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Land-use change modeling in the Brazilian Amazon - Exploring the impact of environmental factors

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Abstract

The Amazon rainforest is the largest tropical rainforest in the world with an extent of approximately 5.5 million km^2. In the last decades the Amazon rainforest has been under increasing human pressure.

Understanding of anthropogenic actions and developments in tropical regions is essential to control human impact on tropical forests and to preserve important ecosystem services. Land-Use and Land-Cover Change (LUCC) Models have been developed to serve this purpose. Statistical models, which can provide the input for these models, reflect connections between different land-use determining factors and land-use types. Another important environmental issue is the interplay between land-use and land-cover changes and the local and global climate system.

This thesis can be seen as a step towards the coupling of climate and LUCC models to improve the representation of the complex bi-directional interactions between these domains. For this purpose a Potential Vegetation Model (CPTEC-PVM) and its corresponding Water Balance Model were implemented in the same modeling environment (TerraME) as a multi-scale, spatially-explicit dynamic LUCC model (AmazonClueINPE). The effect of hydrological and other environmental variables on the occupation process in the Brazilian Amazon was investigated to build statistical models that are capable of reproducing actual deforestation and land-use patterns.

Thus the scientific question of this thesis is to understand how such new environmental variables, derived from the Water Balance Model, in conjunction with additional environmental variables, such as slope and altimetry variables, can help to improve land-use change projections in the Amazon, facilitating the construction of coupled climate-LUCC integrated models in the future.

The statistical analysis results showed good explanatory power of some environmental variables to discriminate temporary crops from pasture patterns at the scale of analysis.

However, on basis of the dynamic modeling results no improvement in the projected patterns of pasture and temporary crops was obtained solely considering the seasonality index or the altimetry and slope variables. Dynamic modeling results were similar, due to the larger impact of other determinant factors, mainly related to connectivity and accessibility.

Nevertheless integrating a combination of hydrological and biophysical data is thought to be a good and reasonable asset in the modeling approach to study land-use type conversions.

Furthermore the implementation of a Potential Vegetation Model and its corresponding Water Balance Model in the TerraME modeling environment opens new possibilities to study the interaction between climate, vegetation and LUCC models like the AmazonClueINPE model used in this thesis.

Zusammenfassung

Der Amazonas-Regenwald ist der größte tropische Regenwald der Welt mit einer Größe von circa 5.5 Millionen km^2. In den letzten Jahrzehnten wurde der Amazonas-Regenwald massivem Druck durch den Menschen ausgesetzt.

Um den menschlichen Einfluss auf tropische Wälder zu kontrollieren und wichtige Ökosystemdienstleistungen zu erhalten, besteht die Notwendigkeit anthropogene Entwicklungen in tropischen Regionen zu verstehen. Land-Use and Land-Cover Change (LUCC) Modelle wurden für diesen Zweck entwickelt. Statistische Modelle, welche als Grundlage für LUCC-Modelle dienen können, spiegeln Verbindungen zwischen unterschiedlichen landnutzungsbestimmenden Faktoren und Landnutzungsklassen wider. Weiters ist das Zusammenspiel zwischen Landnutzungsveränderungen und lokalem und globalem Klima von großer Bedeutung.

Mit dieser Arbeit soll ein Schritt in Richtung Kopplung von Klima- und LUCC-Modellen gemacht werden, um die Repräsentation der komplexen bi-direktionalen Interaktionen zwischen diesen Wissensgebieten zu verbessern. Für diesen Zweck wurden ein Potentielles Vegetations Modell (CPTEC-PVM) und das dazugehörige Wasserhaushaltsmodell in derselben Modellierungsumgebung (TerraME) wie ein auf verschiedenen Maßstäben basierendes, räumlich-explizites, dynamisches LUCC-Modell (AmazonClueINPE) implementiert. Der Einfluss von hydrologischen und weiteren umweltbedingten Faktoren auf die, durch den Menschen beeinflusste, räumliche Entwicklung des brasilianischen Amazonasgebiets wurde untersucht um statistische Modelle zu erstellen. Diese Modelle sollten dazu dienen die räumlichen Abholzung- und Landnutzungsstrukturen zu rekonstruieren.

Die wissenschaftliche Frage dieser Diplomarbeit ist daher zu verstehen wie hydrologische Faktoren von einem Wasserhaushaltsmodell in Verbindung mit weiteren umweltbedingten Variablen, wie Hangneigung und Geländehöhe, helfen können um

Landnutzungsveränderungen im Amazonasgebiet zu prognostizieren und den Aufbau von gekoppelten Klima-LUCC Modellen in der Zukunft zu erleichtern.

Die Resultate der statistischen Analyse zeigten die Aussagekraft einiger hydrologischer und umweltbedingter Faktoren um temporäre Landwirtschaft und Weideland im Untersuchungsmaßstab zu unterscheiden. Jedoch konnte auf Basis der Ergebnisse der dynamischen Modellierung keine Verbesserung ausschließlich aufgrund dieser Faktoren festgestellt werden. Die Resultate waren, bedingt durch den größeren Einfluss anderer bestimmender Faktoren, ähnlich. Diese betrafen hauptsächlich die Konnektivität und Erreichbarkeit.

Dennoch wird erwartet, dass die Integration von hydrologischen und bio-physikalischen Faktoren eine sinnvolle Ergänzung im angewandten Modellierungsverfahren ist, um Landnutzungsveränderungen zu untersuchen.

Weiters liefert die Implementierung des Potentiellen Vegetation Modells und des dazugehörigen Wasserhaushaltsmodell in der TerraME Modellierungsumgebung neue Möglichkeiten um die Interaktion zwischen Klima-, Vegetations- und LUCC-Modellen zu erforschen.

Acknowledgments

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Table of Contents

List of Acronyms

AIC	Akaike Information Criterion
CLUE	The Conversion of Land Use and its Effects
CPRM	Companhia de Pesquisa de Recursos Minerais (Geological Survey of Brazil)
CPTEC	Centro de Previsão de Tempo e Estudos Climáticos (Center for Weather Forecasts and Climate Studies)
FUNAI	Fundação Nacional do Índio (National Indian Foundation)
IBAMA	Instituto Brasileiro do Meio Ambiente e dos Recursos Naturais Renováveis (Brazilian Institute of Environment and Renewable Natural Resources)
IBGE	Instituto Brasileiro de Geografia e Estatística (Brazilian Institute of Geography and Statistics)
INCRA	Instituto Nacional de Colonização e Reforma Agrária (National Institute for Colonization and Agrarian Reform)
INMET	Instituto Nacional de Meteorologia (National Institute for Meteorology)
INPE	Instituto Nacional de Pesquisas Espaciais (National Institute for Space Research)
LUCC	Land-use and Land-cover change
PVM	Potential Vegetation Model
SRTM	Shuttle Radar Topography Mission

1 Introduction

The Amazon rainforest is the largest tropical rainforest in the world. It has an extent of approximately 5.5 million km^2, of which about 60% are located in Brazil (Andersen et al. 2002). Due to its rich biodiversity and its potential role in global climate discussions, deforestation in the Amazon is not only of local interest, but leads to questions of global environmental and economical concern (Andersen et al. 2002; Werth & Avissar 2002; Malhi et al. 2008).

In the last decades the Amazon rainforest has been under increasing human pressure. The so-called Legal Amazon[1] (Amazônia Legal), which comprises nine Brazilian states, experienced a population increase from 4 million people in 1950 (Barreto et al. 2006) to almost 24 million people in 2007 (IBGE 2007). Expansion of pasture areas for cattle-ranching and increasing demand for mechanized agriculture (e.g. soybeans) are seen as the major drivers leading to massive forest clearing especially in the so-called arch of deforestation (Kaimowitz et al. 2004; Becker 2005; Nepstad & Stickler 2006).

Since 1988 the National Institute for Space Resarch INPE (Instituto Nacional de Pesquisas Espaciais) has been monitoring deforestation in the Brazilian Amazon and provides accurate, annual deforestation maps and rates (INPE 2010). Figure 1-1 shows the spatial patterns of deforestation as measured by INPE in 2007. In recent years the deforestation rate reached a maximum of 27423 km^2 in 2004 and had an average value of 17133 km^2 between 1997 and 2009. Figure 1-2 shows annual deforestation rates from 1997 to 2009.

[1] The Legal Amazon (Amazônia Legal) is not an uniform biome, as it initially was defined for regional planning purposes. It mainly consists of forests, savannas/cerrados, inundated lowlands and steppes. (Andersen et al. 2002)

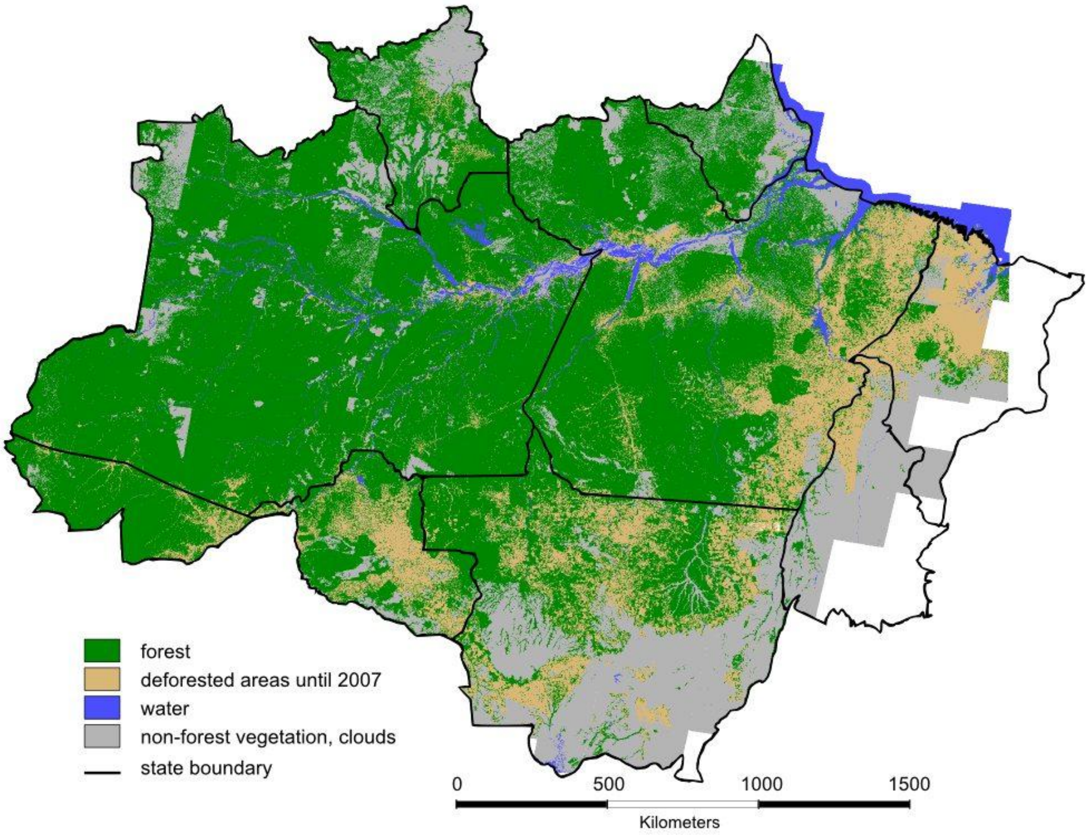

Figure 1-1: Deforestation map of the Brazilian Amazon in 2007 (INPE 2010)

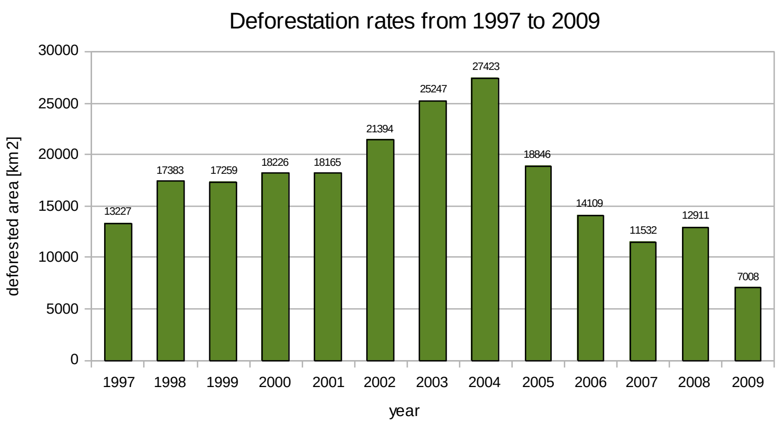

Figure 1-2: Deforestation rates from 1997 to 2009 (INPE 2010)

Tropical deforestation is an issue not only present in South America, but can also be observed in tropics in other parts of the world, where anthropogenic impact leads to land-use and land-cover changes (LUCC). Land-cover refers to the attributes of Earth's land surface and immediate subsurface (e.g. forest, grassland etc.) and land-use to the purposes for which humans exploit the land cover (e.g. forestry, pasture etc.) (Lambin et al. 2006). Research in the area of LUCC modeling tries to investigate and simulate the human influence on once pristine forests. Geist & Lambin (2001) compare various subnational

LUCC case studies to analyze proximate[2] and underlying[3] causes of tropical deforestation. Their findings indicate that tropical deforestation cannot be explained by a single or even a few variables, but by the interplay of several proximate and underlying factors. An infrastructure-agriculture tandem was found as a causative connection at the proximate level, which shows especially for mainland South America relevant importance. In addition biophysical factors as relief or topography in combination with soil quality and water availability shape the patterns of deforestation in cases with high rates of annual deforestation (Geist & Lambin 2001).

Various modeling approaches exist to simulate the dynamics of land-use changes. These range from empirical models, based on statistical analyses like the CLUE model (Veldkamp & Fresco 1996; De Koning et al. 1998; Verburg et al. 1999; Kok et al. 2001) to stochastic cellular automata models like DINAMICA (Soares-Filho 2002) or agent-based models like LUCITA (Deadman et al. 2004). Understanding of past deforestation processes is essential for projecting and exploring of future scenarios, to provide decision makers with reliable tools and fundamental up-to-date information.

Besides the substantial loss of biodiversity due to forest decline (Fearnside 2005; Barreto et al. 2006) the interplay between climate and land-use changes is an important environmental issue. Thus several publications discuss these bi-directional interactions between climate and land-use dynamics to assess the vulnerability of the Amazon to global climate change on one side and the contribution of land-use changes to the climate on the other side (Nobre et al. 1991; Gash 1996; Foley et al. 2003; Aragão et al. 2008; Malhi et al. 2008). No unified agreement on how the Amazonian climate might change due to deforestation has been reached so far, but most studies indicate that surface temperature has the tendency to rise, while precipitation might decrease in some parts of the Amazon, leading to significant drying in some areas during the 21st century (Voldoire & Royer 2004; Malhi et al. 2008). Even tipping the biome-climate system towards a new drier stable equilibrium state by land-use changes seems possible for tropical South America (Oyama & Nobre 2003).

[2] Proximate causes of deforestation are human activities (land uses) that directly affect the environment and thus constitute proximate sources of change. They operate on the local scale and can be structured in three groups: agricultural expansion, wood extraction and infrastructure extension (Geist & Lambin 2001).
[3] Underlying causes of deforestation or driving forces may directly act at the local level or indirectly at national and global level. They are a complex of social, political, economic, technological and cultural variables, which are seen as fundamental forces which underpin proximate causes of deforestation (Geist, Lambin 2001).

The present thesis uses a Potential Vegetation Model (PVM) based on climatic variables, developed at INPE (Oyama & Nobre 2004) to derive additional input parameters for simulation of land-use change processes in the Brazilian Amazon. This PVM incorporates a water balance model from which climate dependent variables, such as soil wetness and a seasonality index, are derived. The Potential Vegetation Model and the hydrological model will be implemented in the same modeling framework as a LUCC model for the Amazon, also previously developed at INPE (Aguiar 2006; Moreira 2009). Thus it will be possible to examine the explanatory power of additional environmental factors in a land-use and land-cover change model, especially to discriminate agriculture from pasture land-use patterns. The combined use of such models allows for comprehensible data integration through the same database and can further be seen as a prerequisite for dynamically coupling climate-LUCC models in the future. Hence this thesis can also be seen as a step towards future research topics regarding the construction of integrated environmental models.

In this context, the scientific question of the thesis is thus to understand how such additional environmental variables, derived from the water balance model, in conjunction with other environmental variables, such as slope and altimetry, can help to improve land-use change projections in the Amazon, facilitating the construction of coupled climate-LUCC integrated models in the future.

1.1 Hypothesis

The inclusion of hydrological, slope and altimetry variables improves the ability to discriminate pasture and agriculture patterns in the Brazilian Amazon.

1.2 Objectives

To address this hypothesis the following objectives were defined for this thesis:

→ Progress towards future coupling of LUCC and climate models by implementing a potential vegetation model and its corresponding water balance model in the same modeling framework as a LUCC model.

→ Verify the adequacy of hydrological variables derived from this water balance model to simulate and discriminate agriculture and pasture patterns in the Brazilian Amazon, using statistical analysis and spatially-explicit dynamic LUCC models.

1.3 Structure of the thesis

The structure of the thesis is the following. Chapter 1 starts with an introduction to the topic, the hypothesis and the objectives of the work. In Chapter 2 a literature review will be summarized to give an overview of the state of research. Chapter 3 describes the study area and the methods that will be used to validate the proposed hypothesis. Chapter 4 shows the results of the dynamic modeling approach. In chapter 5 a summary is given and conclusions are drawn.

2 Literature Review

This chapter consists of a review of LUCC models and the coupling of climatic models to LUCC models.

2.1 LUCC Models

2.1.1 Overview of LUCC modeling approaches

Lambin et al. (2000) and Lambin (2004) distinguish various categories of land-use change models: empirical-statistical, stochastic, optimization, dynamic (process-based) and integrated models. Briassoulis (2000) distinguishes between statistical and econometric, spatial interaction, optimization and integrated models and a class incorporating model types which do not fall into one of these classes, while Heistermann et al. (2006) classify LUCC models into geographic (empirical-statistical or rule-based/process-based), economic and integrated models. No matter which model type is used, modeling of land-use change tries to address at least one of the following questions (Lambin 2004):

- Which socio-economic and biophysical variables contribute most to an explanation of land-use changes and why?

- Which locations are affected by land-use changes – where?

- At what rate do land-use and land-cover changes progress – when?

Another differentiation between land-use change models is defined by the attribute of being spatially-explicit. Goodchild (2002) describes four simple tests to investigate if a LUCC model is spatially-explicit. The invariance test defines a model to be spatially-explicit if its results are not invariant under relocation of the objects of study. If location is included in the representation of the system being modeled, the model is spatially-explicit due to the representation test. The formulation test states that a model is spatially-explicit if spatial concepts such as location or distance appear directly in the model. The outcome test investigates if the spatial forms of inputs and outputs are different, as a spatially-explicit model modifies the landscape on which it operates. Corresponding to the outcome test, the author states that the most important reason for LUCC modeling to be spatially-explicit may relate to the model outcomes, as spatial patterns resulting from the processes of LUCC are of significant interest to policy makers. Hence, if a LUCC model is assessed through the spatial patterns it produces it is defined as being spatially-explicit.

An overview of economic models of deforestation can be found in Kaimowitz & Angelsen (1998), where 150 different models are reviewed. Barbier & Burgess (2001) provide a survey of economic studies on tropical deforestation and land-use at the cross-country level. Geist & Lambin (2001) compare various subnational LUCC case studies to analyze proximate and underlying causes of tropical deforestation.

2.1.2 LUCC models in the Brazilian Amazon

Numerous LUCC studies investigate land-use changes caused by deforestation in tropical South America, ranging from local studies to regional models covering the whole Amazon. The scientific areas of the authors of these studies differ (e.g. GIScience, economics, computer science, remote sensing etc.) and correspondingly vary the types of models and the applied modeling approaches. In the following some modeling approaches of tropical deforestation in the Brazilian Amazon are reviewed.

Andersen & Reis (1997) develop an econometric model of deforestation and economic development in the Brazilian Amazon to evaluate the effects of different policy instruments. The authors use a panel data set covering 316 municipalities from 1970 to 1985 in five year steps. This data set comprises economic, ecological and demographic variables. The two-sector model consists of a rural and an urban sector and six equations. Past characteristics of a region and its neighbors are used by the main equation to predict the demand for newly cleared area, while the remaining equations assess the interaction between rural and urban populations, rural and urban output and land prices. The results of this LUCC study indicate a positive trade-off between economic growth and deforestation for subsidized credit for two main reasons. The authors conclude that subsidized credit promotes higher land prices which imply more efficient land-use and that farmers are stimulated to invest in more profitable and sustainable perennial crops. On the other side they state, based on the results of their model, that road building into pristine areas is harmful, but good in already cleared areas where it improves infrastructure.

Andersen et al. (2002) introduce an econometric model with an updated methodology and data of the model published in Andersen & Reis (1997). This LUCC model simulates land clearing and economic development considering the growth rates of clearing and the growth rates of rural GDP[1]. The model is evaluated for two different time periods. The first period is from 1980 to 1985 and the second from 1985 to 1995. Six endogenous variables are used: land-clearing, rural and urban GDP growth, rural and urban population growth and cattle herd growth. In addition to these variables models of paved and unpaved roads are included. A general-to-simple approach is used to eliminate factors out of the 74 initial potential explanatory variables. The model shows that herd growth and new land clearing are mainly affected by natural frontier spatial processes of maturation and urban demand centers. The results further indicate that building of paved roads in forested areas leads to more clearing than building of unpaved roads. In the model, unpaved roads are associated mainly with land-extensive activities while paved roads correspond to more land-intensive economic activities. The authors expected to find a deforestation reducing effect in regions with high rainfall, but according to the model rainfall did not affect the growth rates of clearing and the growth of rural GDP. Simulating the Avança Brasil[2] road construction plan the LUCC study found economic gains, but no overall increase in cleared area, which the authors explain by a possible underestimation of the impact of paved roads in relatively undisturbed areas. Nevertheless, the authors recommend reducing ecological costs by paving roads only in well-established areas. They further investigate the proposal to modify the “forest law”[3] from 80% to 50% and state that the economic costs of sustaining the 80% threshold outreach the value of forest services. Hence the authors propose to change the law to 50% and to improve infrastructure in settled areas, instead of building roads through undisturbed areas.

Laurance et al. (2002) describe an empirical-statistical land-use change model for the Brazilian Amazon. The study area is subdivided into regular grids at two spatial scales, 50x50 km^2 and 20x20 km^2. Satellite imagery from 1999 is used to estimate the proportion of forest cover, deforested area and natural water bodies in each grid cell. A set of variables comprising human-demographic factors, factors that affect physical accessibility to forests and factors that may affect land-use suitability for human occupation and

[1] GDP: gross domestic product
[2] Avança Brasil is a plan by the Brazilian government which involves a lot of investment in the Amazon region including infrastructure projects, social development projects, environmental projects and information collection (Andersen et al. 2002)
[3] The “forest law” states that 80% of forest inside private properties must be preserved.

agriculture is used in the statistical analysis which is carried out on a random set of 120 cells, out of the 1927 cells at scale 50x50 km^2. A robust ordination method results in the development of two major axes of variation, which leads to the conclusion that highways (paved roads), human population density and dry-season severity are the main factors leading to local deforestation, while rainfall and unpaved roads have a smaller influence. Thus the authors state that highways, human population density and dry-season severity largely determine deforestation in the Brazilian Amazon.

Soares-Filho et al. (2006) focus on modeling conservation in the Amazon basin by using an empirical, policy-sensitive model of deforestation. Eight different scenarios for the time from 2001 to 2050 are utilized to project the influence of conservation approaches on the future development of the Amazonian rainforest. The used method comprehends two models. The first model divides the Amazon basin into 47 socioeconomic subregions and calculates deforestation rates for these regions based on historical trends, a road paving schedule and existing and proposed protected areas. It then passes these rates to a second model. This spatially-explicit model uses DINAMICA (Soares-Filho 2002), a cellular automata model on cells with 1 km^2 resolution to allocate the demand for land clearing and thus simulate the spatial patterns of deforestation using static (e.g. distance to major rivers) and dynamic (e.g. distance to deforested land) variables. The scenarios simulate future forest loss mainly in the eastern Amazon and along the BR-364 road from Rondônia to Acre and thereby reduce the area of closed-canopy forest from 5.3 million km^2 in 2003 to 3.2 million km^2 in the “business-as-usual” scenario and to 4.5 million km^2 under a governance scenario by 2050. Areas in the northwestern part of Amazonas state and areas outside Brazil may remain largely untouched due to their remoteness. According to the authors, protected areas in the Amazon are suitable to maintain mammalian diversity to a large degree, but not to secure critical watersheds and ecoregions from impoverishment, hence they recommend improved conservation strategies outside of protected areas.

Aguiar (2006) introduces an empirical-statistical, spatially-explicit model in the Brazilian Amazon. Spatial lag regression models and multiple linear regression models are used at two spatial scales to find statistical relationships between different land-use types and potential land-use determining factors. These factors come from a list of variables categorized in the following groups: accessibility to markets, economical attractiveness, public policies, agrarian structure, demographical, technological, and environmental factors. The applied modeling approach allows simulating different levels of law enforcement, road paving and creation of protected areas. Various combinations of factors and model parameters are used in five exploration scenarios from 1997 to 2020. Significant variations in relative importance of land-use determining factors are found between different regions. A result of these differences is that the impact of local policies also varies across space. The author thus advises to account for this intra-regional heterogeneity in land-use change models of the Amazon. A further conclusion is that connectivity measures to national markets are amongst the most important factors to capture deforestation dynamics in the new Amazonian frontiers, but they can only explain land-use patterns in combination with other factors.

Moreira et al. (2009) develop an approach to build a multi-scale land-use change model including top-down and bottom-up interactions and test this dynamic coupling effort with a macro model of the Brazilian Amazon and a local model of Iriri/Terra do Meio in Pará state. At the macro scale (25x25 km^2 cells) the empirical-statistical modeling approach and data as described in Aguiar (2006) are used. At the local scale (1x1 km^2 cells) an agent-based model is implemented. Two sets of agents are defined, each with a set of actions and decision rules. The multi-scale model contains top-down actions, e.g. to send demand for land-use types to the local scale, and bottom-up feedbacks, e.g. to notify the global scale that the demand could not be allocated due to local policy restrictions. Four combinations of scenarios at both levels are tested from 1997 to 2025. The results indicate that local conditions do not determine the pressure for land-use change alone, it is also regulated by processes acting at higher hierarchical levels. To account for local and regional land-use change processes under varying biophysical and socioeconomic conditions is expected to be one of the strengths of multi-scale models. The authors thus conclude that models using top-down and bottom-up interactions can detect processes, which might be missed considering single scale models.

2.1.3 CLUE modeling framework and its adaptation to the Amazon

The CLUE (Conversion of Land-Use and its Effects) modeling framework is a dynamic, multi-scale land-use and land-cover change model (Veldkamp & Fresco 1996; De Koning et al. 1998; Verburg et al. 1999; Kok et al. 2001). Currently three different versions exist: CLUE for regional to global scale analysis, CLUE-CR as the first implementation of the CLUE model applied to Costa Rica and CLUE-S for regional scale analysis.

The CLUE model has the objective to provide a spatially-explicit, multi-scale, quantitative description of land-use changes. It explores possible changes in the near future under different development scenarios. The model consists of a demand and an allocation module. In the non-spatial demand module scenarios of the quantity of change define how much change takes place in every time step. The spatial allocation module calculates where the changes are likely to happen. Connections between potential explanatory variables, such as socio-economic or environmental variables and various land-use types are assessed by multiple regression analysis. The CLUE model has been applied to various regions to study a large variety of land-use change issues, e.g. agricultural intensification, urbanization or deforestation (Verburg & Overmars 2007).

CLUE-CR was the first dynamic multi-scale land-use change model based on the CLUE framework. It was applied to Costa Rica at local, regional and national scales (Veldkamp & Fresco 1996b). Written in PASCAL, the model incorporates five different land-use classes in percent of total grid cell cover and uses a set of scale-dependent linear regressions as input. Altitude, temperature, relief, soil drainage, rural and urban population and other data is utilized in the nested scale analysis. Analyzing two scenarios the authors deduced that the CLUE-CR model is able to simulate effects of several driving forces on land-use change in Costa Rica (Veldkamp & Fresco 1996b).

