MODIS for Monitoring Forest Degradation in the Republic of Congo

Master Thesis for completing the Masterstudy of Geodetic Science

08.05.2011

Martin Christoph Unterberger
martin@vub.at

Institut für Fernerkundung und Photogrammetrie, TU Graz

DIGITAL - Institut für Informations- und Kommunikationstechnologien, Forschungsgruppe Fernerkundung und Geoinformation, Graz

Supervisors:

Mag. Dr. Manuela Hirschmugl
Prof. Dr. Mathias Schardt

Abstract

In the worldwide effort to mitigate human induced climate change, Reducing Emissions from Deforestation and Forest Degradation (REDD) represents an instrument of avoiding, monitoring and quantifying cutting activities in tropical rain forests. According to Deforestation and Forest Degradation around 17 % of all greenhouse gases are emitted to the atmosphere. REDD offers financial compensation for countries willing and able to avoid emissions through wood cutting. For these payments carbon quantification based on remote sensing data sets is needed. On the one hand there is deforestation which is detectable since decades, on the other hand the development of methodologies for degradation monitoring is still quite young. This diploma thesis investigates the capacity of the NASA satellites of MODIS (Moderate-resolution Imaging Spectroradiometer) within a REDD project area in the North of the Republic of Congo. MODIS provides coarse resolution data sets in a high temporal resolution. Therefore, mainly methods of Time Series Analysis are investigated. Landsat images serve as visual groundtruth. This study has shown that it is impossible to detect Selective Logging patterns within MODIS data sets. Although the data sets are daily available, it proved impossible to exctract enough pixels without cloud, cloudshadow or aerosol obtruction. The study failed on this fact, which is common in tropical rainforests, with high moisture levels throughout the year.

Acknowledgment

Many people attended me on my way to this work and to complete my studies at university. I want to express my earnest thanks to:

- Prof. Dr. Mathias Schardt, who gave me the idea for this work and also the possibility to work in the scientific ambiance of Joanneum Research, Institute of Remote Sensing and Image Processing.
- Dr. Manuela Hirschmugel, my technical supervisor, who guided me through the challenges of writing a scientific piece of work.
- All my mates during six years of university. Without you, I would still be studying for some basic exams.
- Inge and Erwin, my parents, who gave me all possible support and encouragement to study at university.
- Teresa, my girl friend and best mate, who teaches me to look peacefully into the world.
- Valentin, my son.

Declaration

I declare at this point that this thesis is my original work, written only with the use of documents which are listed in the bibliography.

Graz, 8th May 2011

Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Background

According to the fourth Assessment Report of the United Nations Intergovernmental Panel on Climate Change (IPCC) [23] deforestation and forest degradation contributes around 17 % of all global greenhouse gas emissions, which is more than the transport sector. Number one in producing greenhouse gases is global energy production with 25 %, number two the whole industrial sector. Tropical forests cover around 15 % of the earth's surface and contain around 25 % of all carbon in the terrestrial biosphere. About 13 million hectare of forest are cut down every year. This is equivalent to an area twice the size of France. Mainly forest is converted to agricultural land or used for human infrastructure [13]. Forests are the worlds biggest CO_2 storage on the land surface. Photosynthesis is a biochemical process, which converts carbon dioxide with the aid of water into different types of sugars. This process is driven by the power of sunlight. One of these sugars is cellulose, which is the main structural component for the cell walls of all green plants. Cellulose is the most common organic compound in the world. Carbon dioxide is considered to be the primary cause of human induced climate change. If a forest is degraded by fire-clearing, the CO_2 is emitted immediately into the atmosphere. In comparison, other uses of wood tend to emit CO_2 more slowly. A lot of carbon dioxide is stored in the soil of forests. This CO_2 mitigates to the atmosphere as well. Microorganisms convert this CO_2 and release it to the atmosphere. This process is accelerated by direct solar radiation after tree removal [1].

