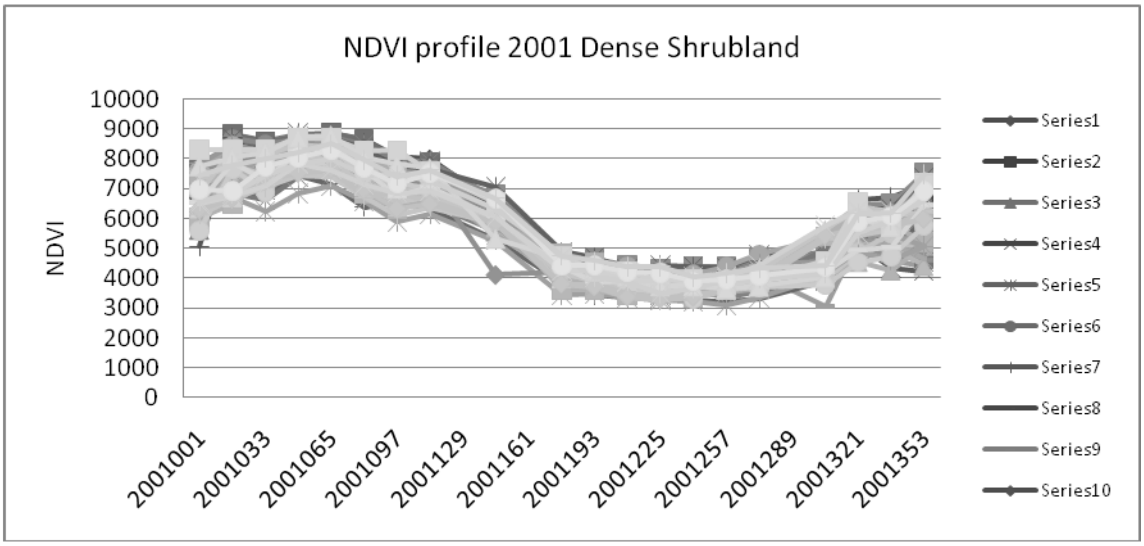
<u>Slope Map from ASTER GDEM</u>

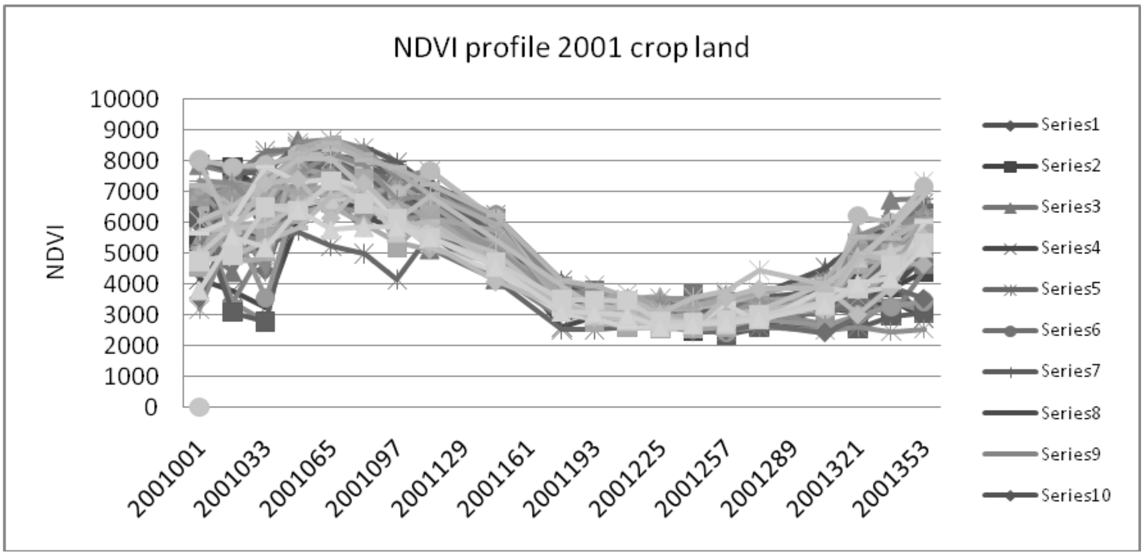


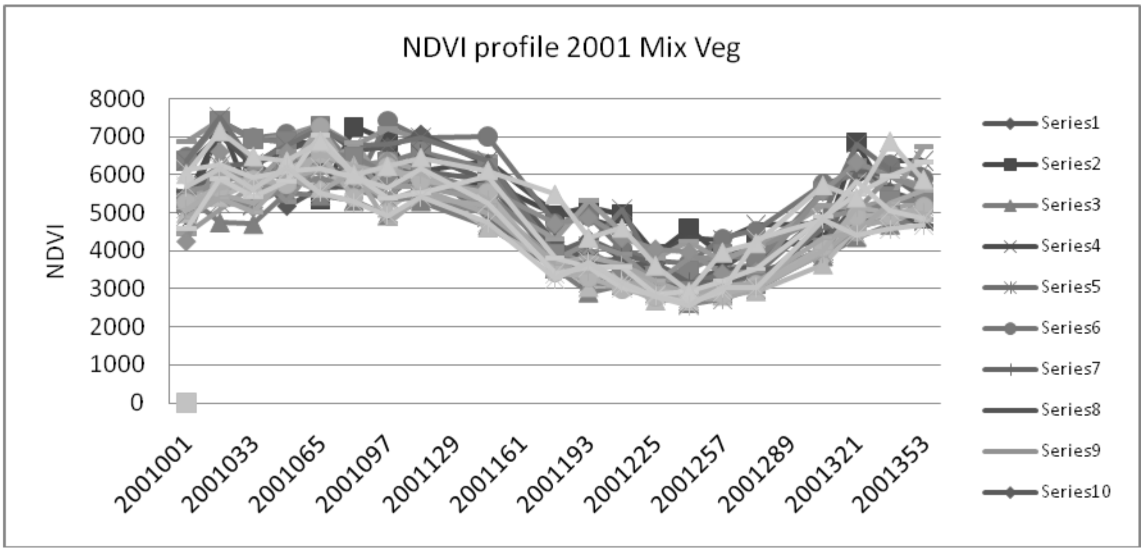
Appendix 2

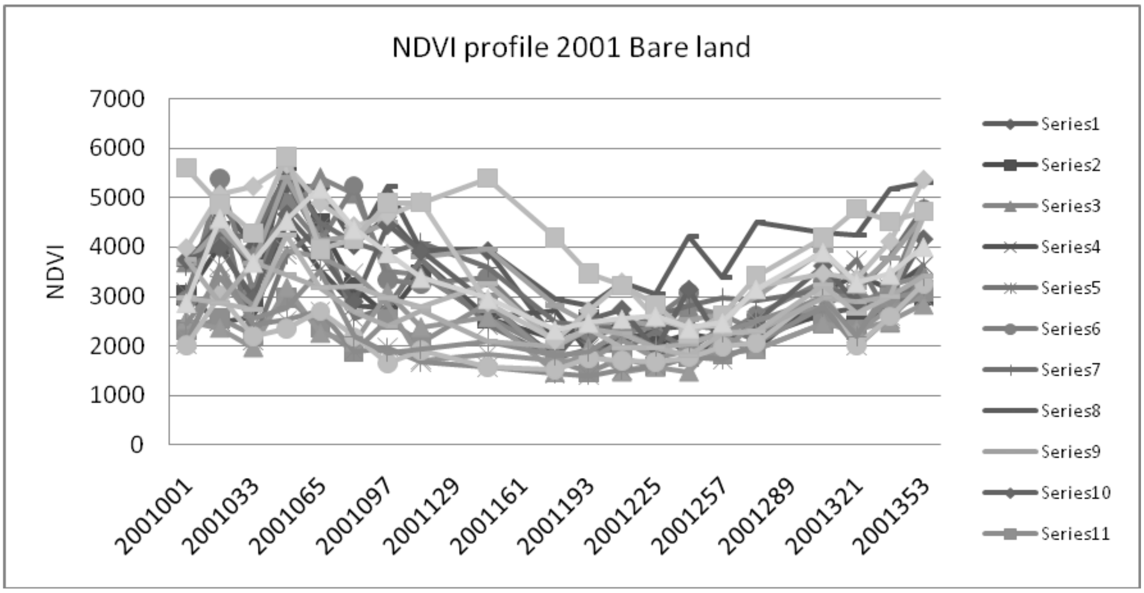
<u>NDVI profiles of sample points</u>






NDVI profile 2001 crop land
NDVI
10000
9000
8000
7000
6000
5000
4000
3000
2000
1000
0
2001001
2001033
2001065
2001097
2001129
2001161
2001193
2001225
2001257
2001289
2001321
2001353
Series1
Series2
Series3
Series4
Series5
Series6
Series7
Series8
Series9
Series10


NDVI profile 2001 Mix Veg
NDVI
8000
7000
6000
5000
4000
3000
2000
1000
0
2001001
2001033
2001065
2001097
2001129
2001161
2001193
2001225
2001257
2001289
2001321
2001353
Series1
Series2
Series3
Series4
Series5
Series6
Series7
Series8
Series9
Series10


NDVI profile 2001 Bare land
7000
6000
5000
4000
3000
2000
1000
0
NDVI
2001001
2001033
2001065
2001097
2001129
2001161
2001193
2001225
2001257
2001289
2001321
2001353
Series1
Series2
Series3
Series4
Series5
Series6
Series7
Series8
Series9
Series10
Series11

Appendix 3

Confusion matrix of supervised maximum likelihood classification and unsupervised isodata classification

Error Matrix Decision tree classification

Error Matrix Decision tree classification					
Classified Data	Dense forest	Crop land	Dense Shrub land	Mix veg	Row Total
Dense forest	56	0	9	1	62
Crop land	0	13	4	25	42
Dense Shrub land	3	6	21	9	39
Mix veg/ Shrub dominant	0	9	15	29	53
Column Total	59	28	49	64	200

Error Matrix unsupervised isodata classification

Error Matrix unsupervised isodata classification					
Classified Data	Dense forest	Crop land	Dense Shrub land	Mix veg	Row Total
Dense forest	50	0	6	1	57
Crop land	2	27	15	27	71
Dense Shrub land	2	1	20	3	26
Mix veg/ Shrub dominant	5	0	8	33	46
Column Total	59	28	49	64	200