CLUE-S (the Conversion of Land-Use and its Effects at Small regional extent) has been developed for regional scale analysis (Veldkamp et al. 2002). The major change to CLUE and CLUE-CR is the different data representation. The land-use is no longer represented as a fraction of total grid cell cover, each grid cell contains only the dominant land-use type. Thus CLUE-S has primarily been developed for resolutions from some meters up to 1000 meters for areas where high-resolution data is available. Two modules are incorporated in the modeling procedure. The non-spatial analysis uses driving factors of change to calculate the demand for the different land-use types, while in the second module the spatial analysis and land-use allocation takes place. The allocation in the CLUE-S model can be determined by four different methods or a combination of them: empirical analysis, decision rules, neighborhood functions and conversion elasticity. The CLUE-S model is a tool for analysis of land-use processes and can be used to study different mechanisms of land allocation (Verburg & Overmars 2007).

A schematic representation of the spatial allocation module of the CLUE model is shown in Figure 2-1. The CLUE model allocates the area of each land-use type as defined by the demand module. This procedure is sequentially realized first for the coarse scale and then for the fine scale. Connections between potential explanatory variables, such as bio-physical or socio-economic variables and the land-use types are assessed by multiple regression analysis. With the help of this set of multiple regressions for all land-use types for both scales, the suitability for each cell for a certain land-use type can be calculated. This suitability ("regression" cover) is compared to the actual cover percentage. Based on this difference the value for the land-use type is changed in an iterative procedure. Competition between land-use types is incorporated in this process if the total cover percentage of all land-use types in a grid cell exceeds the total cell area. In this case the changes in each land-use type are modified corresponding to the competitive strength of each land-use type, which is based on the change in demand and the difference between present cover and "regression" cover. A detailed description can be found in Verburg et al. (1999).

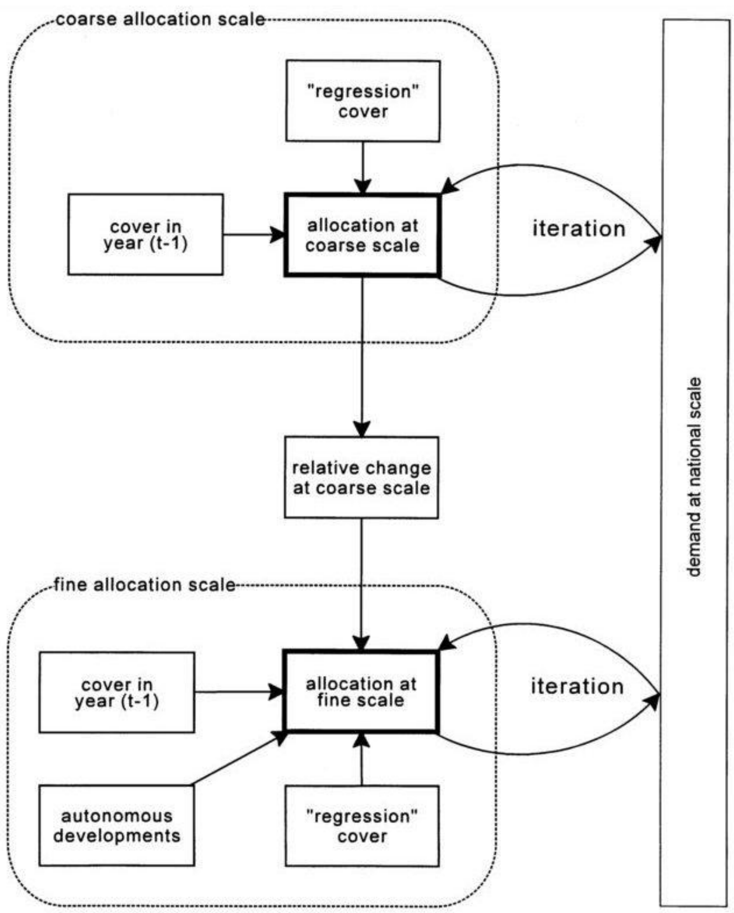

Figure 2-1: Schematic representation of the allocation at two scales (Verburg et al. 1999)

The CLUE model has been adapted by Aguiar (2006) to be applicable to the Brazilian Amazon. For a better distinction, this model, which has been developed at INPE, is called AmazonClueINPE. Several aspects had to be accounted for the implementation of the model and are described in the following paragraphs.

Initial modeling decisions involve the definition of spatial and temporal scales and the choice of land-use classes. Forest and five main agricultural land-uses, namely pasture, temporary crops, permanent crops, planted forest and non-used agricultural areas, serve as dependent variables at a $25x25km^2$ and a $100x100km^2$ scale. Potential explanatory factors comprise accessibility to markets, economical attractiveness, demographical, technological, agrarian structure, public policies and environmental factors. In addition to regarding the whole Brazilian Amazon, the study area is also subdivided into three macro regions at the fine scale, which allows considering diverse characteristics in different regions. These regions are the Densely Populated Arch, the Central Amazon and the Oriental Amazon. The temporal settings of the model show a time span from 1997 to 2020 with a resolution of one year.

The statistical analysis leads to the definition of several alternative models for each region. Log-transformation of the land-use classes and certain potential explanatory variables is used to account for non-linear relationships and thus improved the regression results. Due to correlation some variables cannot be used in the same statistical model.

The AmazonClueINPE model uses a modified allocation procedure to account for specific requirements of the study area and to allow analyzing different law enforcement scenarios. When deforestation reaches a certain threshold (*lim_forest*) in a cell, a different allocation algorithm is used. This method allows simulating if the Federal Law is observed or not. The Federal Law states that 80% of forest inside private properties must be preserved. As this law is currently largely disregarded, this threshold can simulate possible law enforcement actions. A second parameter allows controlling the maximum change in a cell in one period of time. This parameter was introduced because the AmazonClueINPE model initially concentrated changes only in a few cells with high suitability for change. With the *max_change* parameter an upper limit for the possible change in each cell in a given period of time is established.

In addition to *lim_forest* and *max_change*, some other adjustable parameters exist. The scale factor (*scale_fact*) gives the possibility to increase the importance of one scale in respect to the other and thus favor one of the two scales. A value of 1 treats both scales likewise. The *max_iter* value defines the maximum number of iterations in the allocation process. The *max_demand_diff* parameter indicates the maximum allowed difference between demand and allocated change. It is defined in terms of the demand.

Table 2-1: Parameters for the AmazonClueINPE allocation module

parameter	description
lim_forest	forest threshold to preserve 20% of cell area from deforestation
max_change	upper limit for change in one period of time
scale_fact	to favor one scale in respect of the other
max_iter	maximum number of iterations
max_demand_diff	maximum allowed difference between demand and allocated change

Various combinations of demand and allocation scenarios are defined to explore the influence of potential land-use determining factors on land-use changes under certain policy conditions and market constraints in the Brazilian Amazon.

The exploration of different statistical models for the three macro-regions led to an important conclusion. The model results indicate that using the statistical model of the Densely Populated Arch (arch25) in all spatial regions produces more realistic spatial patterns of the deforestation process than using regression models from other macro-regions or the whole Amazon. Aguiar (2006) states that this model (arch25), due to the inclusion of a distance to roads and a connection to markets measure delivers better results of the AmazonClueINPE model. The author points out that applying the arch25 model also to the other macro-regions should not lead to the assumption that the process in the Arch is likely to happen in other regions in the same way, but that it “captures the current and possible axes of development”. Important other variables in this model are protected areas, distance to timber production areas and percentage of fertile soils.

The first version of the AmazonClueINPE model is written in C++ and tested in the before mentioned study (Aguiar 2006). Moreira (2009) implements the AmazonClueINPE model in the TerraME modeling language, which is part of the TerraME modeling framework and described in section 2.3. The modular implementation allows top-down and bottom-up interactions between multiple scales through the integration of spatial, temporal and analytical couplers. A general description of the two studies is given in section 2.1.2.

2.2 Climatic Models coupling to LUCC models

2.2.1 Overview

Climate affects vegetation, but vegetation also has the potential to affect climate (Cox et al. 2004; Foley et al. 2003; Oyama & Nobre 2004). Vegetation models have been developed to investigate these complex bidirectional interactions. According to Cook & Vizy (2008) two kinds of vegetation models are currently in use. The first type is the potential vegetation model, which determines vegetation in equilibrium with a given climate. Due to other vegetation type determining factors apart from climate (i.e. topography, soil type, etc.) there is a discrepancy between the spatial distribution of potential and natural vegetation. Nevertheless reasonable agreement between the global distribution of potential and natural biomes at large spatial scales can be reached (Oyama & Nobre 2004). The second type of vegetation models is the dynamic vegetation model, which is fully interactive and simulates the impact of vegetation on the exchange of moisture, heat and momentum between the atmosphere and the land surface (Cook & Vizy 2008). Researchers can draw important conclusions about vegetation and climate interactions by coupling both kinds of vegetation models to atmospheric general circulation models (AGCM).

The biophysical environment is continuously altered by human influence, which is in general not represented in dynamic global vegetation models (GLP 2005). The Lund-Potsdam-Jena managed Land model (Bondeau et al. 2007) builds an exception, as it integrates dynamic land-use at a global scale.

Numerous LUCC models, as discussed in section 2.1, can be used to study the human involvement in land-use change processes. Consideration of anthropogenic impact is a prerequisite for the construction of integrated land system models as conceptualized in GLP (2005) or Schaldach & Priess (2008). These land system models consist of human and environment sub-systems, which influence each other through land-use and environmental change. Constructing such an integrated land system model, which incorporates biophysical characteristics and biogeochemical cycles, as well as a land-use model as a representation of human decision-making is an ambitious challenge. Due to the complexity of the involved interactions between human and environment subsystems, land system models are still rare in literature (Schaldach & Priess 2008). Further collaborative work between various research areas is inevitable to successfully couple LUCC models to climate or vegetation models, which would be an important step to further explore the Earth System.

2.2.2 CPTEC-PVM

CPTEC-PVM is a potential vegetation model, developed at INPE and introduced in Oyama & Nobre (2004). It comprehends a water balance model to derive water-related quantities from meteorological input data to distinguish between potential vegetation types. In its second generation CPTEC-PVM2 (Lapola et al. 2009) considers CO_2-plant interactions through plant physiological processes and their interactions with the water cycle. The water balance model of CPTEC-PVM2 slightly differs from the first version as it calculates canopy resistance, which is used to estimate evapotranspiration, in terms of net primary productivity and atmospheric CO_2 (Lapola et al. 2009).

Oyama and Nobre (2003) couple the CPTEC-PVM to an AGCM to look for climate-vegetation equilibrium states for Tropical South America under present-day climatic conditions. Two equilibria are identified. The first equilibrium state is the current biome distribution. In the second equilibrium state savanna replaces forests in eastern Amazonia and a semi-desert area appears in the driest portion of Northeastern Brazil. The authors point out that tropical Brazil lies under increasing land-use pressure and that deforestation and other land-cover and land-use changes could weaken the hydrological cycle in Amazonia and Northeastern Brazil and could by itself tip the climate-vegetation system towards this new drier equilibrium state with savannization and desertification (Oyama & Nobre 2003). On the contrary Malhi et al. (2008) point out that resilience of Amazonian forest ecosystems to climatic drying is currently underestimated in vegetation-climate models. According to Oliveira et al. (2005) drought stress is partly being avoided through hydrological redistribution in tropical forests, which corresponds to the water transfer by roots to drier regions of the soil profile. Nepstad et al. (2008) mention that some coupled vegetation-climate models show savannization in parts of the Amazon, but that the majority of these modeling approaches does not support this theory, while noting that effects from factors like fire activity or land-use are not included in these models.

Salazar et al. (2007) use the CPTEC-PVM to asynchronously couple it to fifteen Coupled Ocean-Atmosphere General Circulation Models to reveal the effect of projected climate change on vegetation based on two emission scenarios. The authors compare the projected distribution of biomes to the potential vegetation forced by present-day climate. They mention that though various climate change studies show that climate points towards a warmer future for South America, there is yet uncertainty how rainfall, evapotranspiration and amount of soil water will change due to the changing climate especially in Amazonia and Northeastern Brazil. The authors' findings indicate that vegetation in tropical South America will mainly change through the conversion of tropical forest into savanna, due to an increase in dry season length and/or decrease of annual soil moisture, mainly concentrated in southeastern Amazonia (Salazar et al. 2007).

Cook & Vizy (2008) used CPTEC-PVM to asynchronously couple it to a regional atmospheric model to study the effects of twenty-first-century climate change on the tropical and subtropical climate and vegetation of Southern America. The results of the coupled region model simulations indicate a 70% loss of the Amazon rain forest by the end of the twenty-first century with much of the forest being replaced by savanna vegetation and a southward and westward expansion of caatinga vegetation, which refers to the semi-arid vegetation of mixed shrubland and grassland that primarily exists in the drought-prone northeastern region, into present day savanna regions.

Lapola et al. (2009) used CPTEC-PVM2 driven by meteorological input data from fourteen coupled ocean-atmosphere global climate models under two different greenhouse gas emission scenarios to investigate the role of the CO_2 fertilization effect on future biome distribution in South America. Results show that there must be substantial biome shift in the Amazon, including substitution of forest by savanna if the CO_2 fertilization effect does not play a role in tropical ecosystems or if the dry season length exceeds four months. Otherwise, the CO_2 fertilization effect could prevent major biome changes in the Amazon.

In this thesis a water balance model will be used to derive variables that represent wetter or drier climatic conditions, which can serve as input for the LUCC model. The water balance model is a submodel of CPTEC-PVM as described in Oyama & Nobre (2004). Although, according to Lapola et al. (2009), CPTEC-PVM is limited for future climate-vegetation simulations and its successor CPTEC-PVM2 was already available, in this work the water balance model of CPTEC-PVM is used because it outputs two water-related factors which can be better compared to already existing environmental variables of the LUCC model and thus give comprehensible results.

2.2.2.1 Water Balance Model

The water balance model of CPTEC-PVM is based on the one from Willmott et al. (1985). It produces a consistent global distribution of soil moisture (Oyama & Nobre 2004) by estimating the water balance over a homogeneous soil layer covered by short grass. Different soil and vegetation types are not taken into consideration. The difference to Willmott et al. (1985) is that actual evapotranspiration is calculated using the Penman-Monteith equation, instead of Thornthwaite's equation and that the possibility of soil freezing has been included. The water balance model is used to calculate two moisture variables which later on serve as input in the PVM classification algorithm. The wetness index (H) is used to distinguish between wet and dry climates and the seasonality index (D) to represent the soil moisture seasonality. The variables are defined according to

$$H = \frac{\sum_{i=1}^{12} g_i E_i}{\sum_{i=1}^{12} g_i E_{\max,i}} \qquad D = 1 - \frac{\sum_{i=1}^{12} F(0.5 - w_i)}{6} \qquad \text{Formulas 2-1 and 2-2}$$

$$g = \begin{cases} 1, & unfrozen \\ 0, & frozen \end{cases} \qquad F(x) = \begin{cases} x, & x \geq 0 \\ 0, & x < 0 \end{cases} \qquad \text{Formulas 2-3 and 2-4}$$

where E is the actual and $E_{\max}$ the maximum evapotranspiration, w the soil water degree of saturation (ratio between soil water storage and soil water availability) and i corresponds to the i^{th} month. The detailed formulation of the water balance model can be found in Oyama & Nobre (2004).

2.2.2.2 CPTEC-PVM Classification

The two moisture variables serve as input for the algorithm to define the potential biome distribution based on the classification from Dorman & Sellers (1989). The three other variables in the PVM classification process are related to temperature. They are the mean temperature of the coldest month (T_C) and the number of growing degree days using a 0°C (G_0) and a 5°C (G_5) threshold. The five input variables for the PVM are calculated for each cell or grid point after every run of the water balance model. The algorithm to obtain the potential biome is shown in Figure 2-2.

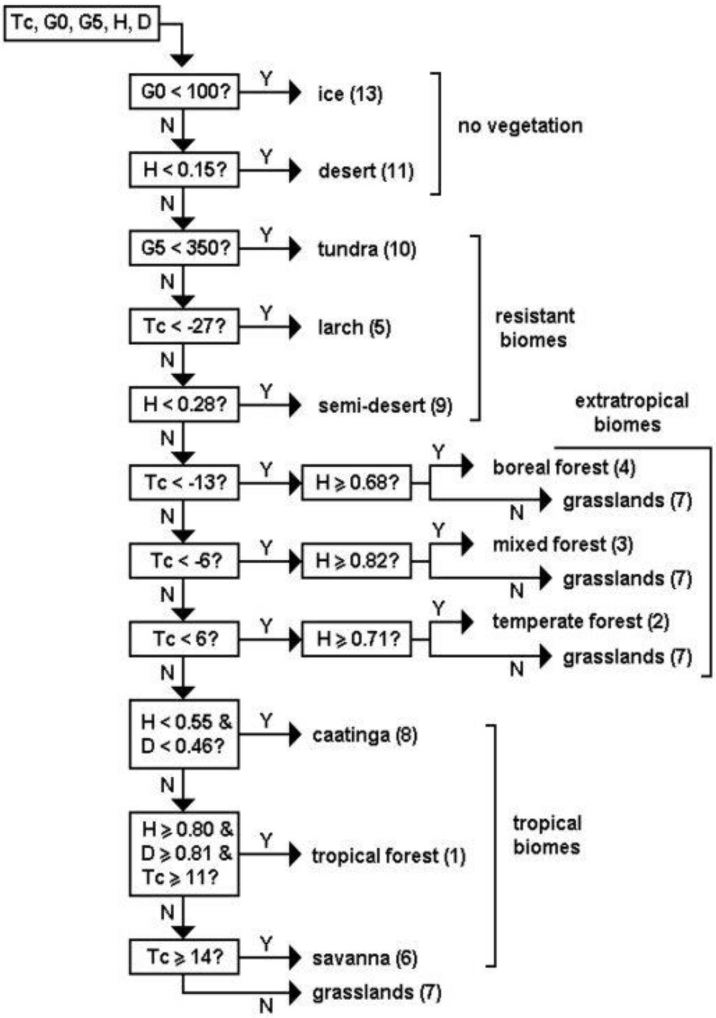

Figure 2-2: Algorithm to obtain the potential biome from environmental variables (Oyama & Nobre 2004) [4]

Following the potential biome classification algorithm the CPTEC-PVM outputs the current potential vegetation as shown in Figure 2-3.

[4] T_c: temperature of the coldest month, G_0: growing degree days with 0°C threshold, G_5: growing degree days with 5°C threshold, H: wetness index, D: seasonality index

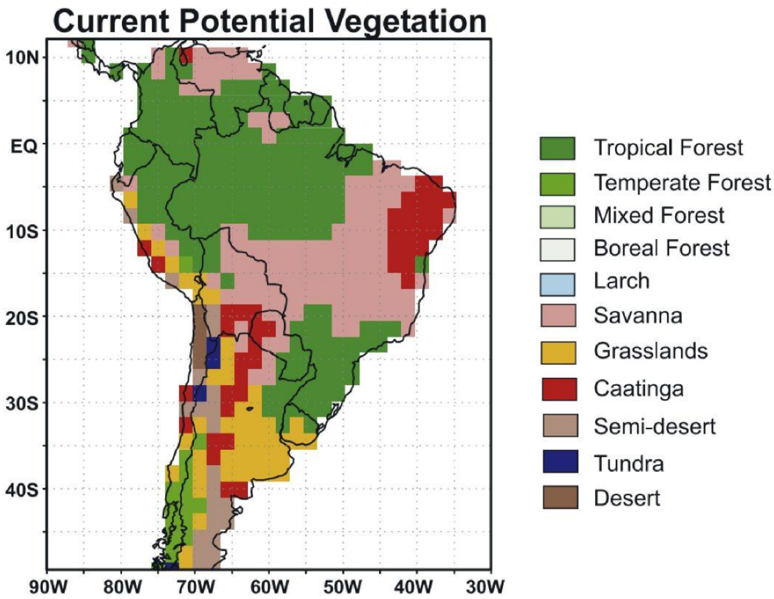

Figure 2-3: Current potential biomes for South America (Salazar et al. 2007)

In this work the biome classification of the CPTEC-PVM is not used. The water balance model is used to derive the two variables wetness- and seasonality index (Formulas 2-1 and 2-2) which are added to the other potential determining factors (Table 3-1) which are used in the analysis of land-use and land-cover changes in the Legal Amazon (Chapter 4).

2.3 *The TerraME modeling environment*

TerraME[5] is a programming environment for spatial dynamical modeling in various application areas (Carneiro 2006). It is based on TerraLib[6], an open source GIS classes and functions library for large-scale environmental and socio-economic applications (Câmara et al. 2008). TerraME provides a nested cellular automata model and services for spatio-temporal data analysis and management, model development, simulation and assessment. It supports cellular automata, agent-based models and network models (TerraME Website 2010). Land-use change models and hydrological models belong to the typical applications of TerraME. The modules and services provided by TerraME are visualized in Figure 2-4. It shows a typical TerraME program sequence. A TerraME model can be written in any text editor. The model source code is syntactically checked and executed by the TerraME interpreter, which retrieves the required data from a TerraLib database and stores it afterwards. TerraView[7] can be used to visualize and analyze the data.

[5] www.terrame.org
[6] www.terralib.org
[7] www.dpi.inpe.br/terraview

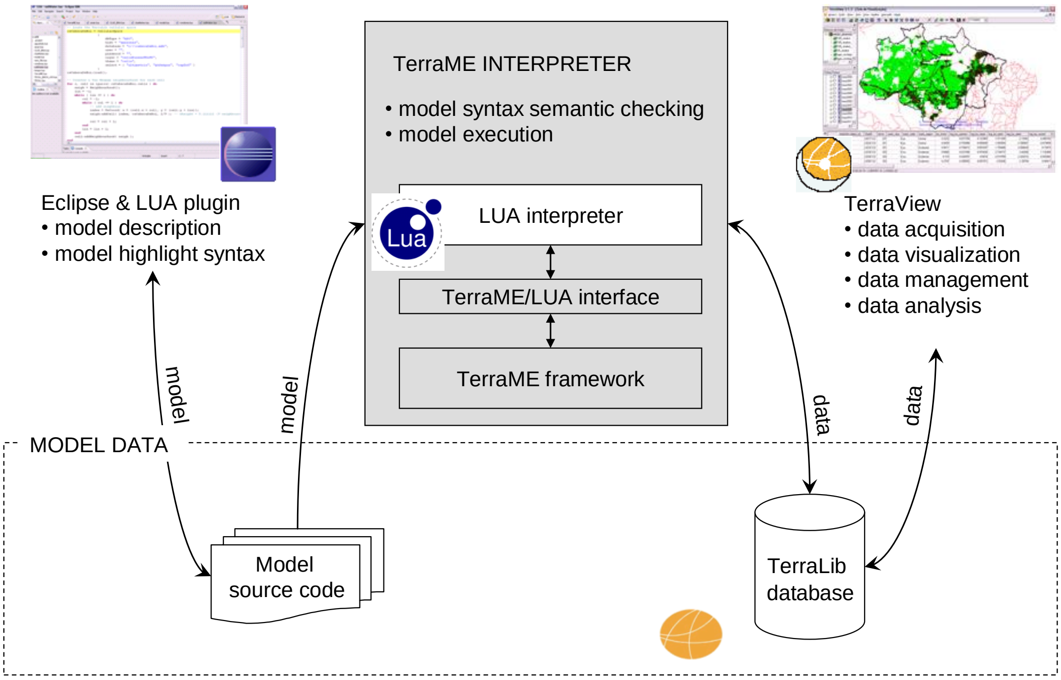

Figure 2-4: TerraME modules and services (Carneiro 2006)

The TerraME modeling language is an extension of the Lua scripting language (Ierusalimschy et al. 1996) and has been designed to allow the development of models in a comprehensible way, also for non-professional programmers.

The current version of TerraME (RC4 for TerraLib 3.2) works under Windows (XP and Vista) and supports Access and MySQL databases. TerraME has been developed as a joint effort among TerraLab (Laboratory for Modelling and Simulation of Land Systems) at Federal University of Ouro Preto with the Image Processing Division (DPI) and the Earth System Science Center (CCST) at INPE (TerraME Website 2010).

TerraView is an open source GIS application based on the TerraLib GIS library for visualization and analysis of geographical data. The software supports various raster and vector data formats. The data is stored in relational or geo-relational databases as ACCESS, PostgreSQL, MySQL or Oracle (TerraView Website 2010). Additional functionality can be reached by adding TerraView plugins, which are constantly developed by the TerraView community.

aRT[8] (Andrade et al. 2005) is a R[9] package which provides the integration between the statistical software R and the GIS library TerraLib. Thus it allows accessing and analyzing of geospatial data from a TerraLib database in R.

[8] www.leg.ufpr.br/doku.php/software:art

TerraME and TerraLib are freely available under the GNU Lesser General Public License, TerraView, R and aRT under the GNU General Public License.

2.4 Summary

In this chapter land-use change studies on deforestation in the Brazilian Amazon are reviewed. The various approaches in land-use change modeling focus on investigating which variables contribute to an explanation of land-use changes, which locations are affected and at what rate these land-use changes progress. Variables concerning paved roads, human population density, dry-season severity, existence of protected areas or connectivity measures to national markets are found to be of relevant importance for land-use change processes. The AmazonClueINPE model as a dynamic, spatially-explicit, multi-scale land-use and land-cover change model allows investigating the impact of different factors on land-use changes.

The present thesis builds on the implementation of the AmazonClueINPE model and adds additional environmental factors to test their influence on land-use changes in the Brazilian Amazon. These additional variables partly arise from the CPTEC-PVM which is implemented in the TerraME modeling environment to allow future coupling of the vegetation model and LUCC models and hence the development of integrated land system models.

[9] www.r-project.org

3 Methods

In this chapter the study area is introduced and the methods are described, followed by sections about the CPTEC-PVM implementation and Land-use change modeling, including database construction, statistical analysis and the dynamic land-use model AmazonClueINPE.

3.1 Study area

The study area is the Brazilian Amazon (Legal Amazon, Amazônia Legal) which consists of the states Acre, Amapá, Amazonas, Mato Grosso, Pará, Rondônia, Roraima, Tocantins and a part of Maranhão. The Legal Amazon comprises an area of approximately 5 million km^2 (58% of Brazilian territory) and was initially introduced for regional planning purposes (Andersen et al. 2002). It can be divided into three macro regions as defined by Becker (2005) and visualized in Figure 3-1. The first macro region is the Densely Populated Arch, where most of the high population density areas, roads and centers of economy are. The second is the Central Amazon, which is the most vulnerable area in the Amazon, because of major roads crossing its interior. The third macro region is called Occidental Amazon, which is the most preserved area, because it is not cut by main roads and people settled to a large extent only in the area around Manaus, while the rest of the region remained mostly abandoned. Figure 3-2 shows the Brazilian Amazon and its road network.