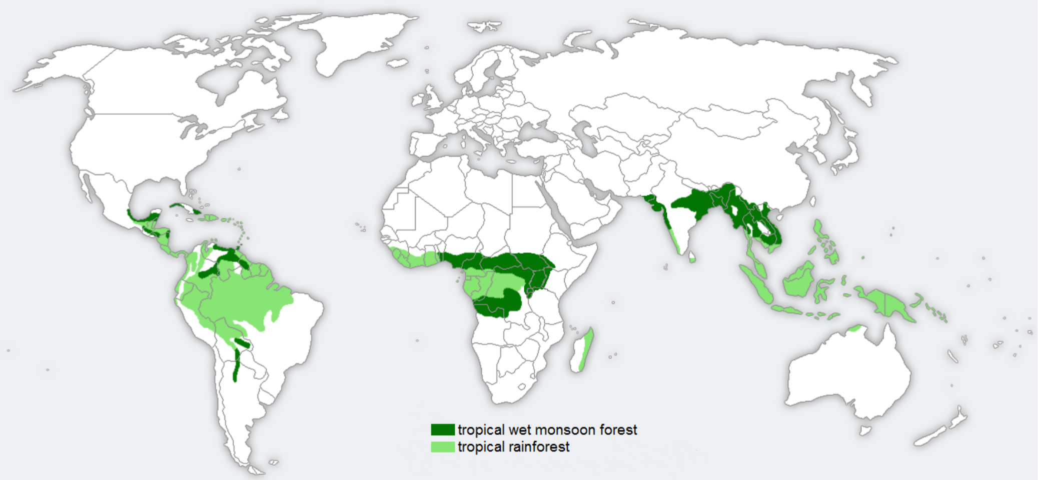


Figure 1.1.1: Spreading of tropical rain forest

Map source:

http://upload.wikimedia.org/wikipedia/commons/0/06/TropischeRegenwaelder.png

1.2 The REDD initiative

REDD is an acronym for Reducing Emissions from Deforestation and Degradation [32]. It is embedded into the United Nations Framework Convention on Climate Change (UNFCCC). The idea behind REDD is the creation of rules and mechanisms for developing countries to protect their forests and promote sustainable use of their forest resources. This is done in the context of the effort against human induced climate change. The aim is to make it more valuable in a monetary sense to leave forests untouched rather than to cut them down. This is done by creating a financial value for carbon stored in the trees. After quantifying the stored carbon, the final phase of REDD involves developed countries paying developing countries for leaving their forests intact. Norway is the first and largest financial donor of the UN-REDD Programme haveing contributed more than 80 million US dollar between 2008-2010. Of course many other countries have also contributed to the initiative. REDD field works take place in forests around the globe.

Monitoring systems are necessary to quantify deforestation as well as regeneration of rainforests. From these quantifications, CO_2 magnitudes of certain areas or forest cuts are derived. In addition to the carbon storage, which plays a role in climate change, forests contribute in many other ways to the living conditions on the earth. Healthy forests store water and protect the soil from excess sun. They provide habitat for animals and plants domiciled there.

1.3 Definition of Forest Degradation

Forest degradation is any decrease of canopy cover or biomass density in a forest through a given time period [19]. The Marrakesh Accords of the Kyoto Protocol [38] provide an agreement on the definition of "forest". Parties should select a single value of crown area, on tree height and area to define a forest within their national boundaries. The values have to be chosen within the following ranges, acccording to the Marrakesh Accords [38]:

- Minimum forest area: 0.05 to 1 ha
- Potential to reach a minimum height at maturity in situ of 2-5m
- Minimum tree crown cover (or equivalent stocking level): 10 to 30 %

However, this is a wide definition making anything from 10 - 100 % tree cover a forest. To build up a monitoring system for degradation, the causes as well as the impact on the local forest ecosystem has to be known [3]:

- Selective logging
- Degradation for living purposes of local people (firewood, timber, conversion to agricultural land)
- Forest fires

1.3.1 Selective logging

This is a commercial timber cutting practice done by international timber companies. Only high quality timbers are harvested. The timbers are brought to rich import countries like many European countries. It needs infrastructure, like logging roads and logging decks in the forest of interest. Sometimes, local sawmills are constructed as well as big transport routes to connect the logging area to the public road or river network. This is necessary in order to be able to transport the logged timber to the next international harbor for export, either by lorry or by the rivers. The special logging procedure of helicopter logging is not very common, but shell be mentioned at this point for the reason of completeness.