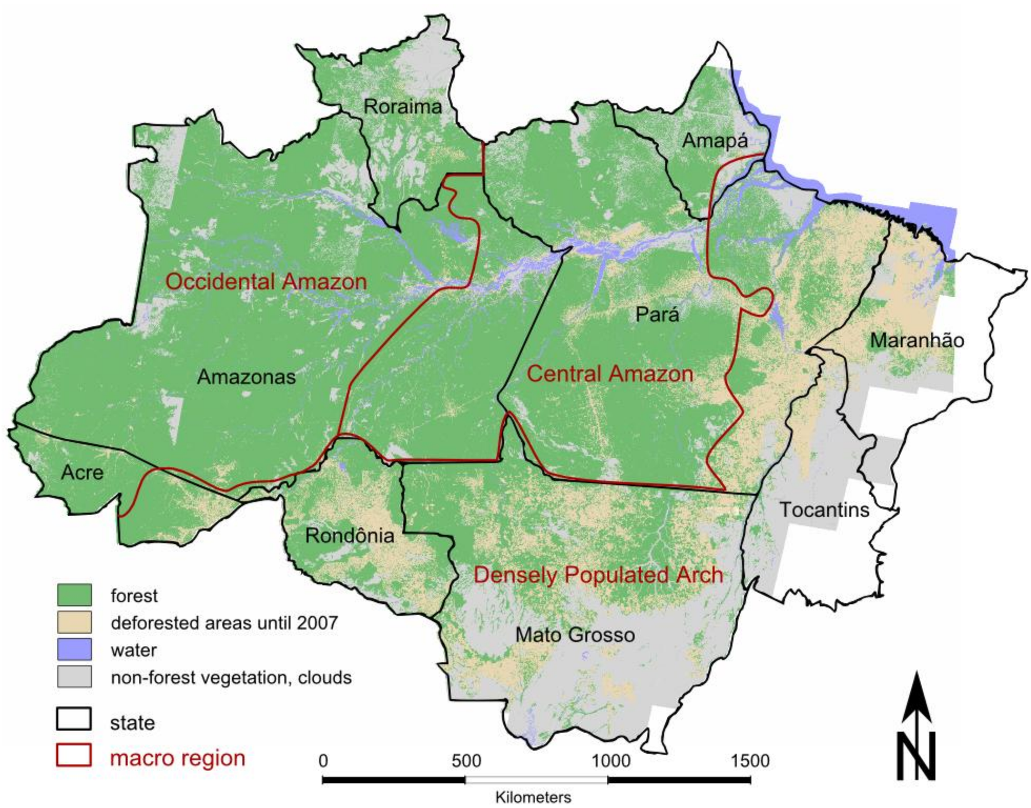

Figure 3-1: The Brazilian Amazon and its three macro regions (Becker 2005; INPE 2010)

The study area is subdivided into regular cells at two spatial resolutions. The cells have an extent of $100x100km^2$ at the coarse scale and $25x25km^2$ at the fine scale. Based on a deforestation map from 1997 derived by INPE through the PRODES project (INPE 2010) cells with a large amount of non-forest vegetation or mainly covered by clouds are excluded from further analysis (Aguiar 2006). This results in the generation of 5228 cells at the fine scale and 363 cells at the coarse scale. The amount of deforestation in each cell is taken from the deforestation map (INPE 2010), while the proportion of the different land-use types in each cell is computed from IBGE Agricultural Census 1996 (IBGE 1996). The detailed process can be found in Aguiar (2006).

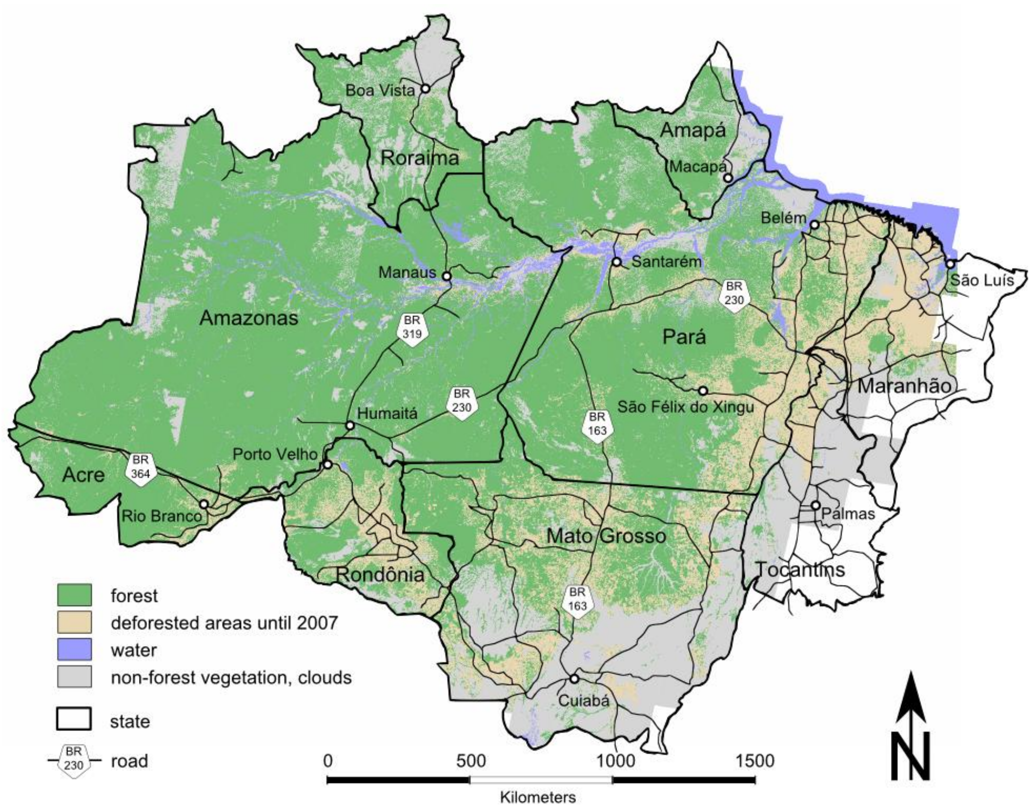

Figure 3-2: The Brazilian Amazon (INPE 2010)

3.2 CPTEC-PVM implementation

The CPTEC-PVM and the corresponding water balance model are implemented in the TerraME modeling language based on the original version (Oyama & Nobre 2004) written in FORTRAN 77. The general description can be found in section 2.2.2. The full mathematical description is available in Oyama & Nobre (2004)[1]. Although only the results of the water balance model are used in this thesis, the PVM is fully implemented to allow for future coupling to other models written in the TerraME modeling language.

The input data for the potential vegetation model, namely the mean values per month for precipitation, surface temperature and surface pressure as well as a land-sea mask are obtained from the climate data archive "Terrestrial Air Temperature and Precipitation: Monthly and Annual Time Series (1950 - 1999) (V 1.02)" (Willmott & Matsuura 2001). A preliminary routine stores it in the database to have simple access to the data. The result of this step is that the data can easily be accessed and processed within the TerraME environment and be visualized with TerraView.

[1] Oyama (2005) changed some threshold values in the biome classification algorithm after the publication of Oyama & Nobre (2004), which led to the generation of CPTEC-PVM v2. The implementation in TerraME corresponds to this version (v2).

The source code is split up into four modules to provide a comprehensible structure.

main.lua sets the directories, loads the three modules and starts the simulation by executing the TerraME environment *env*.

Code 3-1: main.lua

```
-- set directories
----------------------------------------
      DIR = "projects\\pvm\\source\\"
      DATABASEDIR = "database\\"

-- load files
----------------------------------------
      dofile (DIR.."func.lua")
      dofile (DIR.."wbm.lua")
      dofile (DIR.."pvm.lua")

-- run simulation
----------------------------------------
      defBiome:build();
      env:add(cs);
      env:add(defBiome);
      env:execute(1);
```

wbm.lua incorporates the water balance model. From monthly meteorological data of precipitation, surface temperature and surface pressure it calculates the two water-related environmental variables wetness- and seasonality index, which are used as potential land-use determining factors in the LUCC analysis. In addition to these two variables the three other variables needed for the biome classification algorithm, namely the temperature of the coldest month, the growing degree days with 0°C threshold and the growing degree day with 5°C threshold are calculated in this module as well. The module consists of functions for the water balance model, the surface water budget for a month, evapotranspiration and runoff calculations.

pvm.lua comprehends the definition of the cellular space (Code 3-2) and the Automaton to calculate the potential biome number of each cell on basis of the environmental variables delivered by the water balance model module.

Code 3-2: pvm.lua: defining the cellular space

```
-- define cellular space
      cs = CellularSpace{
            dbType = "ADO",
            host = "localhost",
            database = DATABASEDIR.."amazonia.mdb",
            user = "",
            password = "",
            layer = "cells25",
            theme = "cells25",
      }
      cs:load();
```

The biome classification algorithm is implemented as an Automaton, which consists of a State for each biome. These States are composed of Jump and Flow conditions. If the Jump condition applies to the cell it is send to another State. If it does not apply, the Flow condition is executed, which assigns the corresponding value to the potential biome number variable (*bpot*).

Code 3-3: pvm.lua: defining the automaton (extract)

```
-- define automaton
      defBiome = Automaton {
            it = Trajectory {
                  cs,
                  -- only cells that contain data
            function (cell) return true;
                  end,
                  },
...
            State {
                  id = "tropical forest",
                  Jump {
                        function (event, automaton, cell)
                              return cell["weti"] < 0.84 or
                                    cell["seai"] < 0.86 or
                                    cell["tmin"] < 11;
                        end,
                        target = "savanna"
                  },
                  Flow {
                        function(event, automaton, cell)
                              cell.bpot = 1;
                        end
                  }
            },
            State {
                  id = "savanna",
                  Jump {
                        function (event, automaton, cell)
                              return cell["tmin"] < 14;
                        end,
                        target = "grasslands"
                  },
                  Flow {
                        function(event, automaton, cell)
                              cell.bpot = 6;
                        end
                  }
            }
...
}
```

The environment *env* is defined in the PVM module. It defines a timer which includes only one event. This event first calls the water balance model module for each cell to calculate the environmental variables and then executes the *defBiome* automaton to calculate the potential biome numbers. In the last step the five variables and the potential biome number are stored into the new table *env_var* in the database.

Code 3-4: pvm.lua: defining the environment

```
-- define environment
      env = Environment{
      id = "env",
      -- define timer
      time = Timer{
            Pair{
                  Event{ time = 1, period = 1, priority = 0},
                  Message {
                        function (event)
                              -- run water balance model
                              for i, cell in pairs(cs.cells) do
                                    wbm(cell);
                              end;
                              cs:synchronize();

                              -- run potential vegetation model
                              defBiome:setTrajectoryStatus(true);
                              defBiome:execute(event);
                              cs:synchronize();
                              cs:save(event:getTime(), "env var",
{"tmin",
                              "gdd0", "gdd5", "weti", "seai", "bpot"})
                        end
                  }
            },
      }
      }
```

The functions module (func.lua) includes basic auxiliary routines.

The potential biome (bpot) and the five variables needed in the biome classification algorithm, namely wetness index (weti), seasonality index (seai), the mean temperature of the coldest month (tmin) and the number of growing degree days using a 0°C (gdd0) and a 5°C (gdd5) threshold are stored in the database. The results of the CPTEC-PVM implementation are presented in section 4.1.

3.3 Land-use change modeling

3.3.1 Database Construction

3.3.1.1 Land-use classes

Basically two land-cover types are used in this work: forest and deforested areas. For further analysis the class deforested areas is divided into five different subclasses regarding its agricultural use. These classes are pasture, temporary crops, permanent crops, non-used agricultural land and planted forest. Every cell contains the proportion of the area covered by each land-use class inside the cell by total cell area, thus the values of the six land-use classes in each cell sum up to a value of 1.

Forest

The land-use class forest consists of all areas that are classified as primary forest by the PRODES project.

Deforested Areas

This class comprehends all deforested areas detected by INPE until 1997. The PRODES project (INPE 2010) detects clear-cut areas greater than 6.25 ha. A short description of the land-use types based on definitions from the Census of Agriculture 1996 (IBGE 1996) follows.

Pasture

The land-use class pasture includes all areas defined as planted pasture. These areas are especially cultivated for cattle ranching. In 1996 approximately 70% of deforested areas fell into this class, hence it was the major land-use type after forest.

Temporary crops

The class temporary crops includes areas used for planting or being prepared for planting short-term crops, which require new seeding after each harvest (rice, manioc, maize, soybeans, sugarcane etc.). Areas which have previously been used for planting short-term crops, but have not been utilized for no longer than four years, fall also into this class.

Permanent crops

The class permanent crops includes areas used for planting or being prepared for planting long-term crops, which keep producing during successive years without the necessity of new seeding (cacao, coffee, cotton etc.). Also nurseries of permanent-crop seedlings fall into this class.

Non-used agricultural land

The class non-used agricultural land summarizes areas that are abandoned or fallow, as they have not been used for a period of more than four years, although being suitable for crops, pasture or woods.

Planted forest

This land-use class summarizes areas which are cultivated or being prepared for planting trees, e.g. black acacia, eucalyptus, pine. Also seedling nurseries of forest essences fall into this category.

3.3.1.2 Spatial land-use patterns

Deforested Areas

According to measurements by INPE (2010) around 180.000 km^2 of forest have been cut down between 1997 and 2006. The major part of deforestation took place in the Densely Populated Arch in the states of Mato Grosso, Pará, Rondônia and Maranhão. Figure 3-3 shows the total deforested areas map until 1997 and Figure 3-4 the relative deforestation map from 1997 to 2006.

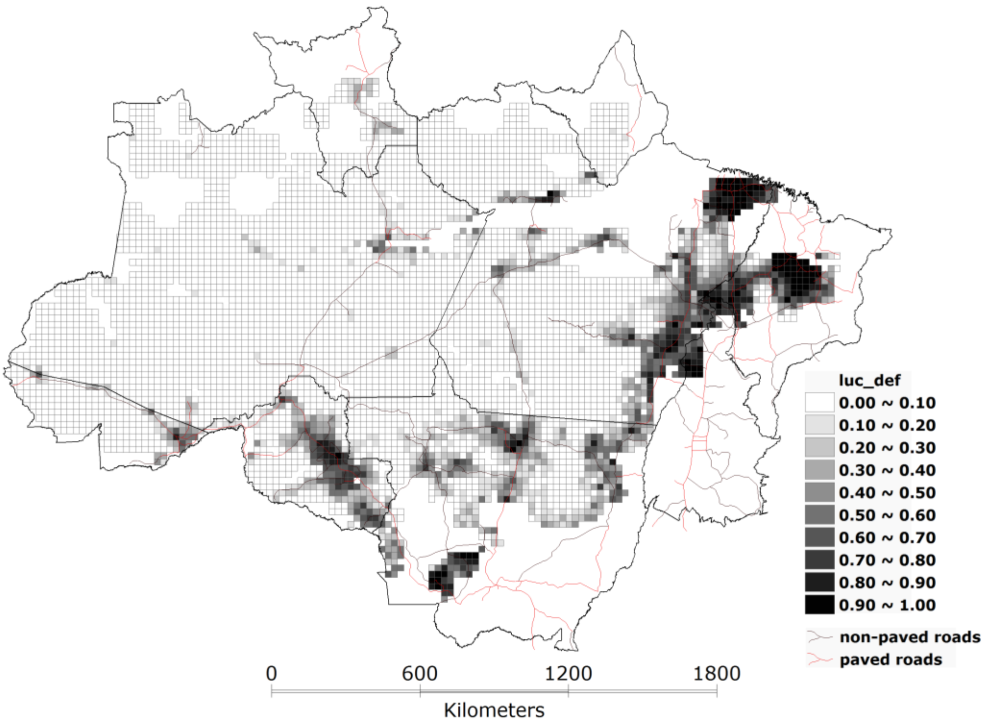

Figure 3-3: Deforested areas in 1997 (fraction of cell area; INPE 2010)

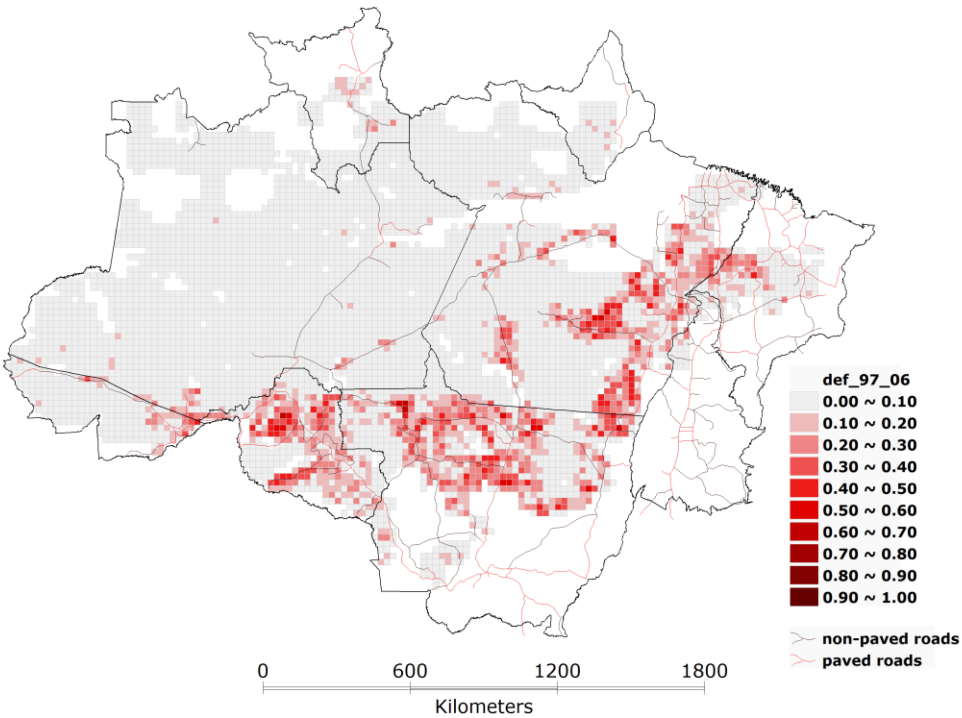

Figure 3-4: New deforestation (change) from 1997 to 2006 (fraction of cell area; INPE 2010)

Pasture and temporary crops

Pasture is the major non-forest land-use type in the Amazon and accounted for almost 70% of deforested areas in 1997. Hence the pattern in 1997 (Figure 3-5) shows high similarity to the deforestation map. Figure 3-6 shows the relative change of pasture between 1997 and 2006 on basis of the Agricultural Census data from IBGE (IBGE 1996; IBGE 2009). A general increase of pasture can be seen in the Densely Populated Arch in the states of Pará, Mato Grosso, Rondonia and Maranhão, since usage as pasture is the most important land-use type for deforested areas. There is also a clear pasture increase along the Transamazônica (BR-230) and along the BR-163 in Pará. There are only a few cells in Mato Grosso and Pará with a decrease in pasture.

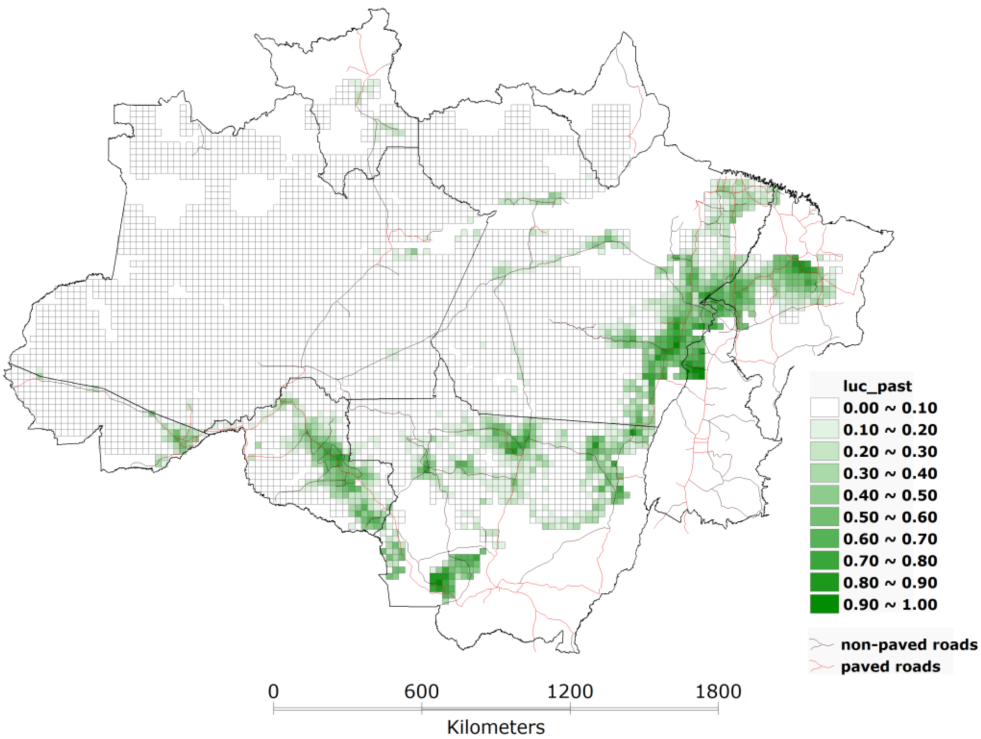

Figure 3-5: Pasture in 1997 (fraction of cell area; IBGE 1996, INPE 2010)

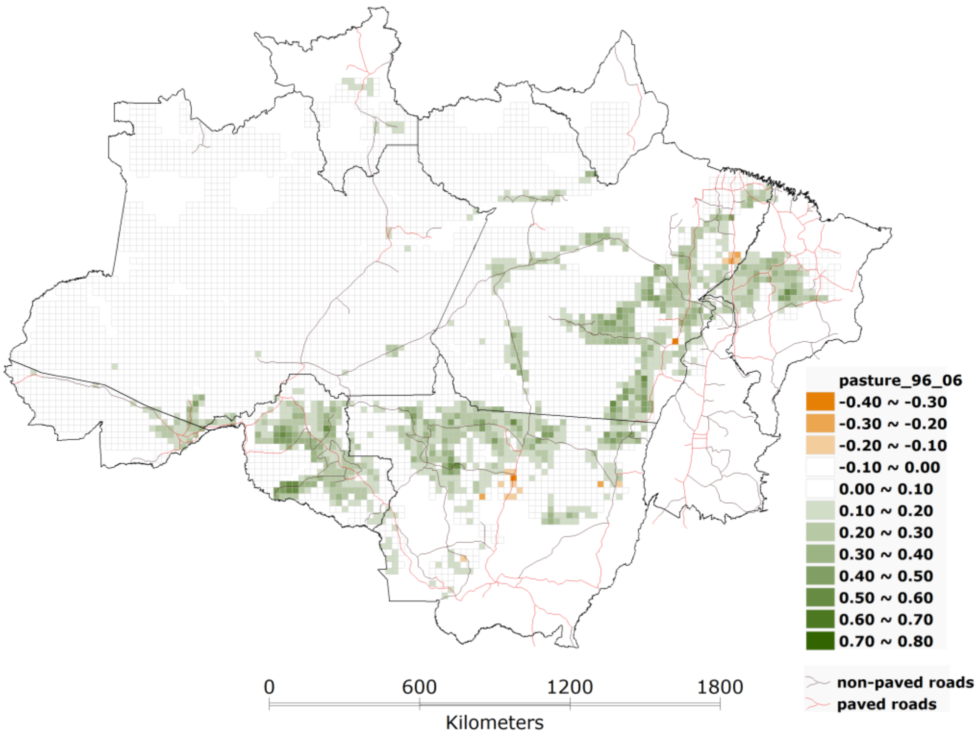

Figure 3-6: Pasture (change) from 1997 to 2006 (fraction of cell area; IBGE 1996, IBGE 2009, INPE 2010)

Temporary crops patterns add up to 14% of deforested area in 1997 (Figure 3-7). Consideration of this land-use class is important to detect land-use change processes related to the cultivation of temporary crops, e.g. soybeans. The analysis of this land-use type in the period of 1997 to 2006 (Figure 3-8) shows two distinct processes, a pattern of decreasing temporary crops in Maranhão and an increasing pattern in Mato Grosso. This increasing pattern in the south of the Brazilian Amazon reflects the expansion of mechanized agriculture in central Mato Grosso, which might also explain some of the decreasing pasture values in this area.

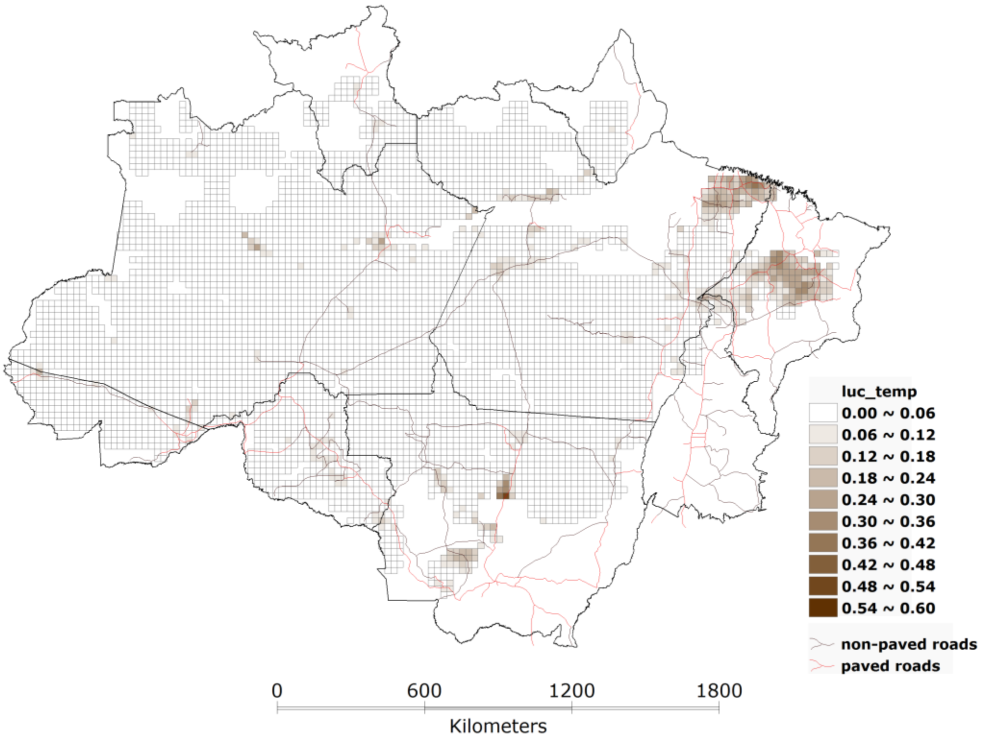

Figure 3-7: Temporary crops in 1997 (fraction of cell area; IBGE 1996, INPE 2010)

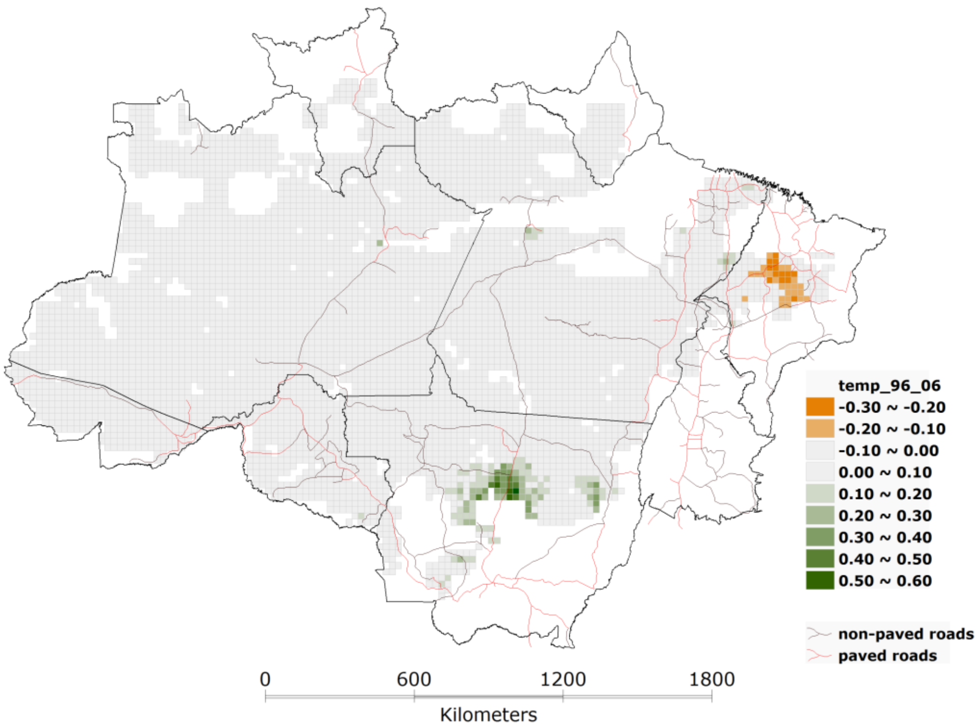

Figure 3-8: Temporary crops (change) from 1997 to 2006 (fraction of cell area; IBGE 1996, IBGE 2009, INPE 2010)

3.3.1.3 Potential land-use determining factors

The potential land-use determining factors used in this work come from a pool of variables defined in Aguiar (2006) and can be grouped into different classes. The six classes are

Accessibility, Economic Attractiveness, Public Policies, Demographics, Agrarian Structure and Environment. The variables derived from the Water Balance Model of the CPTEC-PVM – wetness index and seasonality index – and the slope and altimetry variables are added to the Environment group. Some explanatory variables – as well as the land-use variables – are logarithmic transformed to account for non-linear relationships between them. The variables are listed in Table 3-1. The socioeconomic factors are visualized in Figure 3-9 to Figure 3-20 and the environmental factors in Figure 3-21 to Figure 3-29 for the scale 25x25 km^2.

Table 3-1: Potential land-use determining factors (adapted from Aguiar (2006))

Category	Variablename	Description	Unit	Source
Accessibility	*log_dist_urban_areas*	euclidean distance to urban centers (log)	m (log)	IBGE
	log_dist_roads	euclidean distance to roads (log)	m (log)	IBGE
	log_dist_paved_roads	euclidean distance to paved roads (log)	m (log)	IBGE
	log_dist_non_paved_roads	euclidean distance to non paved roads (log)	m (log)	IBGE
	log_dist_large_rivers	euclidean distance to large rivers (log)	m (log)	IBGE
	conn_markets	indicator of strength of connection to national markets through roads network	-	IBGE
	conn_ports	indicator of strength of connection to ports through roads network	-	IBGE
Economic Attractiveness	*log_dist_wood_extr_poles*	euclidean distance to timber production sites (log)	m (log)	IBAMA
	log_dist_min_deposits	euclidean distance to mineral deposits (log)	m (log)	CPRM
Public policies	*prot_all1*	protected areas	fraction of cell area	IBAMA FUNAI
Demographics	*log_pop_dens_96*	population density in 1996 (log)	people/km^2 (log)	IBGE
	log_setl_nfamilies_70_99	number of settled families from 1970 to 1999 (log)	number of families (log)	INCRA
Agrarian Structure	*agr_area_small*	area of small farms	fraction of area of farms	IBGE
Environment	*soils_fert_B1*	fertile soils	fraction of cell area	IBGE
	soils_fert_B3	wetland soils	fraction of cell area	IBGE
	clima_humi_min_3_ave	average humidity in the three drier months of the year	%	INMET
	weti	wetness index	-	CPTEC-PVM
	seai	seasonality index	-	CPTEC-PVM
	altitude_avg	average elevation	m	SRTM
	slope_flat	flat areas (0°-5°)	fraction of cell area	SRTM
	slope_mod	moderately sloped areas (5°-15°)	fraction of cell area	SRTM
	slope_steep	steeply sloped areas (>15°)	fraction of cell area	SRTM

Socioeconomic factors

Accessibility

This category comprises factors describing the accessibility of a given cell. Variables describe the Euclidean distance to the closest road, urban center or large river and indicate the strength of connection to national markets or ports through the roads network.

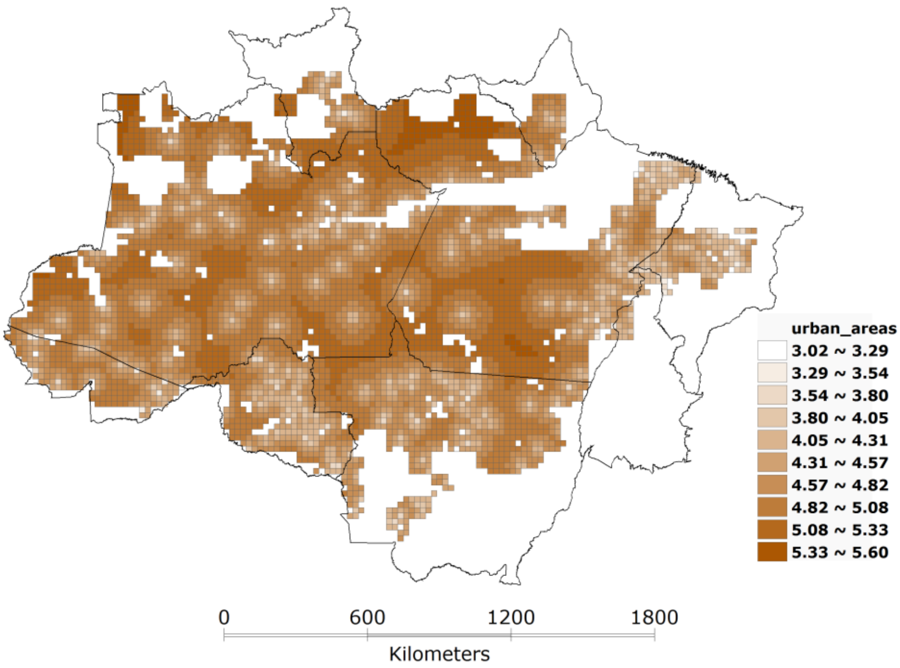

Figure 3-9: distance to urban areas (m (log); log_dist_urban_areas)

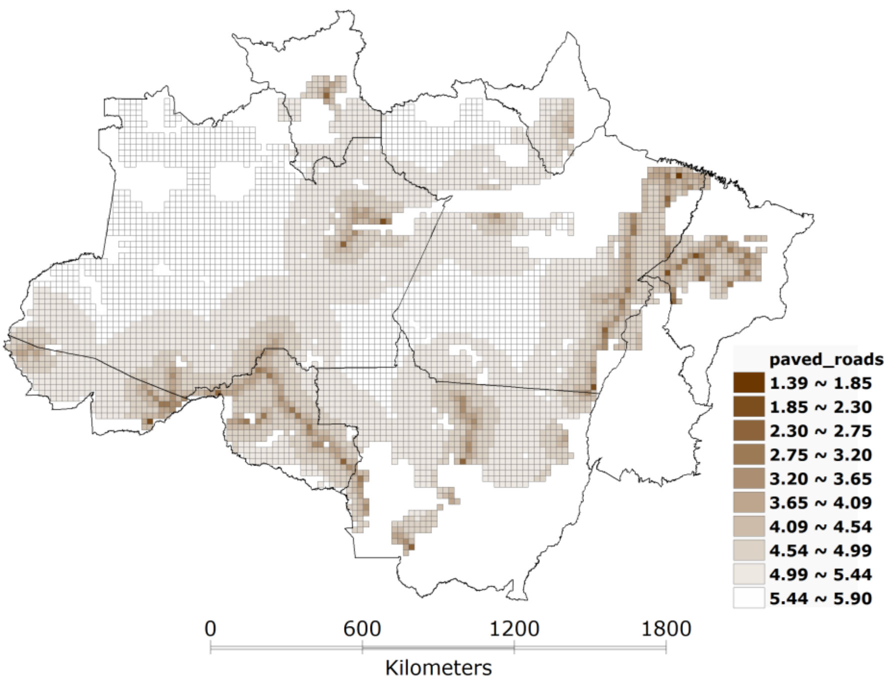

Figure 3-10: distance to paved roads (m (log); log_dist_paved_roads)

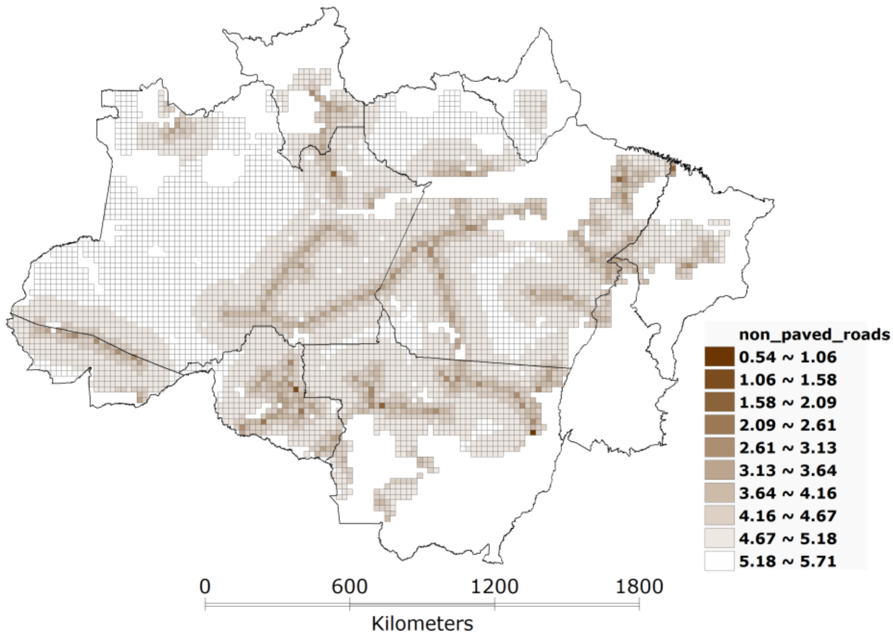

Figure 3-11: distance to non-paved roads (m (log); log_dist_non_paved_roads)

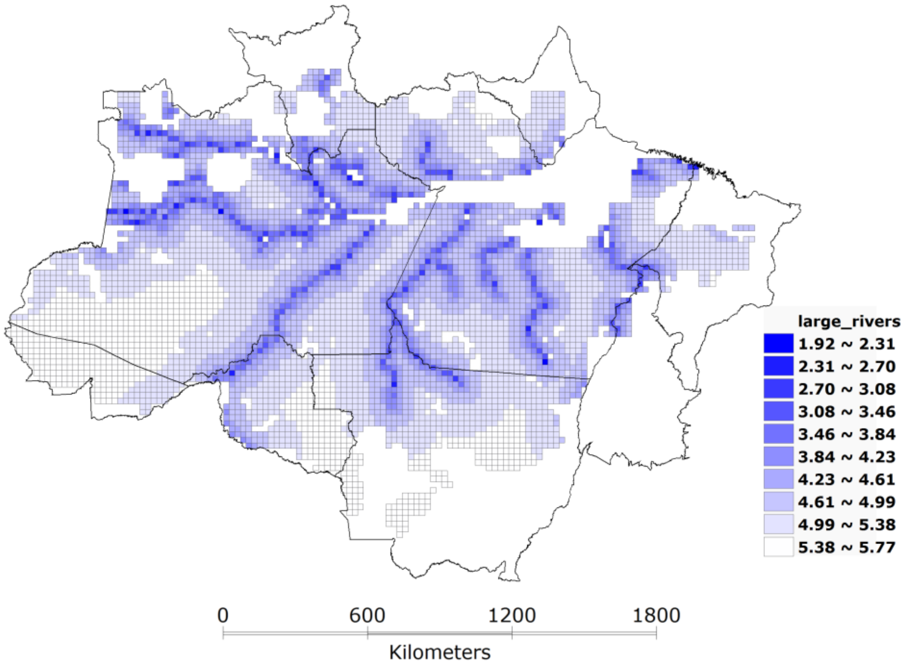

Figure 3-12: distance to large rivers (m (log); log_dist_large_rivers)

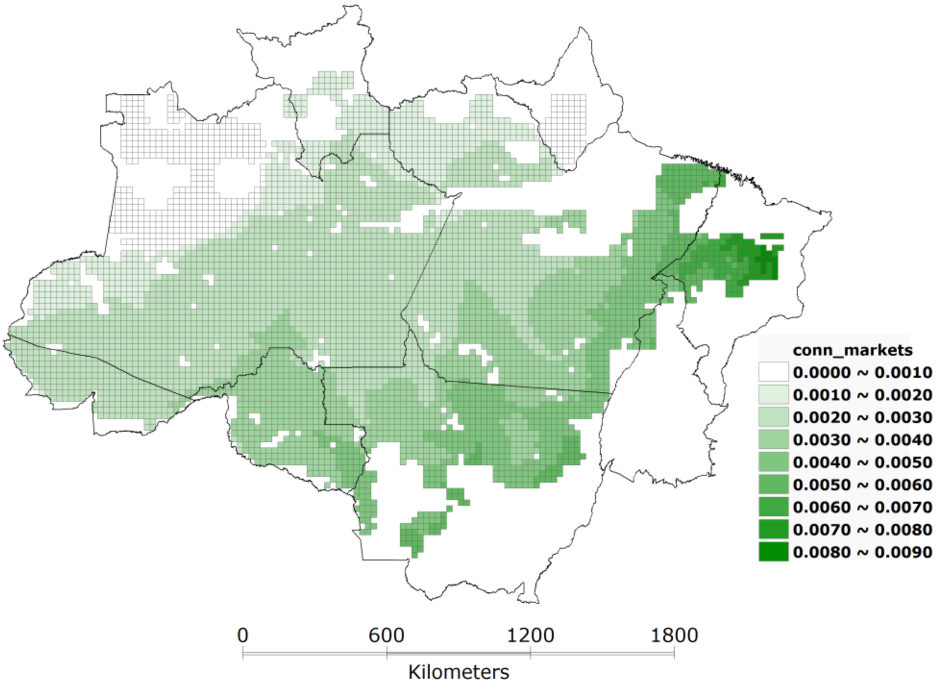

Figure 3-13: connection to markets (conn_markets)

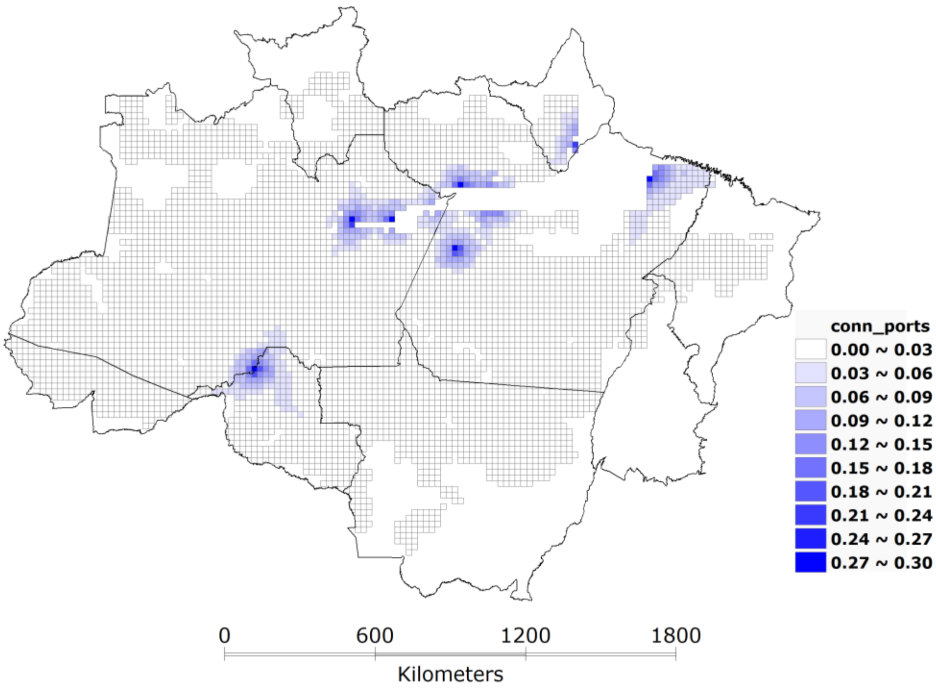

Figure 3-14: connection to ports (conn_ports)

Economic Attractiveness

These factors determine economic attractiveness through the distance to timber production sites and mineral deposits.

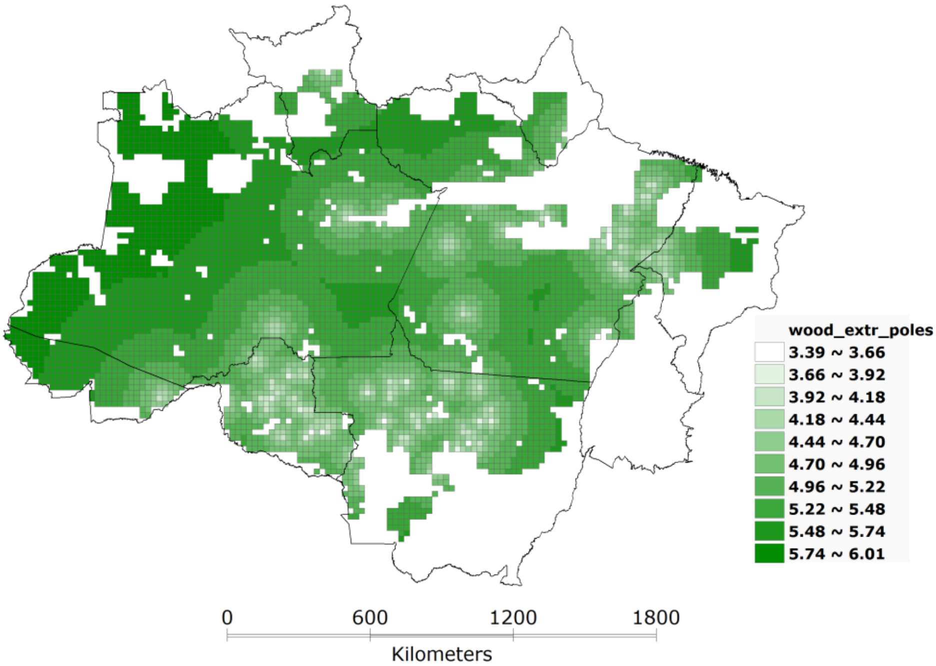

Figure 3-15: distance to timber production sites (m (log); log_dist_wood_extr_poles)

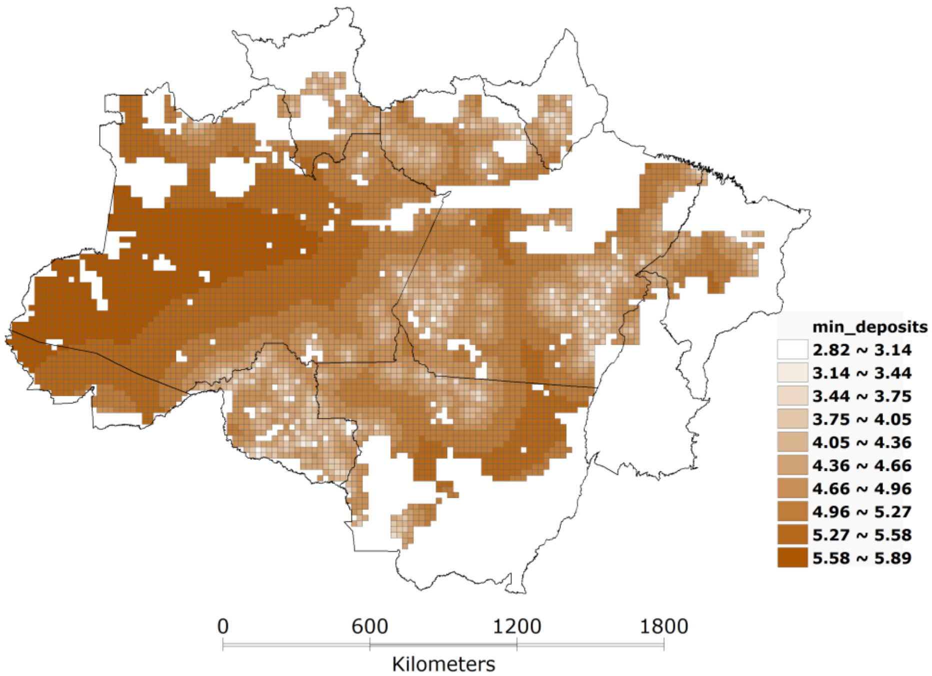

Figure 3-16: distance to mineral deposits (m (log); log_dist_min_deposits)

Public Policies

Various areas in the Brazilian Amazon are declared indigenous land, nature reserve or in some other way protected, which is represented by a protected area variable.

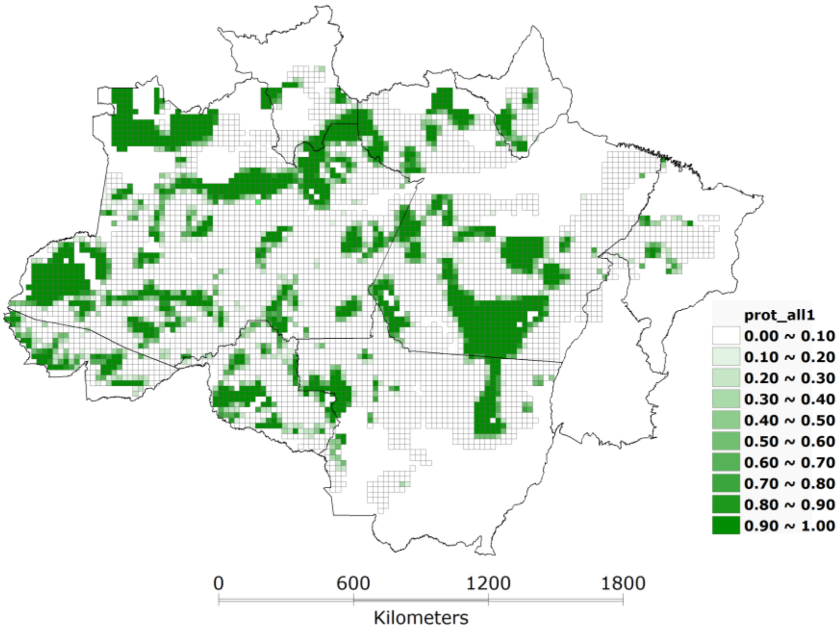

Figure 3-17: protected areas (fraction of cell area; prot_all1)

Demographics

These variables describe the demographic structure in a cell, i.e. population density and the number of settled families.

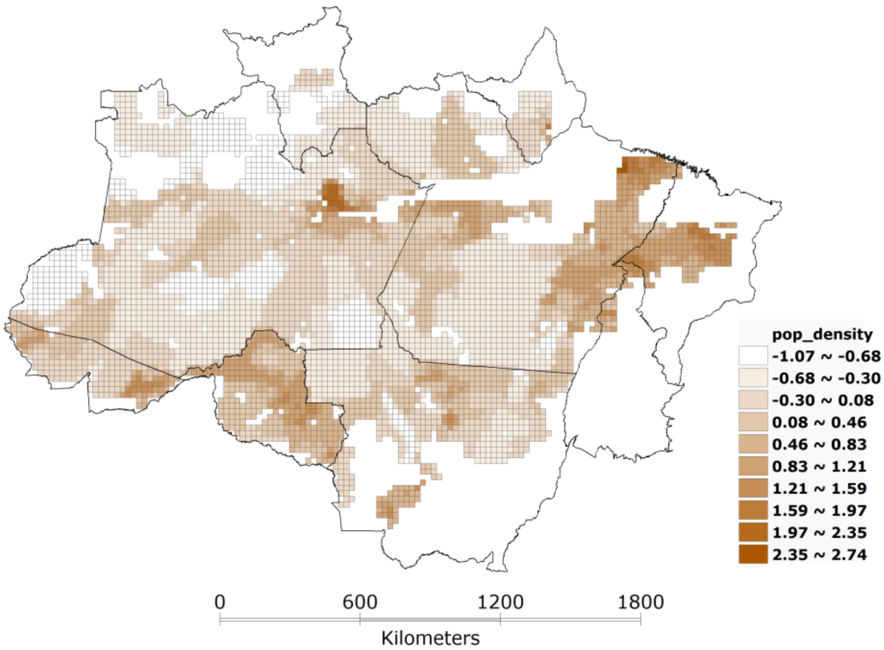

Figure 3-18: population density (people/km^2 (log); log_pop_dens_96)

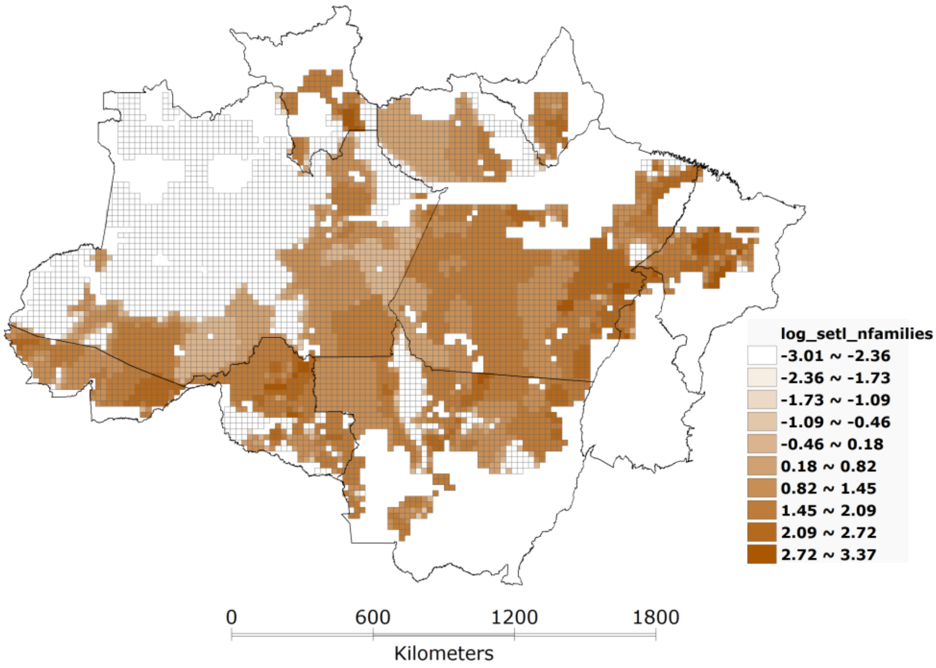

Figure 3-19: settled families from 1970 to 1999 (number of families (log); log_setl_nfamilies_70_99)

Agrarian Structure

The agrarian structure is represented by a variable showing the fraction of small properties in relation to the area of farms.

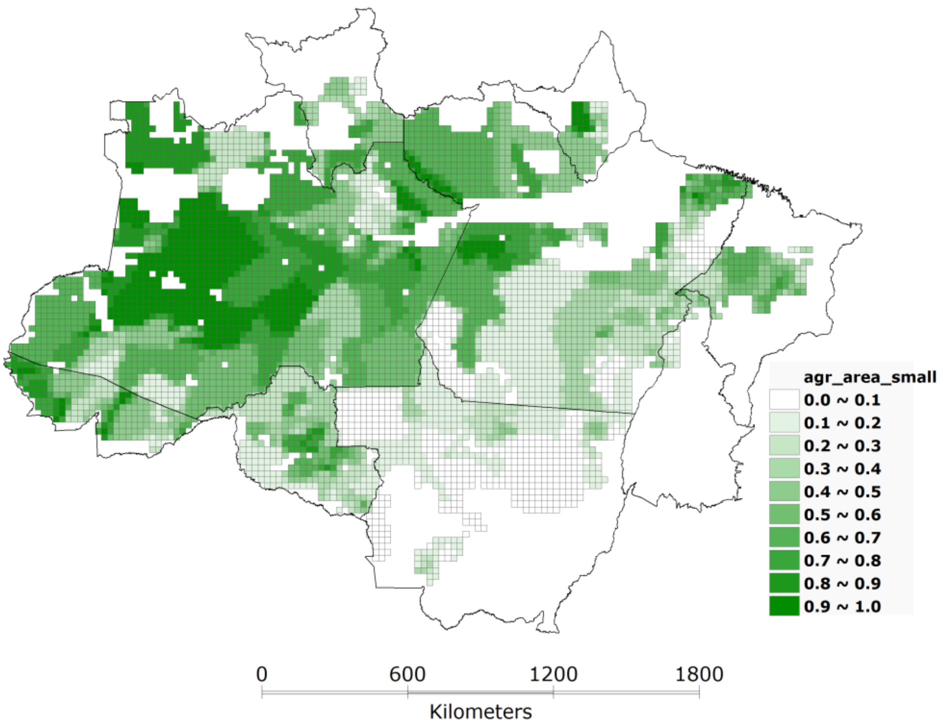

Figure 3-20: areas of small properties (fraction of area of farms; agr_area_small)

Environmental factors

The environmental factors are composed of variables describing bio-physical characteristics (soil fertility, moisture), climatological conditions (humidity, wet-dry climate) and topographic properties (altitude, slope).