Forests degraded by selective logging can be detected by various combinations of three environment types [35]:

- areas of undisturbed forest, which are not degraded at all, either due to a lack of expensive timber species or because of difficult and costly access conditions resulting from the local topography or transport infrastructure
- cleared forests for logging roads and logging decks, needed for the movement of the heavy equipment, for collecting and cleaning the wood and for transporting the timber on trucks
- forests with canopy gaps, as a result of selective tree-felling and extraction during logging operations

Selectively logged forests recover quickly, which leads to a limited timespan, in which the detection of such activities is possible through methods of remote sensing. However, even though the canopy gap of an old tropical tree is closed in the course of a few years, it takes decades or even centuries until the pre-logging status of timber amount and biodiversity is recovered at all. Certain tree species disappear forever, if they are removed systematically from a certain area of forest by selective logging.

1.3.2 Degradation for living purpose of local people

In contrast to the highly organized, mechanized and industrial degradation of selective logging, the degradation done by local people take place on a much smaller scale. In the surroundings of settlements, the populations need the forests for collecting wood for cooking, for construction purposes or for the production of charcoal. Sometimes forest is degraded to gain new areas for planting crops or feed animals. Most of these activities are limited to a few kilometers around the local settlements due to the fact that most african farmers do not have motorized vehicles to reach the forests and to bring the collected wood back home. Areas of forest are also clear-cut, to gain new and fertile grounds for cultivating crops or feeding animals. If a nearby forest has been recently commercially logged, the degradation by the local people is facilitated. Due to over-population even such small-scale degradation often exceeds the regenerative capacity of the forest, leading to a slow degradation process [24]. After the over-exploitation for fuel wood or other local uses of wood, the regeneration of the forests is often prevented by continuous animal grazing. However, these people do not degrade the forest for commercial purposes but only to get very basic materials for daily life.

1.3.3 Forest fires

This kind of degradation mainly happens during the recovery of commercial logged forests. An intact tropical forest shows a high rate of moisture throughout the year. The dense and closed canopy of an intact forests protects the surface below from drying. A constant level of water is stored in the forest through the whole year making the forest resistant to fire. Once the canopy is opened by selective logging, the soil as well as the plants which grow near to the surface are exposed to much higher rates of sunlight, possibly drying them out and making them more vulnerable to forest fires. Thus, these fires may open up gaps of selective logging and convert biomass to Greenhouse Gases [36].

1.3.4 Conclusion

For establishment of a monitoring system, which aims to map any kind of forest degradation, the main degradation type of interest is commercial selective logging. It leaves typical patterns of road networks and logging decks in previously untouched rainforests. In comparison to the degradation for living purpose of local people, the patterns of selective logging are large scale. As mentioned before, degradation by forest fires is a major consequence of commercial selective logging.

1.4 Hot Spot Mapping in REDD

The implementation of hot spot mapping in to the REDD framework should help to establish a worldwide monitoring system. Starting with coarse resolution data sets, containing only a low level of detail, the investigation of a certain area of interest is then continued with higher resolution data sets and may be finished with fieldworks to find out or validate the exact amount of degradation and CO_2 emission. The use of coarse resolution data sets brings several advantages in this context. These data sets cover larger areas than images of finer resolution, they are generally free of charge and also have high temporal resolution. An order of data sets for hot spot mapping in the context of REDD proposed by [3] is shown in table 1.1.