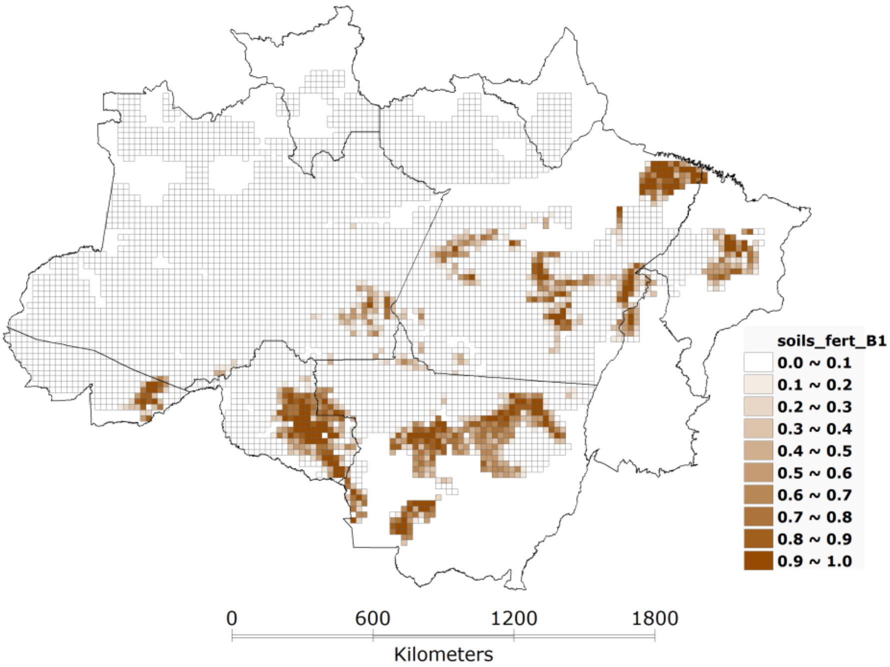

Figure 3-21: fertile soils (fraction of cell area; soils_fert_B1)

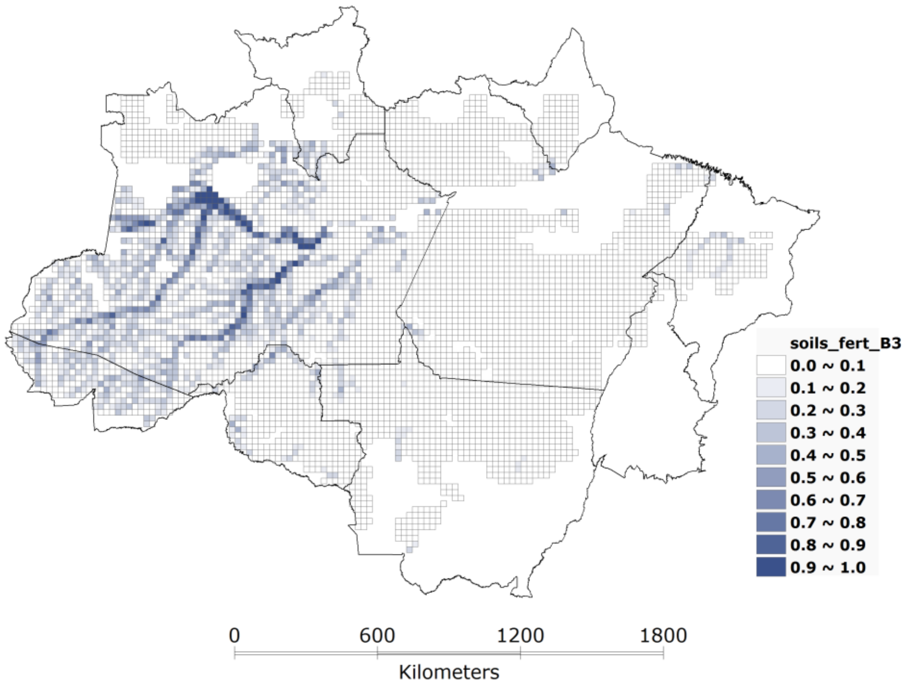

Figure 3-22: wet soils (fraction of cell area; soils_fert_B3)

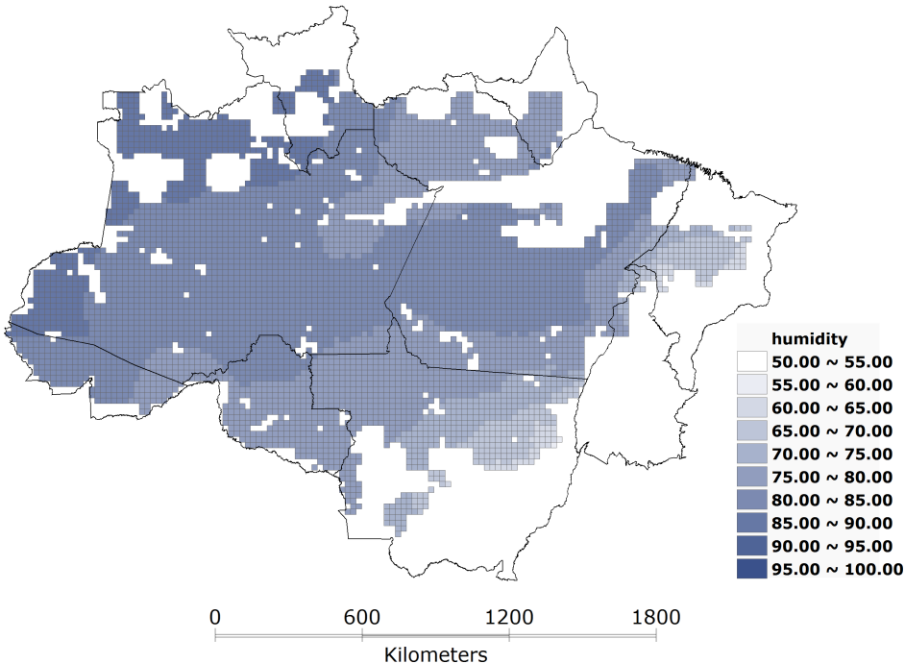

Figure 3-23: humidity (%; clima_humi_min_3_ave)

Environmental factors from CPTEC-PVM

These two environmental variables are derived by the water balance model of the CPTEC-PVM. The wetness index relates to soil wetness to distinguish between wet and dry climate conditions, the seasonality index represents soil moisture seasonality.

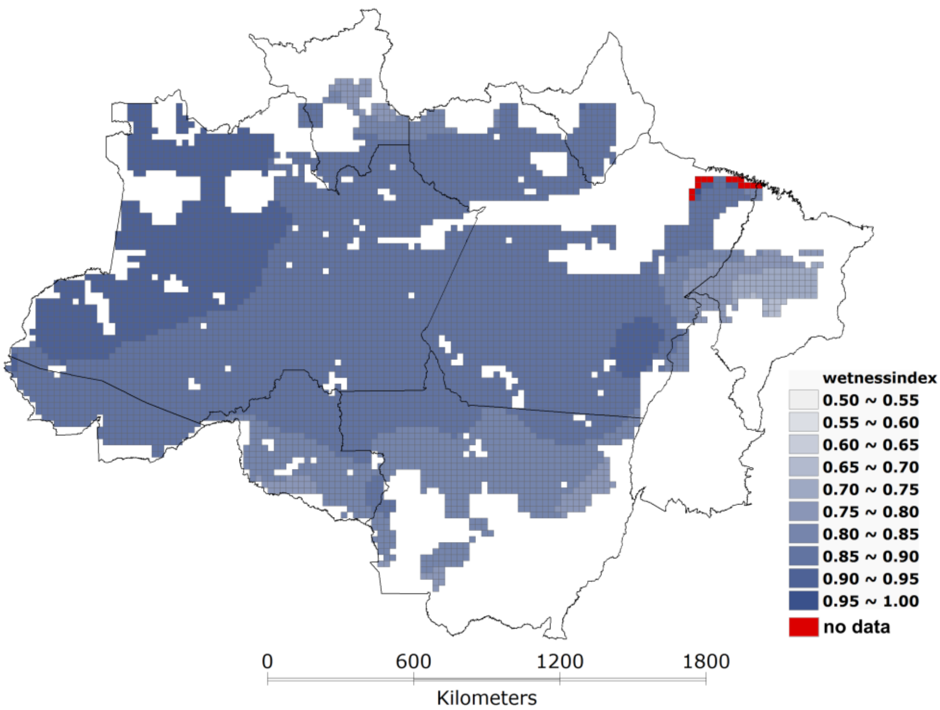

Figure 3-24: wetness index (weti)

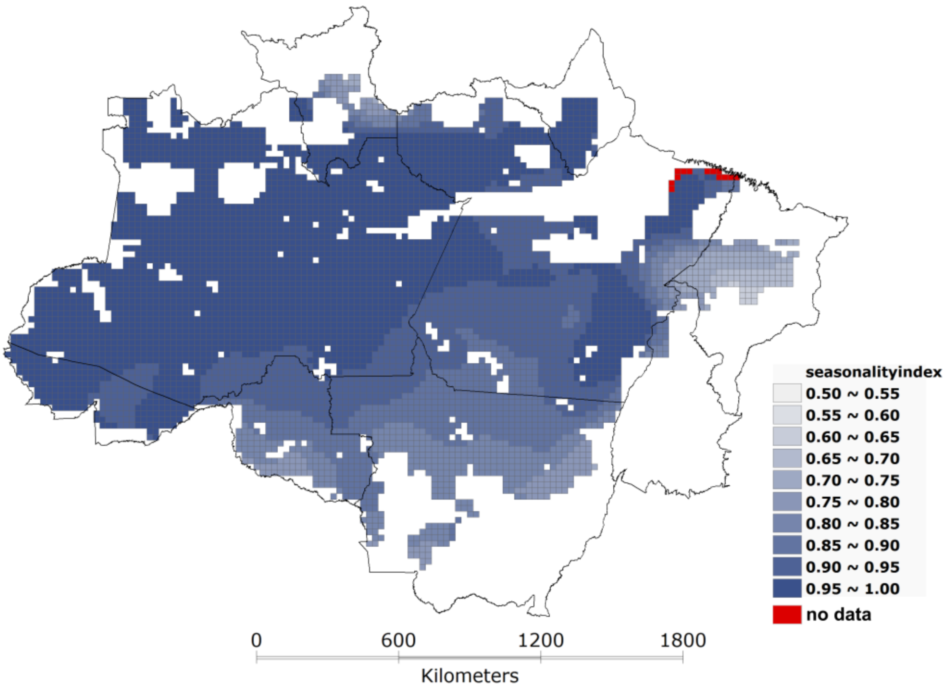

Figure 3-25: seasonality index (seai)

Integrating altimetry and slope data

For a possible improvement in discriminating pasture and agriculture patterns altimetry and slope data are included as additional environmental factors at scale 25x25km^2. The variables are derived from data of the Shuttle Radar Topography Mission (SRTM), which had the objective to generate the most complete high-resolution digital topographic database of the Earth by obtaining elevation data (SRTM Website 2010). The data for the Brazilian Amazon is freely available with a spatial resolution of 3 arc-seconds (approximately 90 meters).

Four variables are introduced, one regarding altitude and three regarding slope. The altitude variable contains the average elevation in meters in each cell. For the generation of the slope variables three classes are defined: flat (0°-5°), moderately sloped (5°-15°) and steeply sloped (>15°). The three variables: slope_flat, slope_mod, slope_steep represent the fraction of each of the corresponding classes in each cell in terms of total cell area.

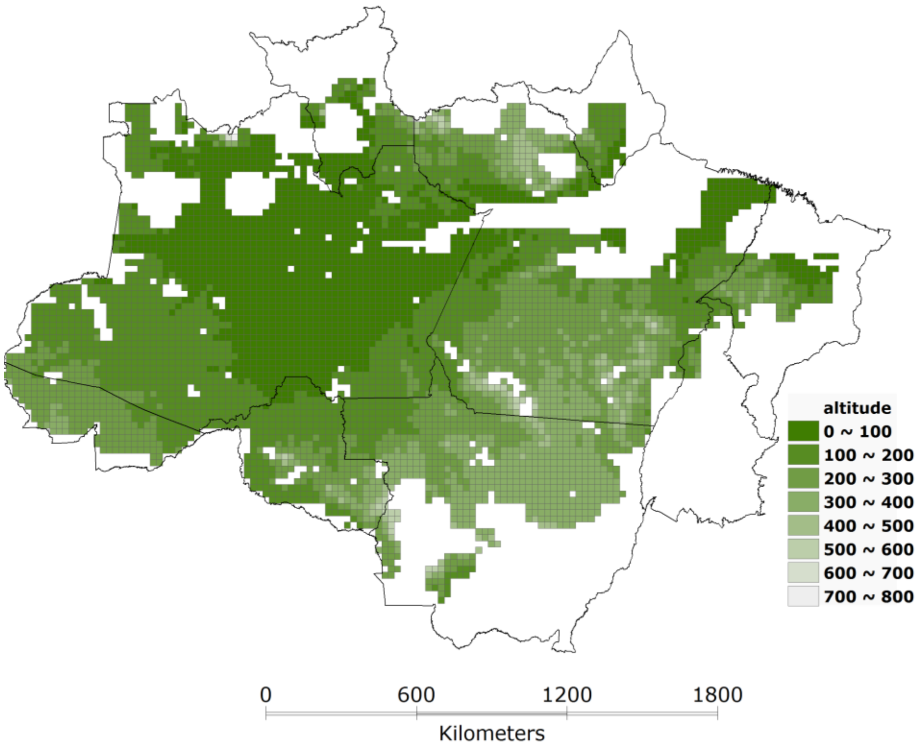

Figure 3-26: altitude (m; altitude_avg)

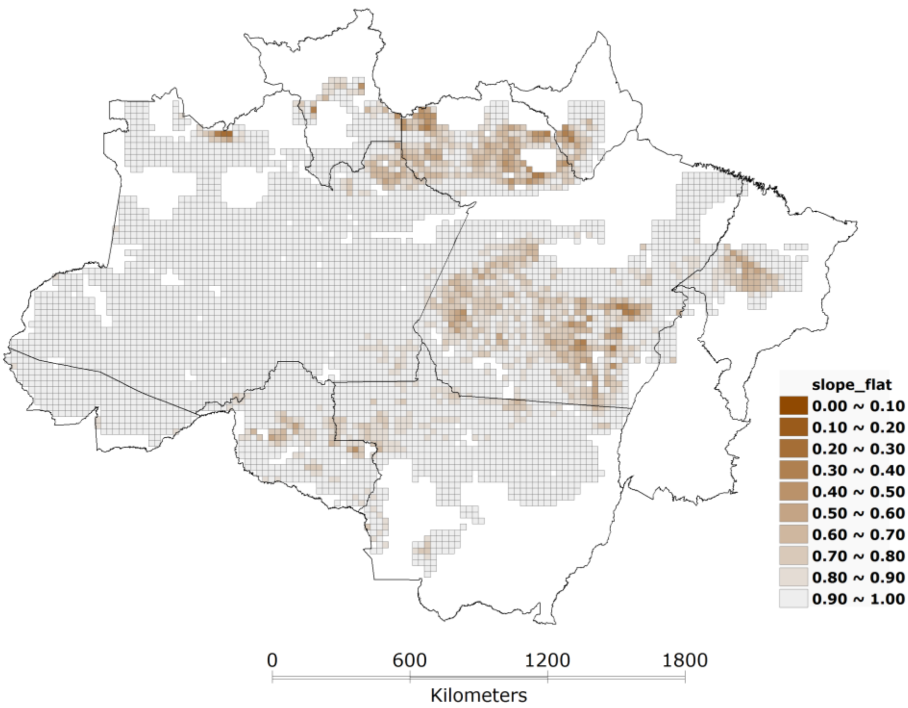

Figure 3-27: flat areas (fraction of cell area; slope_flat)

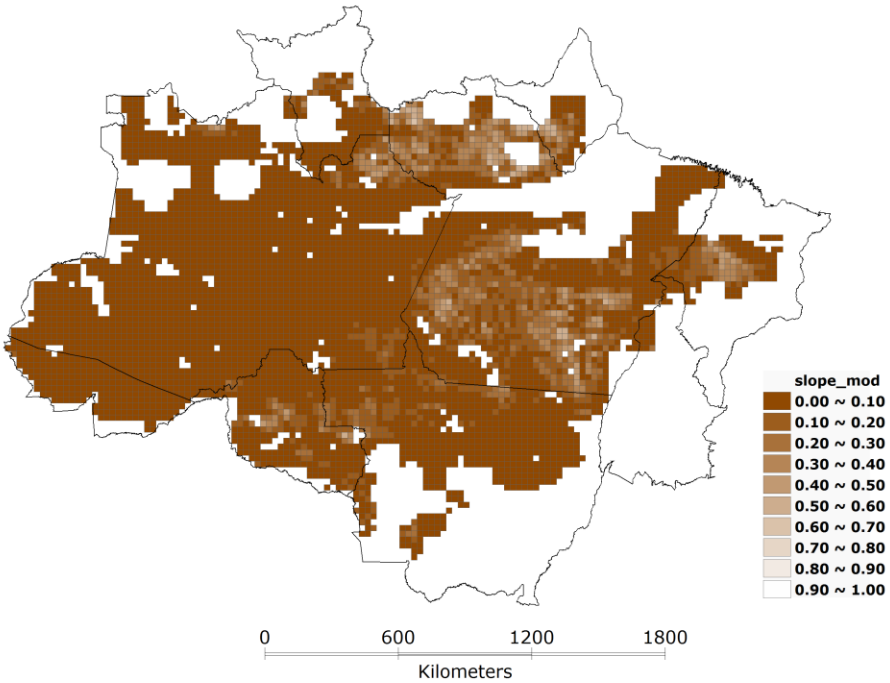

Figure 3-28: moderately sloped areas (fraction of cell area; slope_mod)

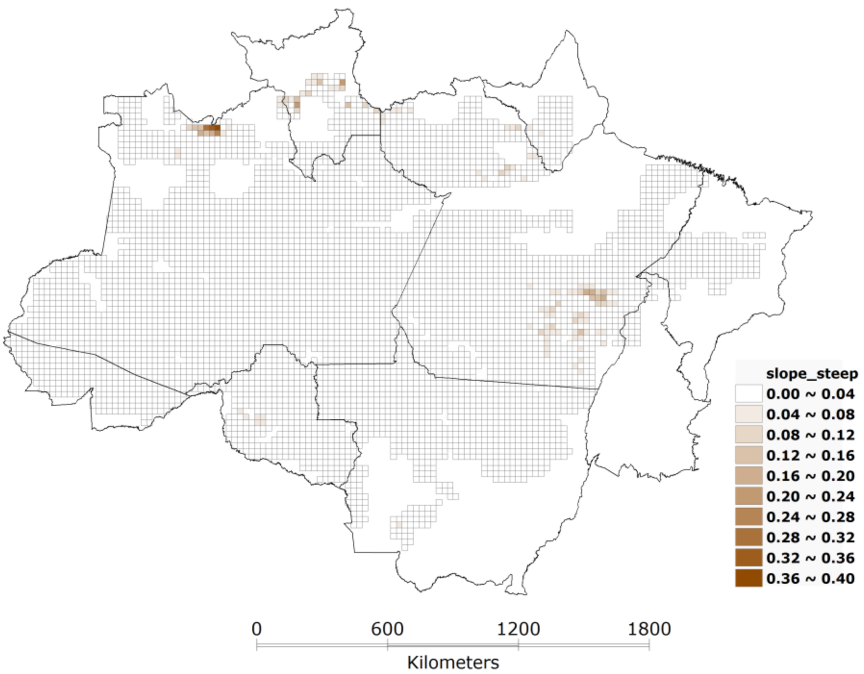

Figure 3-29: steeply sloped areas (fraction of cell area; slope_steep)

3.3.2 Statistical Analysis

Followed by a preliminary survey of the variables from the list of factors defined in Aguiar (2006), the potential land-use determining factors listed in Table 3-1 are selected for further analysis. The objective of the statistical analysis is to find a statistical model that is capable of explaining the deforestation and land-use patterns in the Brazilian Amazon with the help of explanatory variables. Correlation analysis and linear regression analysis are used to detect relationships between the dependent land-use variables (deforested areas, pasture, temporary crops, permanent crops, non-used agricultural land, planted forest and forest) and the independent explanatory variables. Several regression models are defined and compared with special emphasis on the newly integrated environmental variables. Thereafter the most suitable models are selected for the AmazonClueINPE model to test their abilities for allocation and projection of several land-use types.

3.3.2.1 Exploratory Data Analysis

Before carrying out the regression analysis, the potential land-use determining factors and the land-use variables are visually analyzed and undergo a correlation analysis. The Pearson correlation coefficient is defined by $\frac{Cov(X,Y)}{\sqrt{Var(X)*Var(Y)}}$, where Cov(X,Y) stands for the covariance of the two random variables X and Y and Var(X) and Var(Y) for their variance. It is a measure for the linear stochastic relation of X and Y, but it does not describe explicit causal relations (Navratil & Staudinger 2006).

3.3.2.2 Regression Analysis

Based on the exploratory data analysis, multiple linear regression analysis is used to investigate the importance of a number of independent factors on the dependent land-use variables. The mathematical model for each land-use variable is defined by $Y = X\beta + \varepsilon$, where Y is a (n x 1) vector of values for the dependent land-use variable in n cells, X is a (n x k) matrix of a column of ones and (k-1) columns of explanatory variables in n cells, β is an (k x 1) vector of regression coefficients (including intercept) and ε an (n x 1) disturbance vector. The regression coefficients are estimated using the method of linear least squares.

To compare the regression models different criteria are used. One of them is the coefficient of determination R^2, the fraction of variance explained by the model (R Reference Index 2009), which is defined by $R^2 = 1 - \frac{\sum R[i]^2}{\sum (y[i] - \bar{y})^2}$, where $\sum R[i]^2$ is the residual sum of squares and $\sum (y[i] - \bar{y})^2$ the total sum of squares. The adjusted R^2, which penalizes for a higher number of explanatory variables, is also used. The Akaike Information Criterion

(AIC) is another measure used to rank statistical models and hence applicable for model selection. It is defined by $AIC = -2 * \log L + k * edf$, where L is the likelihood and edf the equivalent degrees of freedom. The smaller the value of the AIC, the better is the model. The Akaike Information Criterion is used in a stepwise procedure as a criterion for the selection of variables. To analyze the importance of the factors for a certain land-use the standardized regression coefficients (Beta values) are calculated by $\beta_i' = \beta_i * \frac{sd(X_i)}{sd(Y)}$, where $sd(X_i)$ corresponds to the standard deviation of the i-th independent variable, $sd(Y)$ to the standard deviation of the dependent variable and β_i to the i-th regression coefficient. The standardized regression coefficients can be interpreted as a measure of how many standard deviations of change in the dependent variable are related to a one standard deviation increase in the independent variable (Lesschen et al. 2005). Thus the importance of the different variables can be compared in terms of standard deviation units, disregarding their originally diverse units.

3.3.2.3 Alternative model construction

The potential explanatory variables are grouped into different models for the regression analysis. Difficulties arise when trying to distinguish the effects of explanatory variables due to their tendency to be highly correlated, which is fairly common in land-use analysis (Lesschen et al. 2005). Thus the limitation that the correlation coefficients between variables in the same model are not allowed to have an absolute value higher than 0.5, is considered. Hence probable important factors, for example distance to urban areas, distance to roads, connection to markets or the wetness index cannot all be used together in the same model. This leads to the definition of several models with as little correlation between the factors but as much explanatory power as possible.

One of the objectives of this thesis is to further improve the statistical models defined in Aguiar (2006) for the Densely Populated Arch macro region, to allow better discrimination of pasture and temporary crops patterns. This is attempted by including additional environmental variables from the water balance model of the CPTEC-PVM and altimetry and slope data. The decision to build the statistical models at the fine scale for the Densely Populated Arch and not for the whole Brazilian Amazon is based on results in Aguiar (2006) where using a regression model of the Densely Populated Arch in all spatial regions led to more realistic spatial patterns in the dynamical modeling results. (compare section 2.1.3)

The models are shown in Table 3-2 and Table 3-3 and are named after the probable most influential variables. The label environment includes the seasonality index (seai), the altitude (altitude_avg) and the slope (slope_flat) variable.

Table 3-2: Models at scale 100x100km^2

100.A[2] urban + humidity	100.B[2] roads + humidity	100.C urban + wetness	100.D roads + wetness
log_dist_urban_areas	log_dist_roads	log_dist_urban_areas	log_dist_roads
agr_area_small	agr_area_small	agr_area_small	agr_area_small
conn_ports_inv_p	conn_ports_inv_p	conn_ports_inv_p	conn_ports_inv_p
soils_fert_B1	soils_fert_B1	soils_fert_B1	soils_fert_B1
soils_fert_B3	soils_fert_B3	soils_fert_B3	soils_fert_B3
prot_all1	prot_all1	prot_all1	prot_all1
log_dist_large_rivers	log_dist_large_rivers	log_dist_large_rivers	log_dist_large_rivers
clima_humi_min_3_ave	clima_humi_min_3_ave	weti	weti

Table 3-3: Models at scale 25x25km^2

25.A[2] roads + connection to markets	25.B roads + connection to markets + environment	25.C roads + seasonality	25.D roads + environment + humidity
log_dist_non_paved_road	log_dist_non_paved_road	log_dist_non_paved_road	log_dist_non_paved_road
log_dist_paved_roads	log_dist_paved_roads	log_dist_paved_roads	log_dist_paved_roads
agr_area_small	agr_area_small	agr_area_small	prot_all1
log_setl_nfamilies_70_99	log_setl_nfamilies_70_99	log_setl_nfamilies_70_99	soils_fert_B1
prot_all1	prot_all1	prot_all1	soils_fert_B3
log_dist_large_rivers	log_dist_large_rivers	log_dist_large_rivers	seai
log_dist_min_deposits	log_dist_min_deposits	log_dist_min_deposits	altitude_avg
conn_ports_inv_p	conn_ports_inv_p	conn_ports_inv_p	slope_flat
soils_fert_B1	soils_fert_B1	soils_fert_B1	clima_humi_min_3_ave
soils_fert_B3	soils_fert_B3	soils_fert_B3	
conn_markets_inv_p	conn_markets_inv_p	log_dist_wood_extr_poles	
log_dist_wood_extr_poles	log_dist_wood_extr_poles	seai	
	seai		
	altitude_avg		
	slope_flat		

3.3.3 Dynamical modeling: AmazonClueINPE

The LUCC model used in this work is based on the CLUE (Conversion of Land-Use and its Effects) model (Veldkamp & Fresco 1996; De Koning et al. 1998; Verburg et al. 1999;

[2] adapted from Aguiar (2006)

Kok et al. 2001) and was adapted by Aguiar (2006) to be applicable for the Brazilian Amazon. It has the objective to provide a spatially-explicit, multi-scale, quantitative description of land-use changes. AmazonClueINPE is available in C++ and TerraME. In this thesis the TerraME version introduced in Moreira (2009) has been used. A review of the CLUE modeling framework and its adaptation to the Amazon is given in section 2.1.3.

The AmazonClueINPE model consists of a demand and an allocation module. In the non-spatial demand module scenarios of the quantity of change define how much change takes place every year in each land-use type. These demand values are calculated by multiplying the yearly deforestation rate, published by INPE (2010), with a ratio for each land-use type (Table 3-4).

Table 3-4: Area of land-use type per deforestation area in 1997

Pasture	Temporary crops	Permanent crops	Non-used agricultural areas	Planted forest
0.68	0.14	0.03	0.14	0.01

These ratios – area of land-use type per deforestation area – are calculated on basis of the Census of Agriculture in 1996 (IBGE 1996) and assumed to not change in the time of study. Though values of the Census of Agriculture 2006 (IBGE 2009) could have been used to interpolate the ratios for the intermediate years, it would have lead to problems, since the land-use type non-used agricultural land, which accounted for approximately 14% of total deforested area in 1996, was not included in the agricultural census in 2006.

The following parameters are used in the allocation module (Table 3-5). The model starts in 1997 and runs in one year time-steps until 2006. The deforestation threshold (lim_forest) that tries to slow down deforestation after a certain limit is reached in each cell is set to 0.2. Thus, if less than 20% of the cell area is forest, a different allocation algorithm, which limits further deforestation is used. The maximum change value (max_change) per year is set to 0.5, which limits the change of a land-use type to a maximum of 50% of the cell area per time-step. The minimum elasticity (min_elasticity) is 0.1 for all land-use types and has an influence on the magnitude of change in the cells. The scale factor can be used to provide one of the two scales with higher importance. It is set to 1, hence no scale is favored. The number of iterations per time step is set to 2000. The maximum allowed difference (max_demand_diff) between demand and allocated areas is 0.01 times the demand.