The question which arises in the context of MODIS and the present work is, whether degradation patterns in a tropical forest are detectable in MODIS data sets. In a second phase this area can be investigated in more detail by using other data sets of higher spatial resolution.

Sensor & resolution	Current missions	Costs	Utility for forest monitoring
Coarse (250 - 1 km)	MODIS, MERIS, SPOT-VGT	low or free	annual monitoring to locate hotspots for further analysis
Medium (10-60 m)	Landsat, SPOT, IRS	from \$0.02/km^2 to \$0.5/km^2	primary input to map and estimate area change
Fine ($<$5 m)	Ikonos, Quickbird, aerial photos	high \$2-30/km^2	validation of results, training, and detailed analysis

Table 1.1: Approach of Hot Spot Mapping

1.5 Objectives of the Present Thesis

Monitoring systems need frequent and reliable data input. For global applications, data sets from satellites are very common due to their capacity of measuring the whole globe in very short periods of time. The coarse resolution data sets of MODIS (Moderate-resolution Imaging Spectroradiometer) presented in chapter 3, a remote sensing mission of NASA, are investigated in the present thesis. In general, MODIS data are designed for monitoring whole countries or even continents. Especially short time dynamics of natural processes have been investiaged with MODIS data by the scientific community. [8] [12] [45] The applicability of the data sets for detecting and mapping selective logging in tropical rain forests is assessed. This is done in a project area in the north of the Republic of Congo in Central Africa. The present thesis aims to contribute to future operational REDD monitoring and is part of the Global Monitoring for Environment and Security (GSE) Forest Monitoring (FM) REDD extension programm of the European Space Agency (ESA). The basic aspects of this thesis are listed below:

- ≻ Description of the MODIS mission
- ≻ Preprocessing steps and MODIS data products
- ≻ State of the Art analysis
- ≻ Different temporal approaches of investigation
- ≻ Special focus on time series analysis

Chapter 2

Logging in the Republic of Congo

2.1 Geography and Project Area

The project area investigated in this work is located in the North of the Republic of Congo. The geographic situation is shown in figure 2.1.1. The project area is marked by the white polygon in the satellite picture of the figure. Its spatial extension is around 80x80 km.

Around 3,7 million people are living in the country. The country's area is around 342.000 km^2, at which 60 % is covered by rain forests. In comparison, the size of Austria is around 84.000km^2 and 47 % are covered by forest.

2.2 Climate

Due to the geographic location at the equator, a daytime climate is found in the country. A daytime climate is characterized by low temperature variations between the months and seasons of a year and by larger temperature variations within every single day. The length of day is quite stable throughout the whole year. An alternation of two dry seasons and two rainy season determines the climatic conditions through the year. During the rainy seasons obstruction of the surface by clouds is much more frequent than during the dry season. Therefore all studies shown in this work are based on satellite images taken during dry seasons. The primary dry season is from July to August, the secondary dry season from December to February. However, the images with least cloud obstruction have been made during the secondary dry season. This will be explained in detail in the chapter of results. It is well known that some tropical regions of Africa have been stongly affected

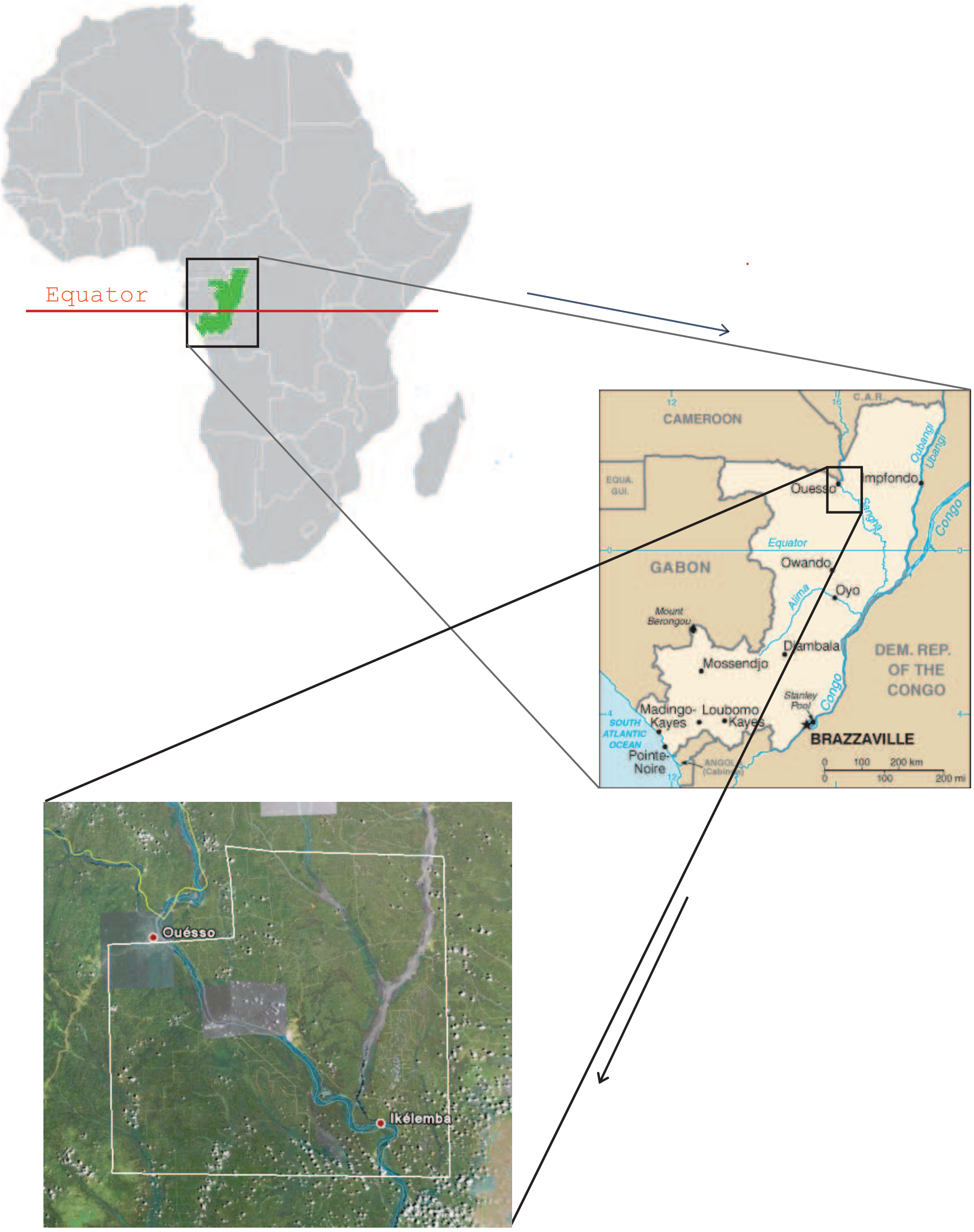


Figure 2.1.1: Geographic Situation,

Map source (edited):

http://en.wikipedia.org/wiki/Republic_of_the_Congo, www.transafrika.org and Goggle Earth by the global climatic change in the last years [22]. Every forest is part of a local water cycle, which serves, for example, as water storage. Especially in forest regions which have been clear cut, or logged within in the last years, these disturbances can cause tremendous changes on the local climate. It is possible that the project area is also affected by climatic changes, which might explain the comparatively unobstructed images in the secondary dry season.