Table 3-5: Parameters for the AmazonClueINPE allocation module

parameter	description	value
lim_forest	forest threshold to preserve 20% of cell area from deforestation	0.2
max_change	upper limit for change in one period of time	0.5
scale_fact	to favor one scale in respect of the other	1
max_iter	maximum number of iterations	2000
max_demand_diff	maximum allowed difference between demand and allocated change	0.01

Some of the potential land-use determining variables are updated during the AmazonClueINPE model runs. These are the connection to markets and ports variables (in 2000), as well as the distance to roads (in 2000) and the protected areas variables (in 2005).

3.3.3.1 Exploration of alternative regression models

An AmazonClueINPE model test plan is developed to test the different models of the regression analysis in a dynamical modeling approach. The attempt is to use as much complementary information at both scales as possible to test the ability of regression model combinations to simulate deforestation patterns and to discriminate different land-use types. Due to dissimilarities between the statistical models different spatial patterns are reproduced for each test. The objective of defining a test plan is to analyze the strengths and constraints of the different regression models and their combinations to find models that are capable of reproducing the actual deforestation and land-use patterns in Legal Amazon.

The hypothesis of this thesis states that the inclusion of hydrological, slope and altimetry variables improves the ability to discriminate pasture and agriculture patterns in the Brazilian Amazon. The following test plan (Table 3-6) is defined to explore this assumption.

- Analysis A uses regression models which include a connection to markets measure, but not the newly integrated environmental variables.

- Analysis B uses regression models which include a connection to markets measure, the wetness index and the seasonality index from CPTEC-PVM and slope and altimetry variables.

- Analysis C uses regression models which include the wetness index and the seasonality index from CPTEC-PVM as well as slope and altimetry variables.

Table 3-6: AmazonClueINPE model test plan

	Test #	regressionmodel 100	regressionmodel 25
Analysis A	**A1**	100.A urban + humid	25.A roads + connection to markets
	A2	100.B roads + humid	25.A roads + connection to markets
Analysis B	**B1**	100.C urban + wetness	25.B roads + connection to markets + environment
	B2	100.D roads + wetness	25.B roads + connection to markets + environment
Analysis C	**C1**	100.C urban + wetness	25.C roads + seasonality
	C2	100.C urban + wetness	25.D roads + environment + humidity

3.3.3.2 Evaluation of dynamic modeling results

The results of the AmazonClueINPE model runs are presented for the Legal Amazon at scale 25x25km^2. The maps for deforested areas, pasture and temporary crops are compared with special emphasis on some of the current hotspots of change (section 3.3.1.2). Due to the absence of the land-use type non-used agricultural land in the agricultural census data of 2006 and the fact that this class remains in the AmazonClueINPE model, quantitative analysis is difficult to accomplish. Hence the evaluation of the AmazonClueINPE model results is mainly carried out visually and not on a cell to cell basis as in different quantitative map comparison methods. Nevertheless, ratios of change are compared per state where appropriate. Thus the analysis focuses more on the formation of new spatial patterns than on comparing specific cell values. Besides looking at the spatial patterns in general, it will be analyzed if the selected variables are capable of forcing the model to allocate the land-use changes in reasonable areas, i.e. areas which currently are or recently have been under human pressure.

3.4 Software

The statistical analysis is carried out in R[3], a free software environment for statistical computing and graphics. The AmazonClueINPE model is run with TerraME[4] RC4 (for

[3] www.r-project.org
[4] www.terrame.org

TerraLib[5] 3.2), the DBMS used is Microsoft Access. The results of the AmazonClueINPE model are analyzed and visualized in TerraView[6] 3.2.0.

[5] www.terralib.org
[6] www.dpi.inpe.br/terraview

4 Results

In this chapter the results of the CPTEC-PVM implementation and the LUCC modeling are presented.

4.1 CPTEC-PVM

The CPTEC-PVM and its water balance model are implemented in the TerraME modeling environment as described in section 3.2. As a result the environmental variables from the water balance model are stored in the database and can be used by the AmazonClueINPE model. In addition to that the potential biome distribution is stored and visualized using TerraView 3.2.0 in Figure 4-1 on a global scale and in Figure 4-3 for the Brazilian Amazon. The spatial patterns of the wetness index and the seasonality index are shown in section 3.3.1.3. Figure 4-2 shows the potential vegetation map of the original version (Oyama & Nobre 2004).

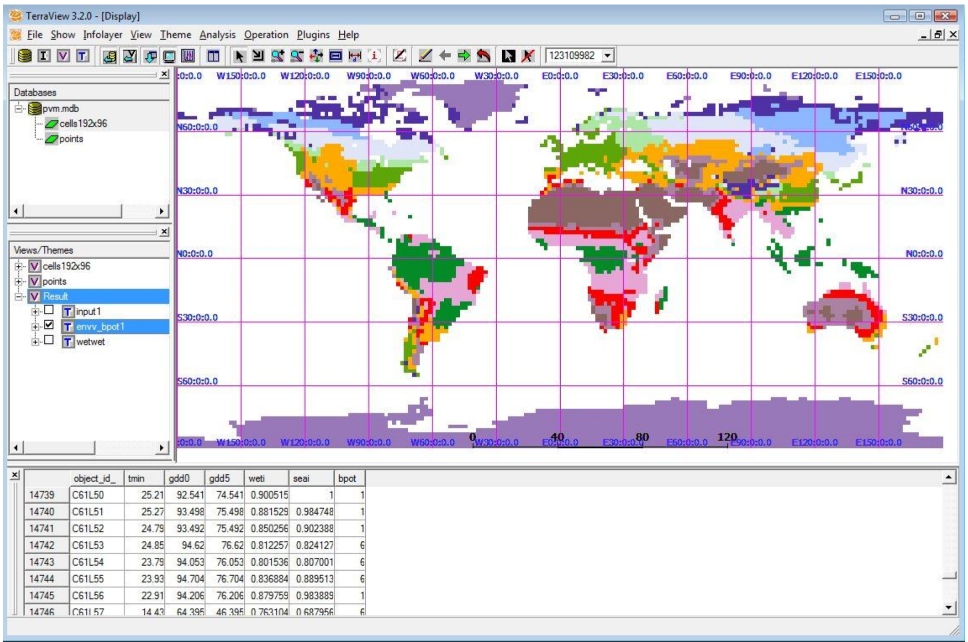

Figure 4-1: TerraView screenshot visualizing the result of the PVM implementation in TerraME

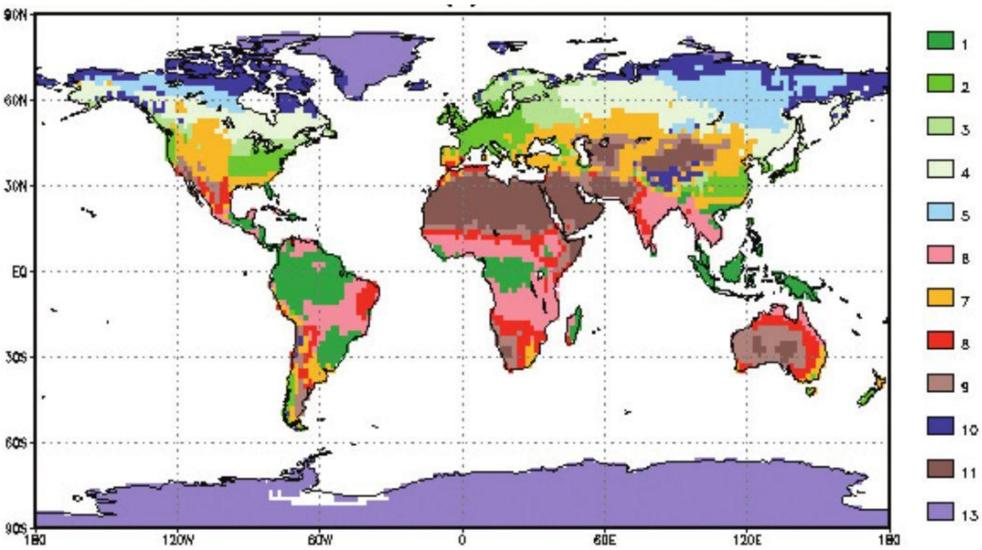

Figure 4-2: Potential vegetation (Oyama & Nobre 2004) [1]

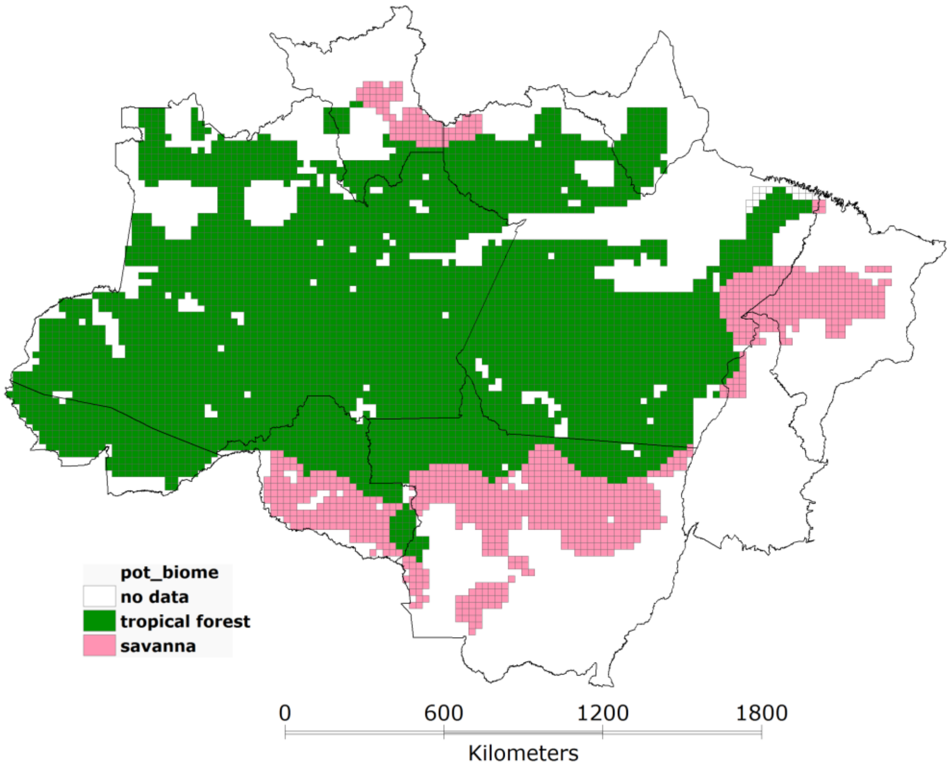

Figure 4-3: Potential vegetation in the Brazilian Amazon

Only the two environmental variables from the water balance model of CPTEC-PVM are used for analysis in the present thesis. The additional three variables, which are needed for the calculation of the potential vegetation are not used. Hence the potential biome classification has no effect on the land-use change modeling in the following section.

[1] Oyama (2005) changed some threshold values in the biome classification algorithm after the publication of Oyama & Nobre (2004), which led to the generation of CPTEC-PVM v2. The implementation in TerraME and the screenshot in this section correspond to this version (v2), which results in minor differences between the figure from the original paper (v1, Figure 4-2) and the screenshot from TerraView (v2, Figure 4-1).

4.2 Land-use change modeling

The hypothesis, that the newly integrated environmental variables can improve the discrimination of pasture and temporary crops patterns, is investigated in this chapter. The following sections show the results of the statistical analysis and a comparison of the land-use change model outcomes.

4.2.1 Statistical Analysis results

The statistical analysis is carried out for two scales, 100x100km^2 and 25x25km^2, as described in section 3.3.2. The descriptions of the used potential land-use determining factors can be found in Table 3-1. The statistical models are listed in Table 3-2 and Table 3-3.

4.2.1.1 Exploratory Data Analysis

The potential land-use determining factors are tested using the Pearson Correlation Coefficient (compare section 3.3.2.1) to find stochastic relations with special emphasis on the additional environmental variables.

The two variables that were derived from the water balance model of the CPTEC-PVM wetness index (Formula 2-1) and seasonality index (Formula 2-2) are almost perfectly positive correlated (0.95), which is strengthened by looking at their spatial patterns (Figure 3-24 and Figure 3-25). Due to their similarity the two indices cannot be used together. Hence the wetness index is used at the coarse scale and the seasonality index at the fine scale. The decision to use the seasonality index at scale 25x25km^2 is based on a comparison of the correlation coefficients of the two environmental variables with the different land-use types. The correlation coefficients between the seasonality index and the land-use variables show in general higher absolute values than the corresponding coefficients for the wetness index (Table 4-1). Thus the assumption is made that the seasonality index is likely to have more explanatory power at this scale and therefore used in the successive analysis.

Table 4-1: Correlation coefficients for the wetness index and the seasonality index with land-use variables in the Arch 25

	forest	deforestation(log)	pasture(log)	temp agric(log)	perm agric(log)	non-used land(log)	planted forest(log)
wetness index	0.25	-0.18	-0.13	-0.29	-0.17	-0.30	-0.07
seasonality index	0.27	-0.22	-0.18	-0.32	-0.12	-0.32	-0.05

In the Densely Populated Arch at scale 25x25km^2 there are two variables, apart from the wetness index, that have an absolute correlation coefficient higher than 0.5 with the seasonality index (Table 4-2). These are the connection to markets (-0.51) and the humidity variable (0.51).

Table 4-2: Highest correlation coefficients for the seasonality index in the Arch 25

	weti	conn_markets	clima_humi_min_3_ave	log_dist_urban_areas	log_pop_dens
seai	0.95	-0.51	0.51	0.26	-0.22

Due to the fact that the correlation coefficients for the connection to markets and the humidity variable only marginally exceed the 0.5 limit, it is decided that these can also be used together with the seasonality index in the regression models, since the former factor can serve as an important connection measure. The correlation coefficient with the former climate variable clima_humi_3_ave is 0.51 and thus confirms to some extent the similar spatial patterns of the seasonality index (Figure 3–24) and the humidity variable (average humidity in the three driest consecutive months, Figure 3-23). To test whether the seasonality index is the more adequate environmental variable in terms of explanation of deforestation and land-use patterns or delivers additional information will be under investigation. It could lead to an improvement of the statistical models and furthermore to better simulations of deforestation and land-use processes.

The correlation coefficients for the soil variables (fertile and wet soils) with the seasonality index are small (Table 4-3). There is almost no correlation with the wet soils variable (0.06) and only a small negative correlation with the fertile soils variable (-0.16).

Table 4-3: Correlation between the seasonality index and the soil variables in the Arch 25

	fertile soils	wet soils
seai	-0.16	0.06

Considering the slope and altitude variables, the correlation coefficients (Table 4-4) indicate that the average altitude is negatively correlated with the fraction of flat slopes (-0.23) and positively correlated with the fraction of moderately (0.23) and steeply sloped areas (0.20). The slope variables show comprehensible correlations, e.g. slope_flat is almost perfectly negative correlated with slope_mod (-0.99) and highly negative correlated with slope_steep (-0.58). Hence only the slope_flat and the altitude_avg variable are used in the regression models.

Table 4-4: Correlation coefficients for the environmental variables in the Arch 25

	altitude_avg	slope_flat	slope_mod	slope_steep
altitude_avg	1	-0.23	0.23	0.20
slope_flat	-0.23	1	-0.99	-0.58
slope_mod	0.23	-0.99	1	0.50
slope_steep	0.20	-0.58	0.50	1

The potential important variables in the regression models do not show high correlation coefficients with the new environmental variables (Table 4-5).

Table 4-5: Correlation coefficients for the environmental variables with important variables in the Arch 25

	log_dist_paved_roads	log_dist_non_paved_roads	prot_all1	conn_markets
altitude_avg	0.25	-0.05	0.12	-0.01
slope_flat	0.03	-0.06	-0.09	-0.06

Correlation coefficients of the environmental variables with the land-use types (Table 4-6) reveal a differentiation between temporary crops and pasture. There is a negative correlation between the seasonality index and the land-use temporary crops (-0.32) and weaker correlations to forest (0.27) and deforestation (-0.22). The altitude variable shows a negative correlation for temporary crops (-0.18) and almost no correlation for deforestation (-0.03) and pasture (0.03). For the slope variable the correlation coefficients show only small values and thus no clear indication for a connection to the land-use types in the Densely Populated Arch at this scale.

Table 4-6: Correlation coefficients for the environmental variables with land-use types in the Arch 25

	forest	deforestation (log)	pasture (log)	temp agric (log)	perm agric (log)	non-used land (log)	planted forest (log)
seai	0.27	-0.22	-0.18	-0.32	-0.12	-0.32	-0.05
altitude_avg	0.21	-0.03	0.03	-0.18	-0.29	-0.16	-0.21
slope_flat	0.02	0.00	-0.02	-0.01	0.06	-0.02	0.06
clima_humi_min_3	0.23	-0.26	-0.27	-0.28	0.13	0.05	-0.24
soils_fert_B1	-0.35	0.31	0.28	0.33	0.34	0.18	0.33
soils_fert_B3	0.08	-0.08	-0.10	-0.04	-0.05	0.00	-0.04

In general potential important variables like distance to urban areas, distance to roads, connection to markets and population density are to a high degree correlated (Table 4-7).

Table 4-7: Correlations for the Arch 25

	log_dist_urban_areas	log_dist_paved_road	log_dist_n_pav_road	conn_mkt	log_pop_dens
log_dist_urban_areas	1	0.51	0.44	-0.46	-0.56
log_dist_paved_road	0.51	1	0.12	-0.44	-0.63
log_dist_n_paved_road	0.44	0.12	1	-0.27	-0.29
conn_mkt	-0.46	-0.44	-0.27	1	0.48
log_pop_dens	-0.56	-0.63	-0.29	0.48	1

4.2.1.2 Regression Analysis

The results of the multiple linear regression analysis are presented for the Densely Populated Arch at scale 25x25km^2 for deforestation and the land-use types pasture and temporary crops with special emphasis on the environmental variables. Variables that are not significant at the 5% level, i.e. their p-values are greater than 0.05, are eliminated.

Twelve variables are included in the model 25.A – roads + connection to markets. The two soil variables (soil_fert_B1 and soil_fert_B3) are the only environmental variables in this model. The humidity variable (clima_humi_min_3_ave) cannot be used because of its correlation with the connection to markets variable (-0.59). The model 25.B – roads + connection to markets + environment further includes the seasonality index from the CPTEC-PVM and the altimetry and slope factors. The model 25.C – roads + seasonality includes the seasonality index. The model 25.D – roads + environment + humidity uses all environmental variables, including the humidity variable, but excludes some factors describing economic attractiveness and accessibility. The 25.C and 25.D model do not use the connection to markets variable. The models are summarized in Table 3-3.

Deforestation

Considering the adjusted coefficient of determination (adj. R^2) and the Akaike Information Criterion (AIC) the performance of the regression models for deforestation does not vary significantly (Table 4-8). The adjusted R^2 ranges from 0.58 to 0.64. The most important factors are the protected areas variable and accessibility variables like connection to markets, which show a positive relation to deforestation, and distance to roads with a negative relation to deforestation. The highest absolute values in terms of standardized regression coefficients in all four models are represented by the protected areas (prot_all1) variable, which shows negative beta values between -0.37 and -0.42 and hence strong indications for a deforestation avoiding factor. The environmental variables are not amongst the main determinants of deforestation. The highest absolute beta values are -0.20 for the humidity variable in model 25.D and -0.14 for the seasonality index in 25.C. The soils variables do not exceed beta values of 0.12 and also the slope and altimetry variables show small statistical relations to deforestation. Some variables are not significant and therefore excluded from the regression models like connection to ports, distance to large rivers and average altitude.

Table 4-8: Regression models of deforestation for the Arch 25

25.A - roads + connection to markets			25.B - roads + connection to markets + environment		
	beta	p-value		beta	p-value
log_dist_non_paved_road	-0.21	0.00	log_dist_non_paved_road	-0.21	0.00
log_dist_paved_roads	-0.21	0.00	log_dist_paved_roads	-0.21	0.00
agr_area_small	-0.08	0.00	agr_area_small	-0.07	0.00
log_setl_nfamilies_70_99	0.05	0.00	log_setl_nfamilies_70_99	0.04	0.00
prot_all1	-0.37	0.00	prot_all1	-0.38	0.00
log_dist_min_deposits	-0.05	0.00	log_dist_min_deposits	-0.04	0.01
soils_fert_B1	0.10	0.00	soils_fert_B1	0.11	0.00
soils_fert_B3	0.04	0.01	soils_fert_B3	0.05	0.00
conn_markets_inv_p	0.34	0.00	conn_markets_inv_p	0.34	0.00
log_dist_wood_extr_poles	-0.11	0.00	log_dist_wood_extr_poles	-0.11	0.00
			altitude_avg	0.04	0.02
			slope_flat	-0.04	0.01
	adj. R^2	AIC		adj. R^2	AIC
	0.64	-1786.79		0.64	-1800.83
25.C - roads + seasonality			25.D - roads + environment + humidity		
	beta	p-value		beta	p-value
log_dist_non_paved_road	-0.27	0.00	log_dist_non_paved_road	-0.29	0.00
log_dist_paved_roads	-0.36	0.00	log_dist_paved_roads	-0.34	0.00
agr_area_small	-0.09	0.00	prot_all1	-0.42	0.00
log_setl_nfamilies_70_99	0.07	0.00	soils_fert_B1	0.12	0.00
prot_all1	-0.41	0.00	slope_flat	-0.08	0.00
conn_ports_inv_p	-0.04	0.02	clima_humi_min_3_ave	-0.20	0.00
soils_fert_B1	0.12	0.00			
log_dist_wood_extr_poles	-0.05	0.00			
seai	-0.14	0.00			
	adj. R^2	AIC		adj. R^2	AIC
	0.58	-1540.10		0.60	-1612.47

Pasture

The major land-use type for deforested areas in the Brazilian Amazon in 1997 was pasture with approximately 68% of all deforested areas (compare section 3.3.3). Hence the regression for this land-use type shows similar results to the regression results of deforestation. The adjusted R^2 reaches values between 0.57 and 0.63. The most important factors are again the protected areas variable and the accessibility factors. The indicator for the agrarian structure (agr_area_small) gains some importance in comparison to the standardized regression coefficients of deforestation. Regarding the environmental factors the seasonality index, the humidity variable and the soil variables lose some explanatory power, whereas the absolute beta values for the altitude variable increase, compared to deforestation.

Table 4-9: Regression models of pasture for the Arch 25

25.A - roads + connection to markets			25.B - roads + connection to markets + environment		
	beta	p-value		beta	p-value
log_dist_non_paved_road	-0.22	0.00	log_dist_non_paved_road	-0.22	0.00
log_dist_paved_roads	-0.20	0.00	log_dist_paved_roads	-0.21	0.00
agr_area_small	-0.14	0.00	agr_area_small	-0.12	0.00
log_setl_nfamilies_70_99	0.07	0.00	log_setl_nfamilies_70_99	0.07	0.00
prot_all1	-0.36	0.00	prot_all1	-0.37	0.00
log_dist_min_deposits	-0.08	0.00	log_dist_min_deposits	-0.08	0.00
conn_ports_inv_p	-0.04	0.02	soils_fert_B1	0.09	0.00
soils_fert_B1	0.09	0.00	soils_fert_B3	0.05	0.00
soils_fert_B3	0.04	0.02	conn_markets_inv_p	0.34	0.00
conn_markets_inv_p	0.35	0.00	log_dist_wood_extr_poles	-0.10	0.00
log_dist_wood_extr_poles	-0.11	0.00	altitude_avg	0.09	0.00
			slope_flat	-0.04	0.01
	adj. R^2	AIC		adj. R^2	AIC
	0.63	-1837.88		0.63	-1872.63
25.C - roads + seasonality			25.D - roads + environment + humidity		
	beta	p-value		beta	p-value
log_dist_non_paved_road	-0.28	0.00	log_dist_non_paved_road	-0.30	0.00
log_dist_paved_roads	-0.35	0.00	log_dist_paved_roads	-0.34	0.00
agr_area_small	-0.15	0.00	prot_all1	-0.42	0.00
log_setl_nfamilies_70_99	0.09	0.00	soils_fert_B1	0.10	0.00
prot_all1	-0.40	0.00	altitude_avg	0.08	0.00
log_dist_large_rivers	0.04	0.02	slope_flat	-0.07	0.00
log_dist_min_deposits	-0.06	0.00	clima_humi_min_3_ave	-0.18	0.00
conn_ports_inv_p	-0.08	0.00			
soils_fert_B1	0.10	0.00			
log_dist_wood_extr_poles	-0.04	0.02			
seai	-0.12	0.00			
	adj. R^2	AIC		adj. R^2	AIC
	0.57	-1574.65		0.58	-1618.65

Temporary crops

For the land-use type temporary crops the adjusted coefficients of determination for model 25.A and 25.B have values around 0.70, whereas the other two models show smaller values of 0.61. This can be explained by the exclusion of the connection to markets variable in the latter two models. The connection to markets and the protected areas variable are the most important factors in 25.A and 25.B. In the other two models the road variables gain importance, but the paved roads variable shows significantly more impact than the non-paved roads variable. A positive factor for temporary crops is the agrarian structure variable (agr_area_small). Considering the environmental variables the seasonality index (in model 25.C) and the humidity variable (in model 25.D) show large negative beta values. Out of the other environmental factors in model 25.D the soil fertility factor (soil_fert_B1) and the altitude variable have the most influence on the land-use type temporary crops.

Table 4-10: Regression models of temporary crops for the Arch 25

25.A - roads + connection to markets			25.B - roads + connection to markets + environment		
	beta	p-value		beta	p-value
log_dist_non_paved_road	-0.08	0.00	log_dist_non_paved_road	-0.08	0.00
log_dist_paved_roads	-0.19	0.00	log_dist_paved_roads	-0.20	0.00
agr_area_small	0.18	0.00	agr_area_small	0.17	0.00
log_setl_nfamilies_70_99	0.07	0.00	log_setl_nfamilies_70_99	0.08	0.00
prot_all1	-0.27	0.00	prot_all1	-0.28	0.00
soils_fert_B1	0.11	0.00	soils_fert_B1	0.11	0.00
soils_fert_B3	0.04	0.01	soils_fert_B3	0.04	0.01
conn_markets_inv_p	0.46	0.00	conn_markets_inv_p	0.43	0.00
log_dist_wood_extr_poles	-0.13	0.00	log_dist_wood_extr_poles	-0.13	0.00
			seai	-0.06	0.00
	adj. R^2	AIC		adj. R^2	AIC
	0.69	-3184.99		0.70	-3198.35
25.C - roads + seasonality			25.D - roads + environment + humidity		
	beta	p-value		beta	p-value
log_dist_non_paved_road	-0.16	0.00	log_dist_non_paved_road	-0.21	0.00
log_dist_paved_roads	-0.36	0.00	log_dist_paved_roads	-0.40	0.00
agr_area_small	0.15	0.00	prot_all1	-0.32	0.00
log_setl_nfamilies_70_99	0.11	0.00	soils_fert_B1	0.15	0.00
prot_all1	-0.34	0.00	seai	-0.10	0.00
log_dist_large_rivers	0.07	0.00	altitude_avg	-0.15	0.00
soils_fert_B1	0.12	0.00	slope_flat	-0.10	0.00
log_dist_wood_extr_poles	-0.04	0.01	clima_humi_min_3_ave	-0.22	0.00
seai	-0.25	0.00			
	adj. R^2	AIC		adj. R^2	AIC
	0.61	-2765.07		0.61	-2764.78

The regression analysis shows that the beforehand defined potential leading factors like distance to roads and connection to markets are amongst the most important variables in the various models. The variable for protected areas (prot_all1) plays a decisive role for all land-use types. The seasonality index, the humidity variable, the altitude variable and the agrarian structure variable show especially for temporary crops higher importance. An interesting aspect is that the agrarian structure variable has negative regression coefficients for deforested areas and pasture, but positive coefficients for temporary crops, as discussed in Aguiar et al. (2007), reflecting the fact that in 1997 temporary crops concentrated on areas with a high percentage of small farms. Another variable that switches the sign of the regression coefficients is the altitude variable in model 25.D, which shows beta values of 0.08 for pasture and -0.15 for temporary crops.

The regression results indicate that the environmental variables are in most models not amongst the main land-use determining factors.

4.2.2 Dynamic modeling: AmazonClueINPE

The AmazonClueINPE model is used as dynamic modeling approach to simulate land-use change processes in the Brazilian Amazon. The LUCC model and its parameters are described in section 3.3.3.

The results of the AmazonClueINPE model are presented for deforestation and the land-use types pasture and temporary crops for scale 25x25km^2. To allow for visual comparison with the actual maps of change between the years 1997 and 2006 (Figure 3-4, Figure 3-6 and Figure 3-8), the relative change between these years has been computed.

4.2.2.1 Analysis of deforestation patterns

Analysis A

The regression models in Analysis A do not include the newly integrated variables. The spatial outcomes of model A1 (Figure 4-4) and A2 (Figure 4-5) vary due to the different regression models at the coarse scale. The results show spatial patterns that are mostly aligned along the roads because of the importance of the distance to paved and unpaved roads variables in the regression models. The two models do not reproduce the actual intensification of forest destruction in northern Mato Grosso and eastern Pará, but have especially in the result of A1 a strong diffusive pattern close to Porto Velho (RO) and Humaitá (AM) spreading along the BR-319 road to Manaus (AM). The BR-319 is currently in bad condition and for the most part not viable for transportation purposes (Fearnside & Graça 2006), but according to the governmental plans to reconstruct this connection, new deforestation areas could emerge as Barni et al. (2009) point out. The strong deforestation patterns around São Félix do Xingu in Pará that advance into the region of Terra do Meio are in a limited amount reproduced by the models, but their simulated pattern sprawls more along the road in comparison to the diffusive pattern present at the actual deforestation map (Figure 3-4). The forest destruction along the BR-163 connecting Cuiabá (MT) and Santarém (PA) is to some extent captured.

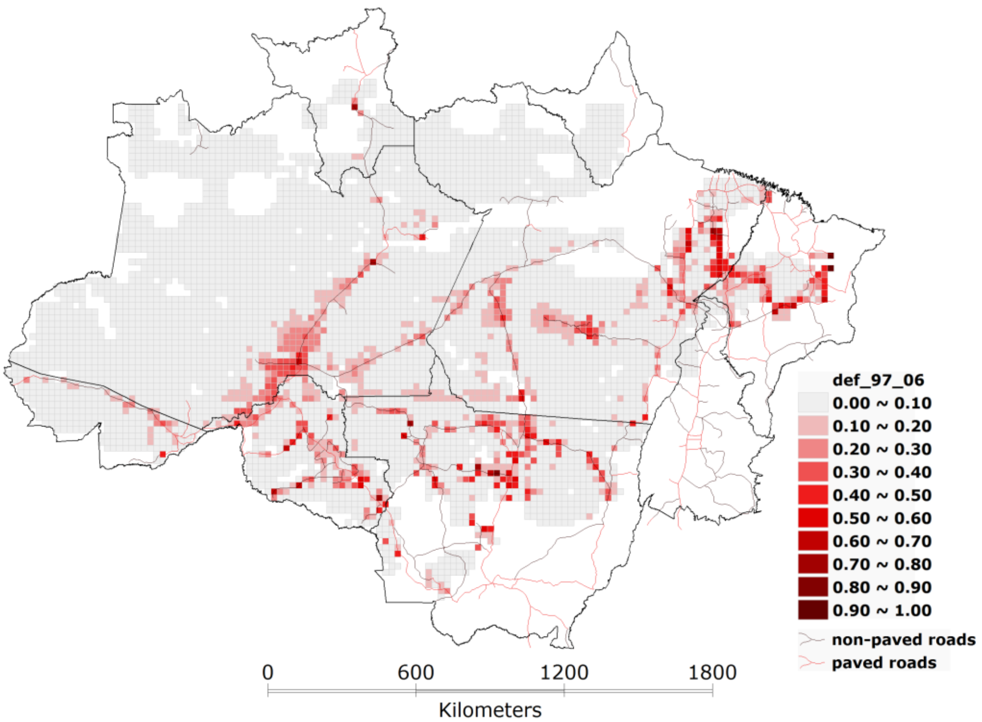

Figure 4-4: A1 – Deforestation (change) from 1997 to 2006 (fraction of cell area)

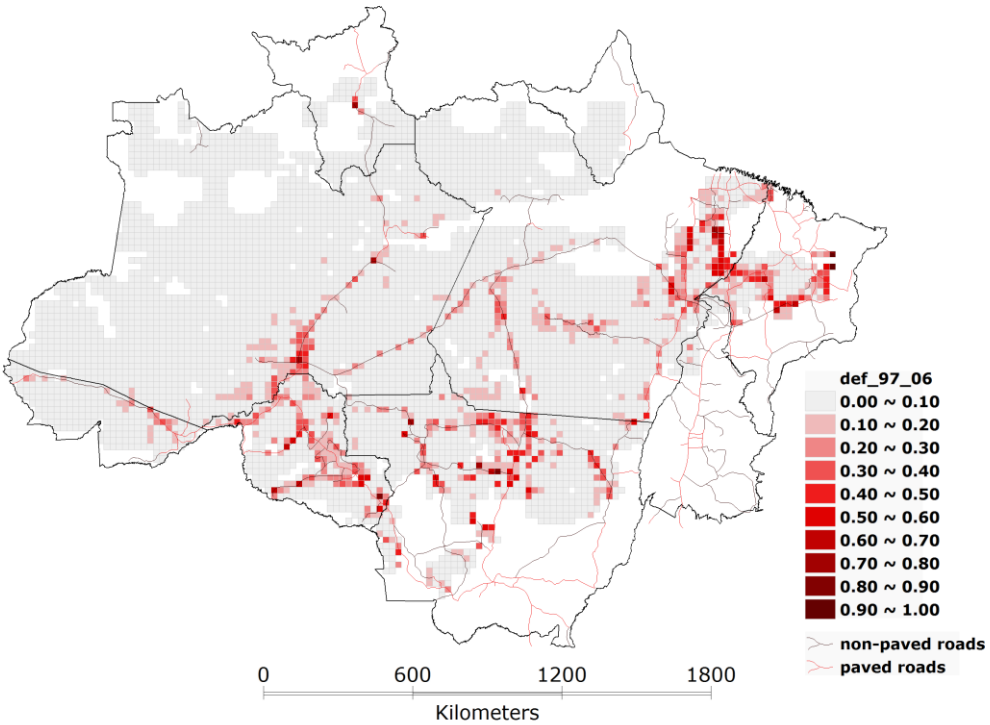

Figure 4-5: A2 – Deforestation (change) from 1997 to 2006 (fraction of cell area)

Analysis B

The models B1 (Figure 4-6) and B2 (Figure 4-7) apply regression models including the wetness index and the seasonality index from CPTEC-PVM and slope and altimetry variables. In addition to the environmental variables a connection to markets measure is used at the fine scale as in Analysis A. The consequence is that deforestation remains at a low level in the states of Roraima, Amapá and Acre, due to their distance to national markets in the south-east and north-east. In states which are better connected to these markets, deforestation is allocated close to roads, e.g. in Mato Grosso and Rondônia. The outcomes are reasonable results in the mentioned states in consideration of the actual reference deforestation map (Figure 3-4). But apart from these desirable changes simulated deforestation patterns also exist in the state of Amazonas around Humaitá and along the BR-319, where only small changes in forest cover took place in this period.

The humidity variable has higher absolute standardized regression coefficient values in the coarse scale models of Analysis A than the wetness index in Analysis B and thus more influence in the regression models. This fact is not obvious when analyzing the results of the AmazonClueINPE model. The difference between using the wetness index or the humidity variable in the coarse scale models is quite small and hence influences the results only to a small extent. The resulting deforestation patterns are almost the same, only the intensity slightly differs. Probably the two environmental variables are in the coarse scale regression models not important enough to produce significant differences in the results of the AmazonClueINPE model for deforestation.

In the fine scale regression model used in Analysis B (25.B roads + connection to markets + environment) the environmental factors were not amongst the main determinants of deforestation. Hence the resulting spatial patterns are quite similar to the results of Analysis A, as they are mainly dominated by variables like distance to roads, connection to markets and the protected areas variable.

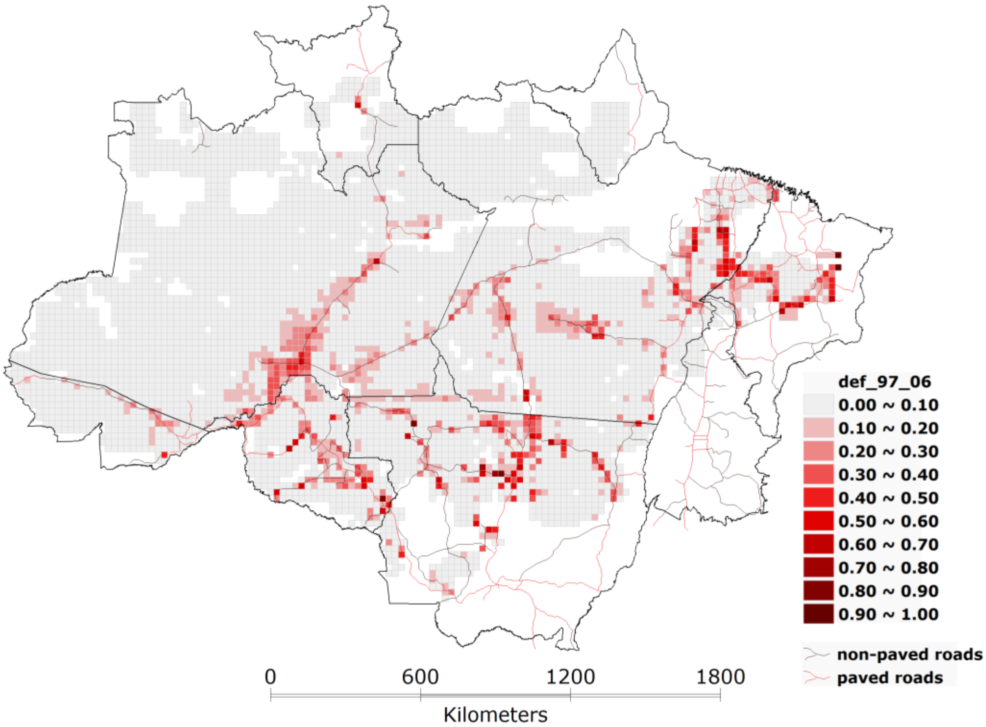

Figure 4-6: B1 – Deforestation (change) from 1997 to 2006 (fraction of cell area)

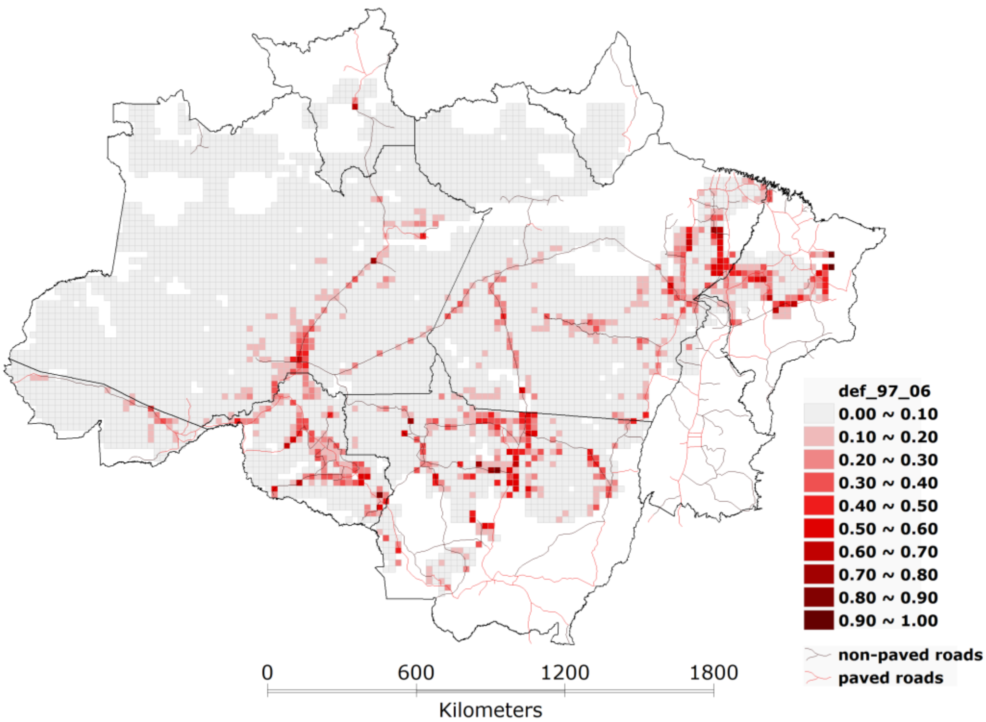

Figure 4-7: B2 – Deforestation (change) from 1997 to 2006 (fraction of cell area)

Analysis C

In Analysis C at the fine scale the seasonality index is included in the regression model of model C1 (Figure 4-8) and all environmental variables are included in the regression model of model C2 (Figure 4-9). Due to the exclusion of the connection to markets measure, deforestation is allocated in the more remote areas of the Brazilian Amazon, namely the states of Roraima, Amapá and Acre, which leads to an underestimation of land-use change in Mato Grosso, Pará and Rondônia. Comparing model C1 and C2, it can be noticed that even more concentrated deforestation patterns exist around the BR-319 road in Amazonas state in C2. Neither the humidity variable nor the seasonality index show enough strength in the regression models to limit deforestation in this area, as areas with a drier climate exist for example in Mato Grosso or Rondônia. Considering the analysis of the regression results (section 4.2.1) it was assumed that the effect of adding the slope and the altitude variable would not bring major changes in the results of the AmazonClueINPE model because these environmental variables were not among the main land-use determining factors. Comparing the dynamic modeling results of Analysis C no major changes due to the inclusion of environmental variables can be detected, as distance to roads and the protected areas variable still serve as the major determinants of deforestation in C2. Hence the inclusion of the environmental variables does not lead to the generation of new spatial deforestation patterns, only the intensity of land-use change slightly differs in some areas.

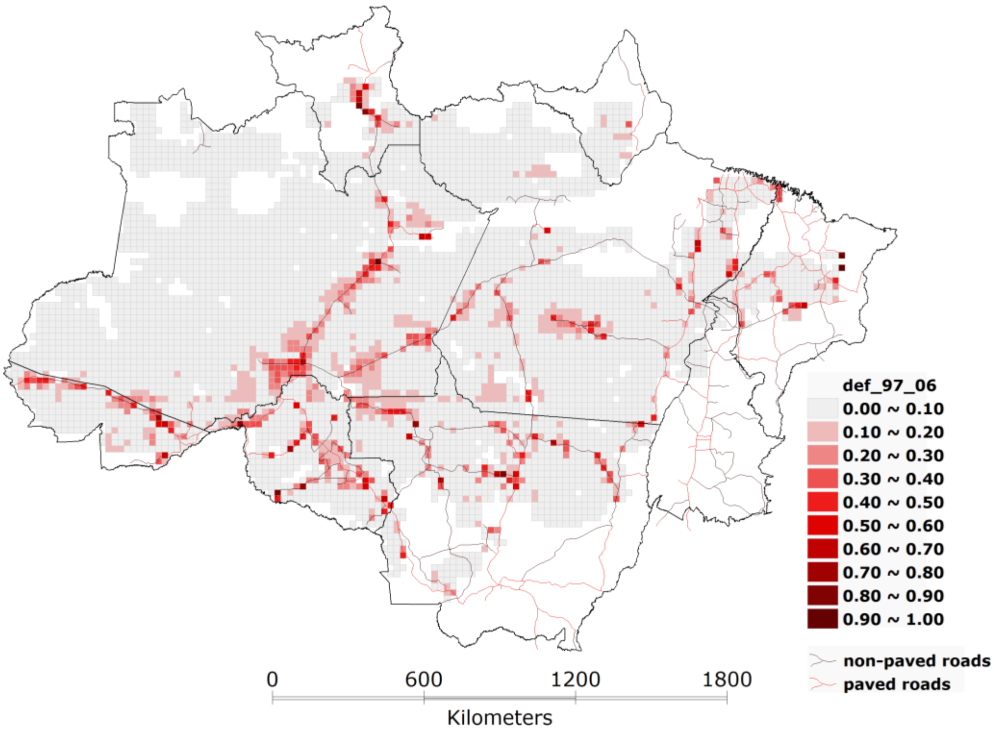

Figure 4-8: C1 – Deforestation (change) from 1997 to 2006 (fraction of cell area)

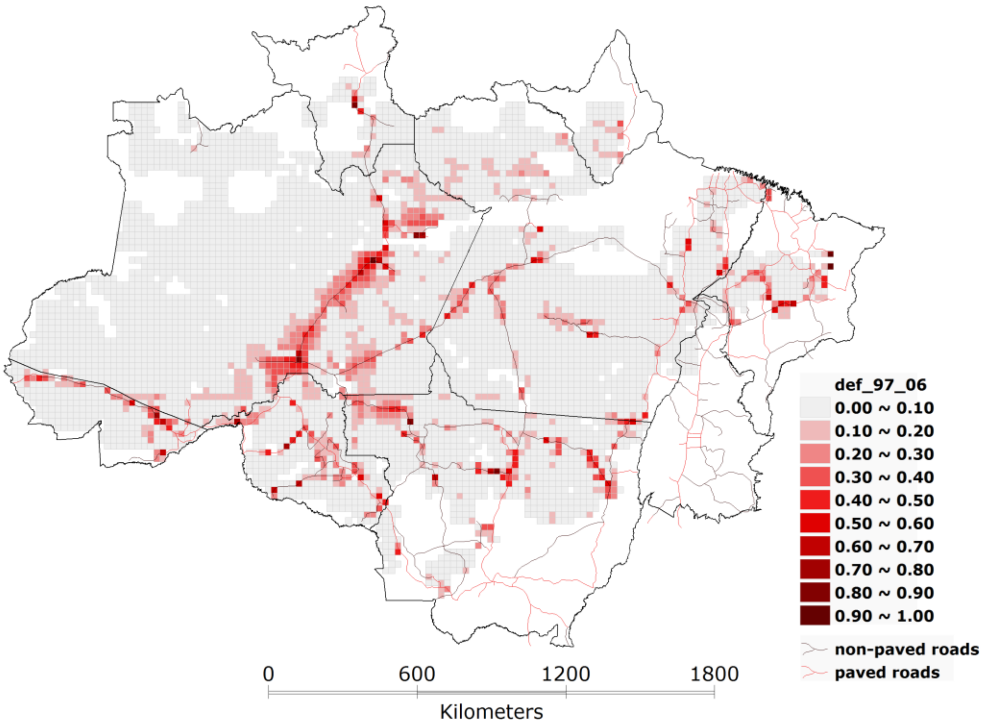

Figure 4-9: C2 – Deforestation (change) from 1997 to 2006 (fraction of cell area)

The results of the AmazonClueINPE model for deforestation cannot fully explain the role of the newly integrated environmental factors on the allocation of specific land-use changes. Hence the resulting patterns for pasture and temporary crops are analyzed separately to further determine the effect of environmental factors on the discrimination of pasture and temporary crops patterns.

4.2.2.2 Analysis of pasture and temporary crops patterns

Analysis A

The models in Analysis A serve as comparison to the models including the newly integrated variables in Analysis B and C to verify whether an improvement in explaining land-use patterns takes place.

The pasture patterns of model A1 (Figure 4-10) and A2 show only minor differences, as they use the same fine scale regression model, but different models at the coarse scale. The land-use type pasture increases in all states and does not show any decreasing patterns in this period. Compared to the pasture reference map (Figure 3-6), which is based on the agricultural census, too little change is allocated in eastern Para, northern Mato Grosso and Rondônia. This corresponds to the analysis of deforestation patterns for these models in the previous section.

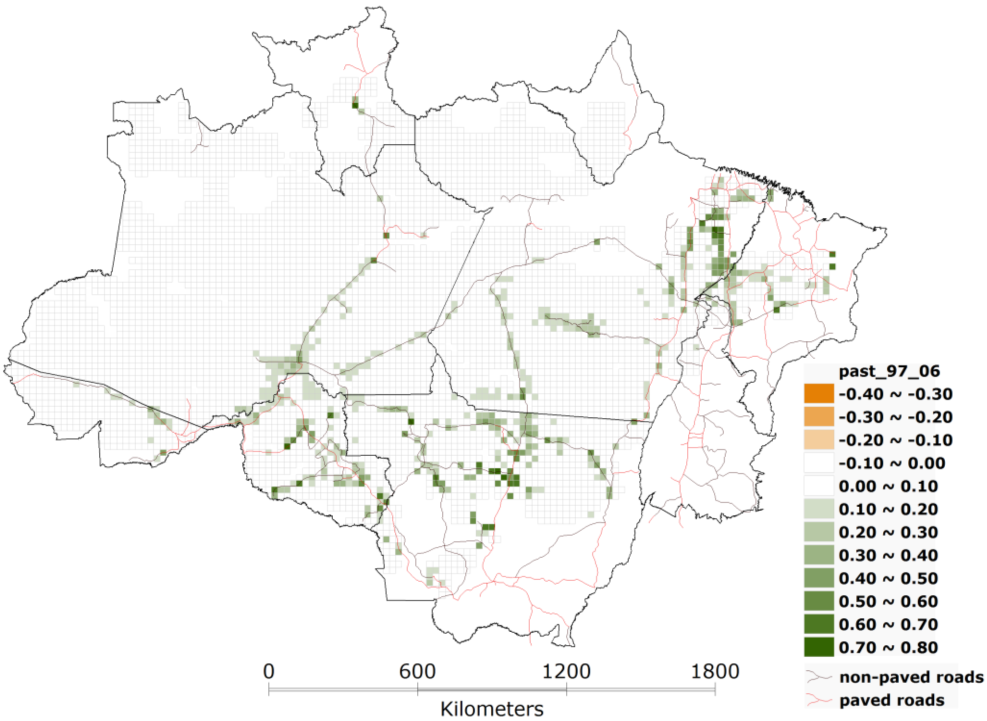

Figure 4-10: A1 – Pasture (change) from 1997 to 2006 (fraction of cell area)

The temporary crops patterns of the models A1 (Figure 4-11) and A2 cannot capture the increasing pattern in Mato Grosso. The change allocated in this state shows decreasing values. On the contrary temporary crops are favored in Rondônia and Amazonas state. Increasing spatial patterns can also be found in north-eastern Pará and Maranhão.

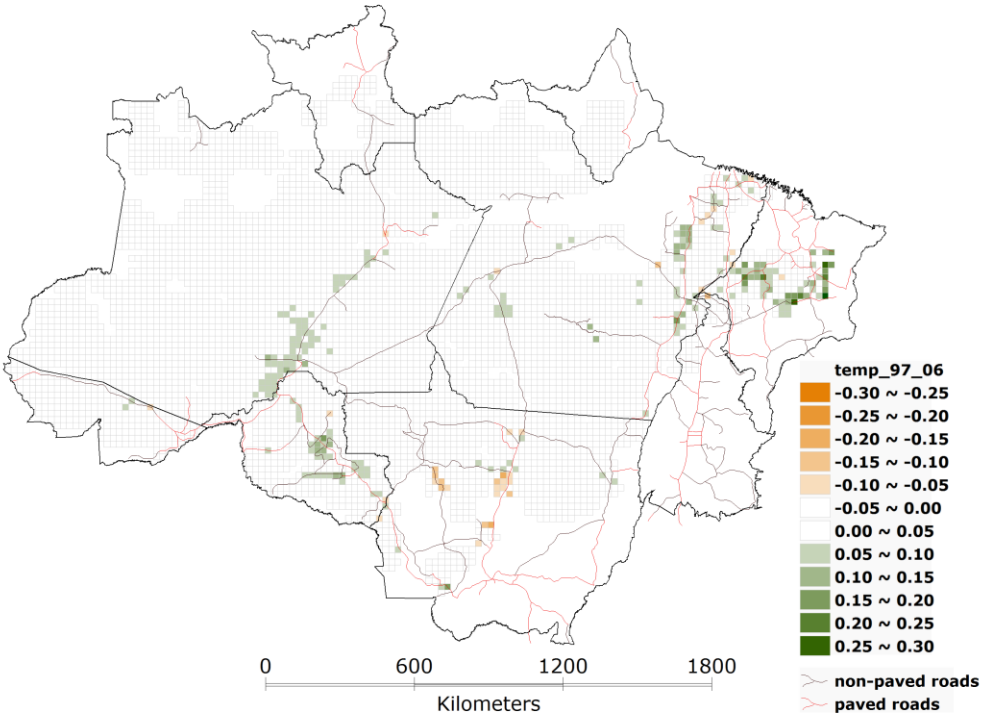

Figure 4-11: A1 – Temporary crops (change) from 1997 to 2006 (fraction of cell area)

Analysis B

The wetness index and the seasonality index from CPTEC-PVM and the slope and altimetry variables are included in the regression models used in Analysis B. For the land-use type pasture the regression model 25.B roads + connection to markets + environment showed only minor standardized regression coefficients for the altitude and the slope variables. The seasonality index was not significant and therefore had to be excluded. Hence the spatial pasture patterns of model B1 (Figure 4–12) and B2 do not significantly differ from the patterns in Analysis A.

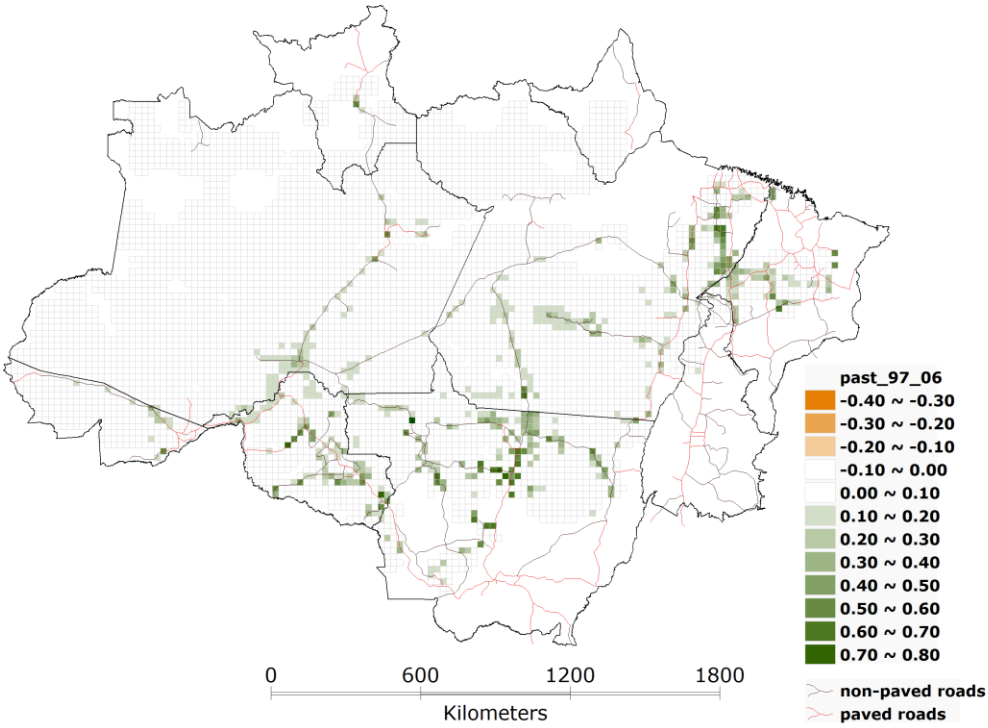

Figure 4-12: B1 – Pasture (change) from 1997 to 2006 (fraction of cell area)

For the land-use type temporary crops the altitude and slope factors were not significant in the used fine scale regression model 25.B roads + connection to markets + environment. In comparison to the other factors the seasonality index had a relatively small absolute Beta value. Hence the differences between the spatial outcomes of model A1 and B1, respectively A2 and B2 are marginal. They again show the increasing spatial pattern around the southern part of the BR-319 road in Amazonas state as well as decreasing patterns in Mato Grosso.