2.3 Commercial Logging in RB Congo

In the Republic of Congo, timber export represents the second major source of export after oil. The forestry sector provides 10 percent of formal employment. In the second half of the 1980s, timber production grew consistently, attaining a total amount of 883,000 cubic meters in 1990 [15].
For better understanding, in Austria the annual amount of harvested wood is 20,000,000 cubic meters (www.proholz.at). Around 30,000,000 cubic meters grow back each year, leading to in fact total increase of living wood. However, the consequences for the local people and for the local biodiversity cannot be compared. In the Republic of Congo, logging is done in primeval forest. In Austria, there is no such untouched forest, all logging take place in planted, mostly monocultural forests. The primeval forests of Austria have already been cut in earlier times. However, in Austria it is possible to cultivate primeval-like forests. In tropical regions this is not possible. After removing an area of forest, the soil degrades very quickly, through intensive sun radiation and heavy rain. Once the soil is removed it is impossible to recultivate the original situation. The soil in Austria stays fertile, even if it is not protected by trees.

Especially the method of selective logging has significant impact on the local ecosystem. Roads are cut into primeval forests, and only certain tree species of commercial interest are cut out of the forest. The amount of harvested timber does not equal the amount of impact on the whole forest system, because large areas are affected by road construction and by the whole activity of wood working. Roads open the forest to animal hunters. Local people, like the Pygmies, who rely on the forest for game, other food and raw materials are threatened by these activities (on 'their' wood, where they never gave permission to). In some areas the trees are carried away by helicopters, which reduces the amount of logging roads.

After years of political wars (1995 - 2002), in which the timber production decreased, the government began to actively court multinational logging companies in order to accelerate the exploitation of the forests. After years of war, the country's infrastructure was too weak to produce the same amounts of timber as before the civil war. The European Union is the primary destination of the timber exports of Congo, with France, Germany, Italy, Portugal and Spain being the main importers. Outside the EU, the most important importer is Japan [15].

2.4 Logging Companies in the Project Area

For logging, the forests are divided into concession areas, which are sold to international companies for a number of years. A map of the concessions in the North of the country is given in figure 2.4.1. Concession areas number 11 and 13 are part of the project area of this thesis.

- Company of concession 13 (right area, red in the map): Congolaise Industrielle des bois (CIB), period of permission 1996 - 2011
- Company of concession 11 (left area, green in the map): Société Industrielle Forestière de Ouesso (IFO), period of permission 1999 - 2014

2.4.1 Congolaise Industrielle des Bois (CIB)

CIB is a subsidiary of Feldmeyer. Feldmeyer is a German timber company. Three concessions in the North of the country belong to CIB. The company exports around 100.000 cubic meters of logs each year. Before the civil wars CIB used to float its logs down to Brazzaville. It was then transported to the Atlantic coast per rail, from where it was shipped to Europe. When this railway connection was destroyed in the civil wars, CIB constructed a 150 kilometer road to connect with road network of Cameroon. Again, the logs are transported to the coast at Cameron and then shipped to Europe. Although the company is considered to be one of the more sustainable and economically working ones in Central Africa, the construction of the road to Cameroon founded some serious problems. Workers of CIB where found to be involved in illegal bushmeat and timber trade. Illegal goods can be transported to Cameroon easily in the absence of rigorous border controls [2].