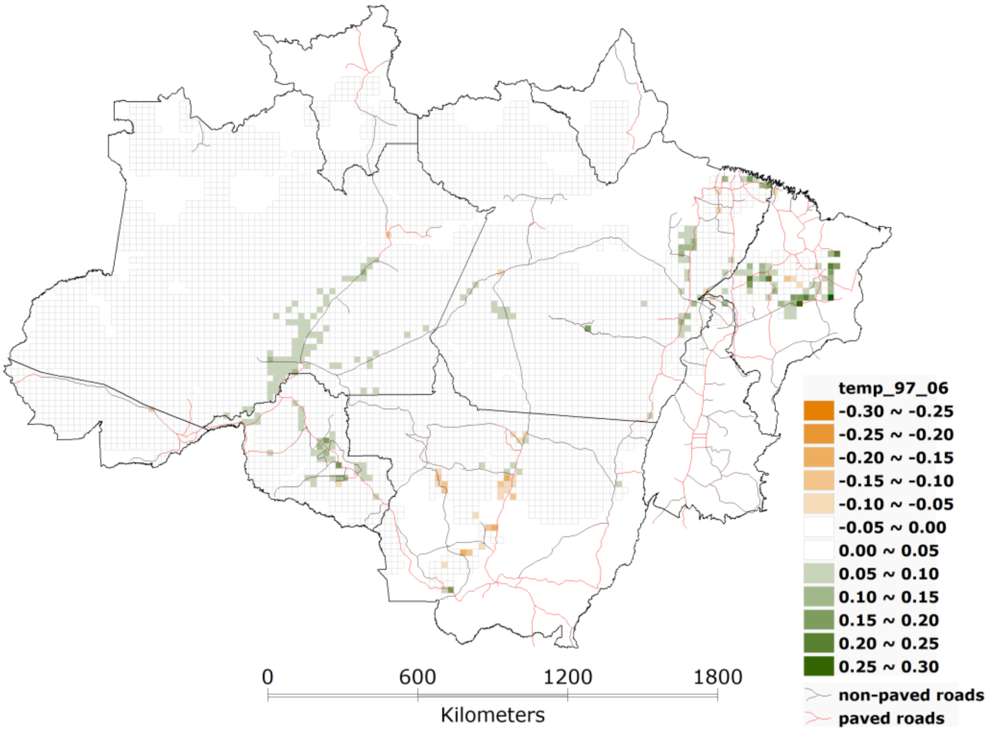

Figure 4-13: B1 – Temporary crops (change) from 1997 to 2006 (fraction of cell area)

Analysis C

The increasing spatial pattern around Rio Branco in Acre in the pasture reference map (Figure 3-6) is not correctly reproduced by the models C1 (Figure 4-14) and C2 (Figure 4-15). The models show an increase in pasture in this area, but more along the BR-364 road spreading westwards towards the Peruvian border than around Rio Branco itself. In Amazonas state the importance of the BR-319 road is overestimated, similar to the results of previous models. Apparently some modification of the models or the land-use determining factors in this area needs to be incorporated to diminish this effect. Comparing the two models, C2 allocates significantly more pasture in Amazonas state as model C1, as can be seen in Figure 4-17. In Rondônia the models show a significant pasture increase concentrated along the roads, while the pasture reference map shows a widespread pattern in almost the whole state, apart from an area in the west of the state. The positive pasture change in Mato Grosso state is to some extent captured by the models, but again it does not show the diffusive character visible in the reference map in the north of the state. In central Mato Grosso, where the census data shows a decrease in pasture, no decline is simulated in the models C1 and C2. In Pará the models show some increasing pasture patterns along the BR-163 road, but no distinctive pattern as in the census map. Also the spatial patterns concentrated along the BR-230 are, apart from some changes close to the BR-163 in model

C2, not captured by the models. The spatial patterns in the area around São Félix do Xingu in Pará are limited to areas close to roads, a possible spreading northeastwards as shown in the reference map is possibly suppressed by the protected areas in this region and the importance of the corresponding variable in the regression models.

There is a discrepancy in the amount of land-use change between the AmazonClueINPE model results and the census reference map, as the AmazonClueINPE model uses fixed demand ratios based on the agricultural census of 1996. Thus the relative change per state in terms of total amount of land-use change in Legal Amazon is calculated and compared. Figure 4-16 confirms the overestimation of change of land-use type pasture in the time of study in the state of Amazonas, which accounts for 24% (model C1) and 34% (model C2) of the overall pasture change in the Legal Amazon, while the census data shows only an increase of 5%. In Pará, Rondonia and Mato Grosso too little change is allocated, compensating for the surplus in Amazonas. The other states consist of too few cells to make an assumption.

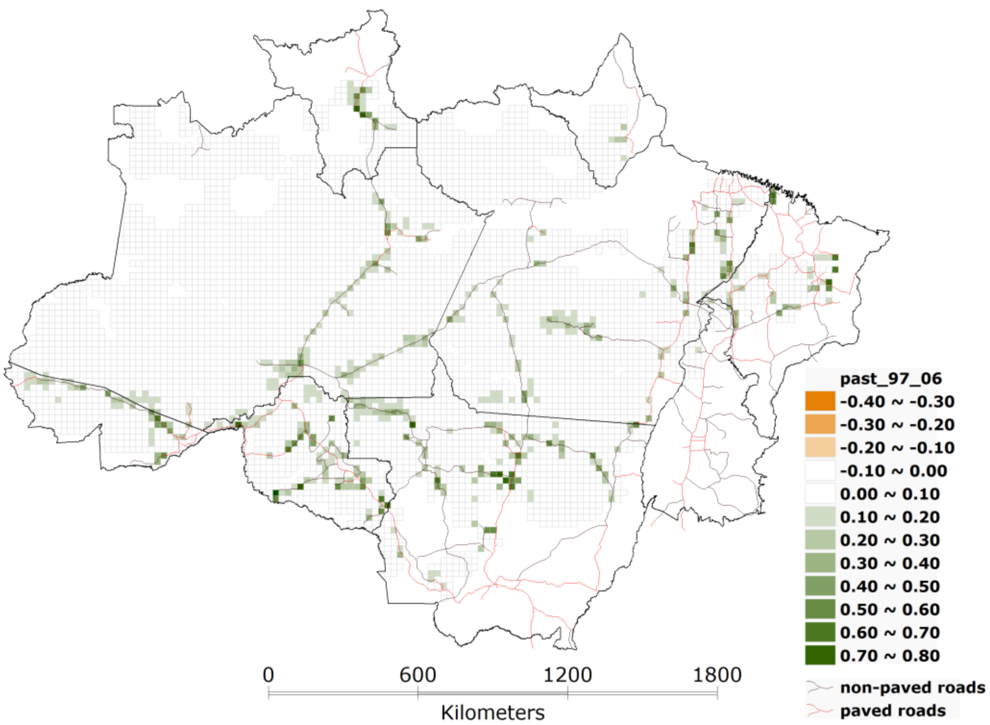

Figure 4-14: C1 - Pasture (change) from 1997 to 2006 (fraction of cell area)

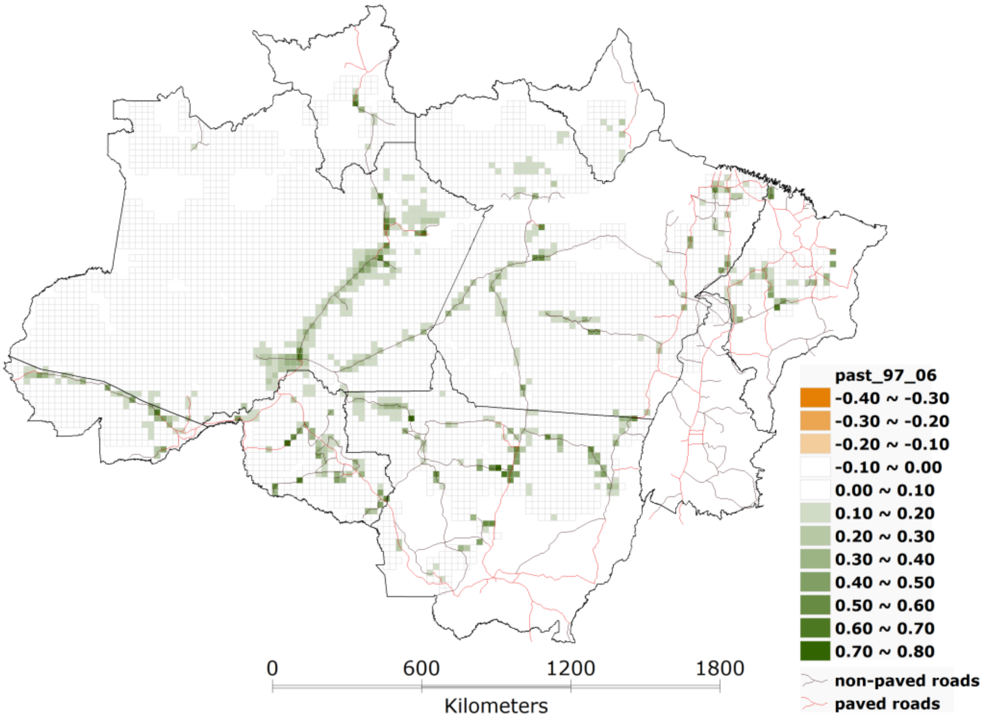

Figure 4-15: C2 - Pasture (change) from 1997 to 2006 (fraction of cell area)

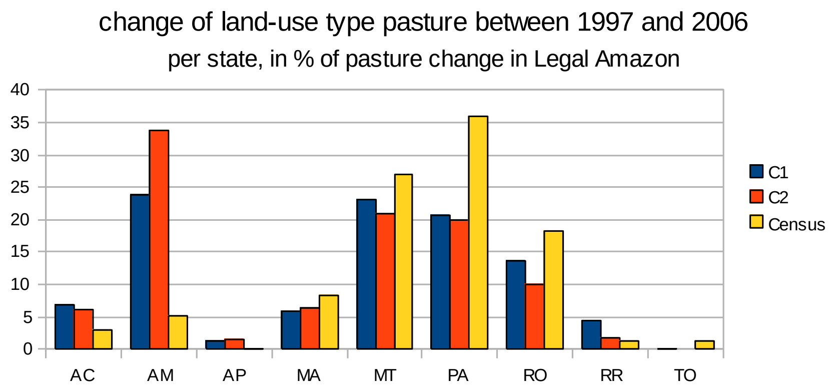

Figure 4-16: Pasture (change) per state between 1997 and 2006

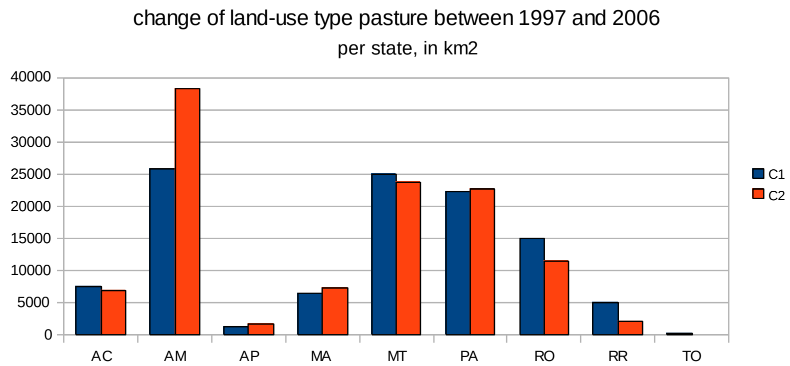

Figure 4-17: Pasture (change) per state between 1997 and 2006

In the census reference map for the land-use type temporary crops (Figure 3-8) two clear spatial patterns are visible. The first one is located in Mato Grosso and shows an increase in temporary crops for the period of 1997 to 2006, while the other one in Maranhão shows a decrease in temporary crops. These two distinct processes are not captured by the models C1 (Figure 4-18) and C2 (Figure 4-19). Both models show a general increase along the BR-319 road in Amazonas state and in Rondônia, but also some decreasing temporary crops patterns in central Mato Grosso. Comparing the land-use changes per state (Figure 4-20), it can be seen that model C2 allocates more change of temporary crops in Mato Grosso than model C1. The results of model C2 show some positive land-use changes in the north-east and the south-west of this state.

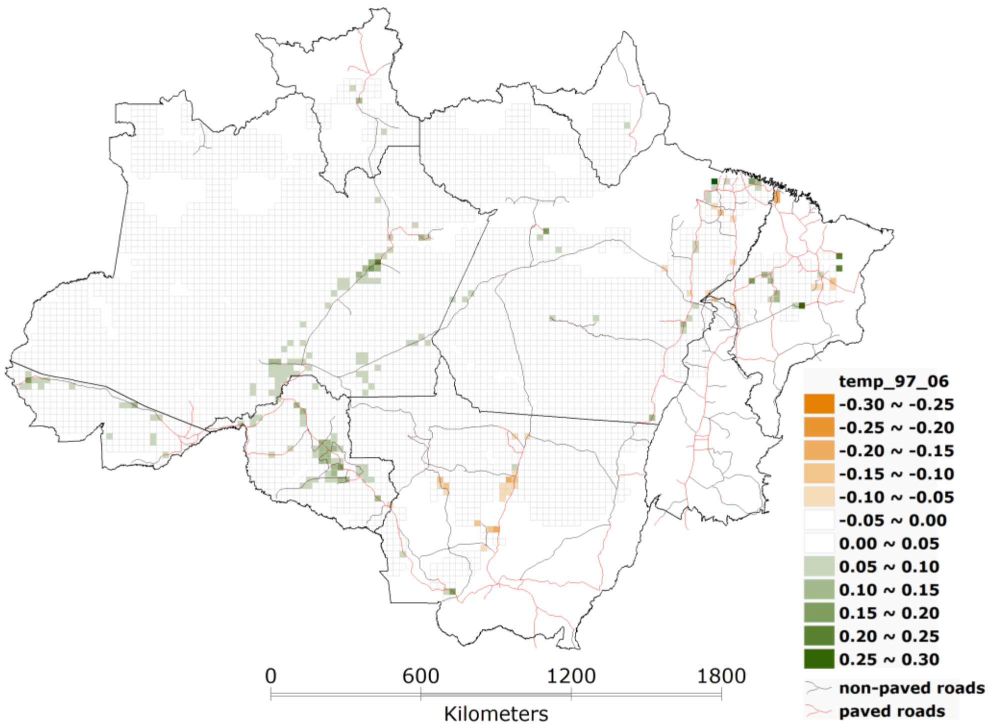

Figure 4-18: C1 - Temporary crops (change) from 1997 to 2006 (fraction of cell area)

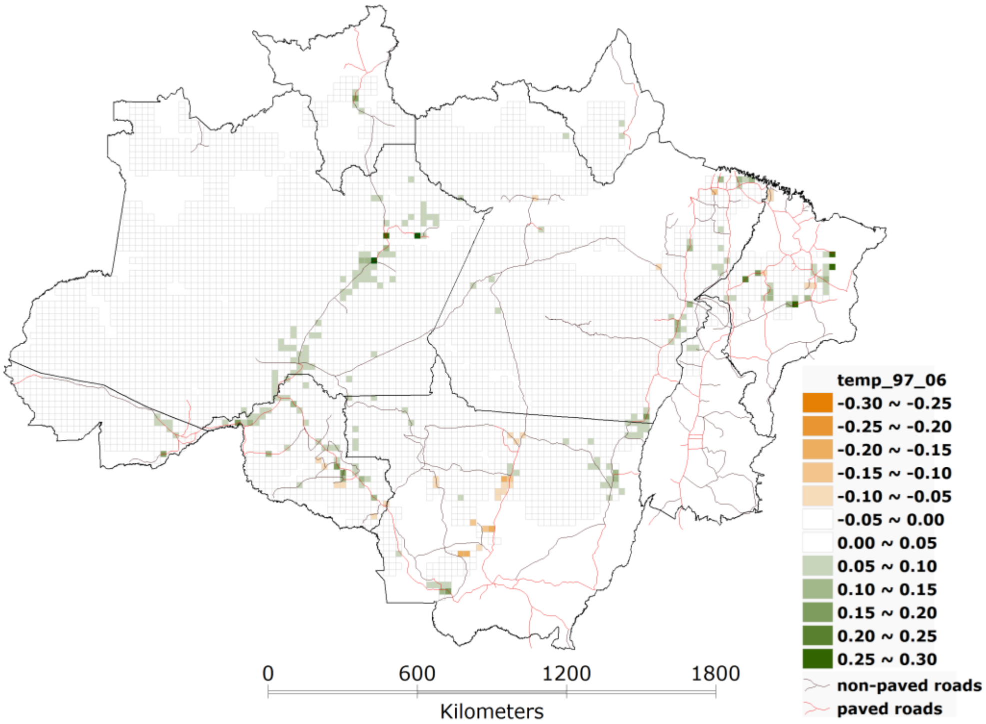

Figure 4-19: C2 - Temporary crops (change) from 1997 to 2006 (fraction of cell area)

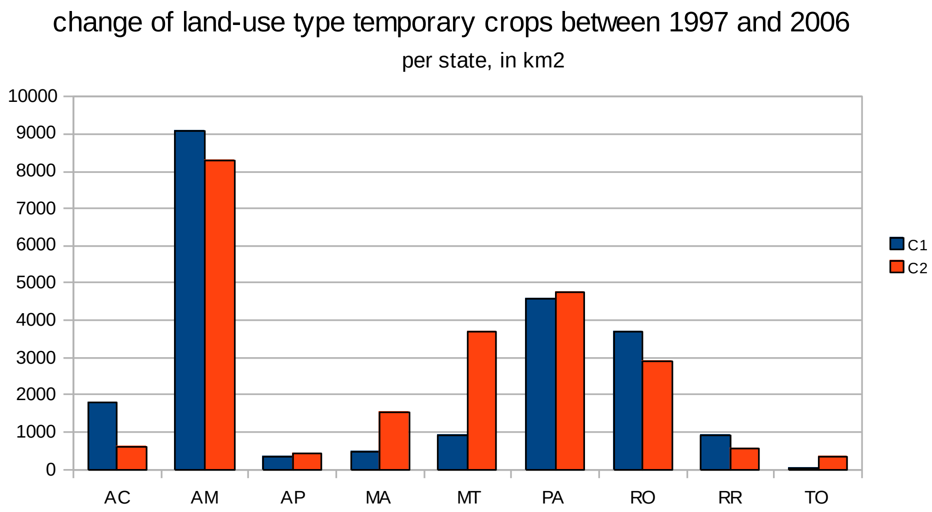

Figure 4-20: Temporary crops (change) per state between 1997 and 2006

4.3 Discussion

The implementation of the CPTEC-PVM in the TerraME modeling framework allows the integration of additional environmental factors in the AmazonClueINPE model. The consideration of supplementary biophysical parameters for slope and altimetry adds further possibilities to explore different factor combinations. The statistical analysis investigates the role of several variables and especially the importance of the environmental factors on land-use change processes. These statistics reveal that the environmental variables are in general not amongst the main land-use determining factors in the Brazilian Amazon. The seasonality index, which originates from the water balance model of the CPTEC-PVM, the humidity variable and the altitude variable build an exception and show relevant contribution especially for the land-use type temporary crops, if the connection to markets measure is not considered. The defined regression models serve as basis for the spatially-explicit AmazonClueINPE model. This dynamic modeling approach allows further exploration of the potential land-use determining factors. The objective is to distinguish the effect of the environmental variables in the allocation process of pasture and temporary crops changes.

The results of the AmazonClueINPE model indicate that the inclusion of the additional environmental variables does not result in major differences in deforestation patterns compared to models that do not use these variables. Analyzing the land-use types pasture and temporary crops it can be noticed that different regression models promote better or worse conditions for a land-use type in a specific region, depending on which variables are included. To some extent the pasture patterns can be reproduced by the models, but the temporary crops patterns cannot be predicted correctly. This statement holds for the tested models, no matter whether the new environmental variables are included or not. Hence no improvement in the discrimination of pasture and temporary crops patterns due to the inclusion of new environmental factors can be stated.

Nevertheless the integration of slope and altimetry data and environmental variables like the wetness index, the seasonality index or the humidity variable is capable of giving additional information on the formation of spatial patterns of land-use change, even though they do not show the explanatory power that other more dominant factors like distance to roads or connection to markets demonstrate.

Although the results do not promote an improvement through the inclusion of the new variables, the implementation of the CPTEC-PVM in the dynamic modeling environment can be seen as an important step, as it establishes new interaction possibilities to land-use change models like AmazonClueINPE or other models written in the TerraME modeling language.

Thus future work on improving the AmazonClueINPE model should also consider the use of these variables.

5 Conclusion

After a short summary of the results of this thesis, the hypothesis will be evaluated, followed by a general discussion and an outlook on possible future work.

5.1 Summary

The hypothesis of this thesis is the following.

The inclusion of hydrological, slope and altimetry variables improves the ability to discriminate pasture and agriculture patterns in the Brazilian Amazon.

This hypothesis was tried to be corroborated by feeding a multi-scale LUCC model with data from a water balance model, SRTM and other data. Various combinations of regression models at two scales were tested to draw conclusions about the influence and explanatory power of each of the used factors. The results from Chapter 4 are shortly summarized below.

By following an AmazonClueINPE model test plan the statistical models were tested in a dynamical modeling approach. The preliminary regression analysis revealed that some factors like protected areas, distance to roads, distance to urban areas or connection to markets determine most of the deforestation patterns, in accordance to what was previously found in Aguiar et al. (2007). The seasonality index also has important character, especially for the land-use type temporary crops. At the fine scale, models led by the distance to roads variables were used instead of the distance to urban areas variable, as these produced more reasonable spatial patterns. The connection to markets measure showed to be a good factor to limit patterns to emerge in remote areas. Interchanging the humidity variable and the wetness index at the coarse scale did not reveal major changes in the model results.

For a better understanding of the role of the seasonality index, the wetness index and the new biophysical variables the spatial patterns of pasture and temporary crops were analyzed. The pasture patterns were to some extent correctly predicted by the AmazonClueINPE model simulations, while the temporary crops patterns could not be reproduced. The results intensify the assumption that some sort of overestimation of land-use changes in the state of Amazonas takes place in most models. This may be explained by the importance of the distance to roads variables in all models and the fact that the BR-319 is currently in bad condition and for the most part not viable for transportation purposes (Fearnside & Graça 2006). However, the models show the potential for new deforestation areas to emerge as Barni et al. (2009) point out, according to governmental plans to reconstruct this connection. The spatial outcomes of the AmazonClueINPE model also indicate that the resulting patterns are dominated by factors like accessibility to markets, distance to roads or presence of protected areas and only to a smaller degree by the slope, altimetry and other environmental variables. However the newly integrated variables influence the AmazonClueINPE model results, but their explanatory power is rather small in comparison to the dominant factors.

5.2 Hypothesis

Statistical Analysis results in Chapter 4 showed good explanatory power of some environmental variables to discriminate temporary crops from pasture patterns at the scale of analysis. However, on basis of the dynamic modeling results no improvement in the projected patterns of pasture and temporary crops was obtained solely considering the seasonality index or the altimetry and slope variables. Dynamic modeling results are similar, due to the larger impact of other determinant factors, mainly related to connectivity and accessibility.

Nevertheless integrating a combination of hydrological and biophysical data is thought to be a good and reasonable asset in the modeling approach to study land-use type conversions. Albeit these variables do not act as the main determinant factors they can support LUCC model simulations to discriminate pasture and agriculture patterns.

5.3 Discussion and Outlook

5.3.1 Statistical analysis

Several assumptions are usually made when using conventional statistical methods like multiple linear regression, e.g. data should be statistically independent and identically distributed (Cliff & Ord 1981; Overmars & Veldkamp 2003; Lesschen et al. 2005; Aguiar

2006). These assumptions cannot be fully satisfied by LUCC models, as land-use data usually has the tendency to be autocorrelated (Overmars & Veldkamp 2003; Aguiar 2006). This spatial dependence is on one hand undesirable, but is also what gives information on spatial pattern (Gould 1970; Overmars & Veldkamp 2003; Aguiar 2006).

As it is fairly common that collinearity exists in land-use analysis, it is difficult to separate the effects of each variable (Lesschen et al. 2005). As a way to reduce collinearity in this thesis a correlation analysis between the independent variables and a stepwise regression has been applied. Though this procedure might eliminate important factors, it is expected to be capable of selecting an adequate subset of variables through disregarding of non significant variables (Lesschen et al. 2005).

Aguiar (2006) tested a spatial lag model to simulate deforestation in the Brazilian Amazon and compared it to a multiple linear regression model. The findings were that by using the spatial lag model the resulting model allocates land-use changes mainly in previously occupied areas and thus prohibits the appearance of new patterns. Therefore the linear regression model was favored, while incorporating the diffusive nature of deforestation through scenario-dependent variables like distance to roads or connection to markets. Based on these conclusions by Aguiar (2006) it was decided to use a multiple linear regression model in this thesis.

5.3.2 Data Quality

The connection to markets measure proved to be a good factor to limit patterns to emerge in remote areas, but have to be further improved as already mentioned in Aguiar (2006). The connection measures should also incorporate river networks. In addition to this the distinction between paved and non-paved roads is not sufficient. Quality of roads or waterways has to be incorporated as a proxy for the usability of a connection to get better measures for travel and transportation costs.

The CPTEC-PVM and its corresponding water balance model were initially developed for global purposes with a coarser resolution than used in this thesis. Thus the question arises if seasonality- and wetness index fed with detailed meteorological data are also feasible for finer resolutions or if better estimates for hydrological processes and regional climate exist for studies covering the Brazilian Amazon.

5.3.3 Regional models – local studies

Regarding Lesschen et al. (2005) the scale of modeling has an effect on the type of pattern that will occur. Zhang et al. (2004) add that correlations found at one scale might not be applicable at another, as different processes are primarily dominant at different scales. Thus the question can be asked if the applied spatial scales and factors in this thesis are suitable to model deforestation processes in the study area. To simulate processes in large areas like the Brazilian Amazon with one set of regressions, assuming that the same factors are important everywhere, is an ambitious challenge. The region is probably too diverse to be represented by one model, thus intra-regional heterogeneity should be taken into account (Aguiar 2006). Local studies and regional models both have their individual strengths, thus both types of land-use analysis approaches can strongly benefit from one another. They do not only differ in the size of the study area, but also often in the methods used to simulate land-use change processes. Geist & Lambin (2001) mention that a systematic comparison of local-scale case studies is a powerful tool to extract generalities on processes and causes of land-use change and provides more realistic insights than cross-national statistical analyses. The AmazonClueINPE model as applied in this thesis allows for a comprehensible way to model land-use change processes with the help of a set of factors, based on statistical relations between them, without the necessity of expert knowledge, but not leading to the explanatory power that some local studies might reveal. Being aware of the strengths and limitations of the utilized methodology is essential to correctly evaluate the results of LUCC modeling studies.

5.3.4 Outlook

The most important factors to correctly capture deforestation, pasture and temporary crops patterns are connectivity and accessibility factors. Future work should focus on improving such measures, considering for example different market chain connections (beef, soybeans), as pointed out in Aguiar (2006), besides integrating the combination of hydrological and biophysical variables discussed in the present thesis. Further improvement could be reached by optimizing the regression models for each land-use type with the help of expert knowledge and using the more recent IBGE Agricultural census information. Temporary crops regression analysis, for instance, should differentiate small scale agriculture, which was dominant in 1996, from large scale, highly mechanized agriculture, practiced currently specially in Mato Grosso (Aguiar et al. 2007).

To further test the AmazonClueINPE model based on the data used in this thesis, one possibility would be to adapt the land-use classes of the agricultural census 1996 to exclude the non-used agricultural areas and change the demand values based on yearly PRODES deforestation data and the census data from 2006 to allow for quantitative comparison between the model results and the data.

The implementation of the CPTEC-PVM and its corresponding water balance model in the TerraME modeling environment opens new possibilities to study the interaction between climate, vegetation and LUCC models like the AmazonClueINPE model. Future studies could investigate the benefit of dynamic coupling of these models.

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