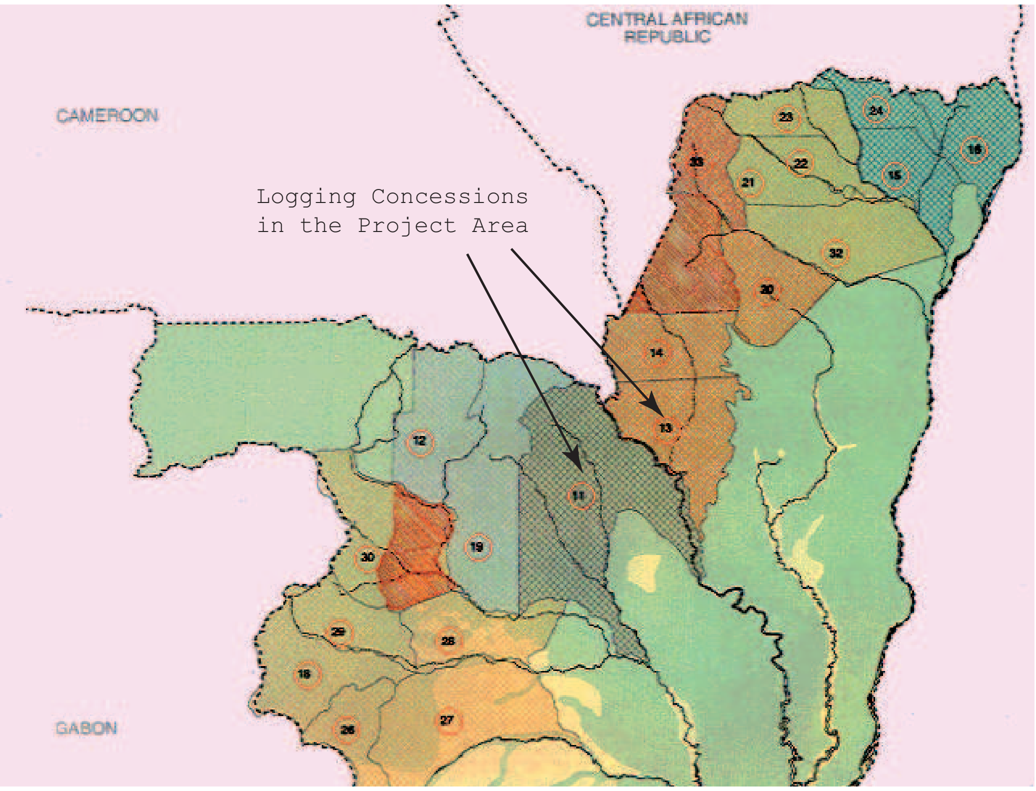


Figure 2.4.1: Logging concessions,Map source (edited) www.forestmonitor.org/congo.html

2.4.2 Société Industrielle Forestière de Ouesso(IFO)

IFO is a subsidiary of the Danzer Group. This group is a global timber business, held by a Swiss holding company. The principal operations of the company are done in Germany, in Austria, in Belgium, in France and in the United Kingdom. Danzer is one of the world biggest producers of veneers. Around 10 percent of the group's veneer sales are derived from tropical timbers, mainly harvested in Africa [2]. The company's involvement in the Republic of Congo is limited to the North of the country. The company is much more strongly involved in the neighboring Democratic Republic of Congo, where it was responsible for 40 percent of all commercial timber production in the 1990's. Currently the company has stopped logging in this country due to political instability of the region.

Chapter 3

MODIS Mission - Concept and Preprocessing

3.1 Concept

The earth is a highly dynamic system. To monitor the temporal variety and the short-time dynamics of the earth, the National Aeronautics and Space Administration (NASA) of the United States of America developed two Earth Observation (EO) satellites. The first satellite is named Terra and was launched in 1999. The second satellite is named Aqua and was launched in 2002. Both satellites use the Moderate Resolution Imaging Spectroradiometer (MODIS), which measures electromagnetic radiations of the earth in 36 channels. This is done every day due to the coarse ground resolution of the satellites. The MODIS detectors for all 36 bands are grouped on four focal planes. The earth is scanned in across-track lines. The electromagnetic radiation reflected or emitted from the earth reaches the satellite and is reflected by a rotating mirror at constant speed to the detection units. The observations are taken at equal time intervals and the scan angle of the mirror is calculated through electro-opticall calculations. The MODIS point-spread function is triangular in the across-track scan direction and rectangular in the track direction. Especially short time dynamics within one season or even one month can be investigated with these data sets. The channels are designed for all kind of environmental applications. A 48 bit information for each pixel is given, with detailed quality informations. A detailed description of the MODIS bands is given in table 3.1 on the following page. All kind of MODIS data products are available at no charge.

(https://lpdaac.usgs.gov/lpdaac/get_data/data_pool)

Primary Use	Band	Band with	Spatial resolution
Land/ Cloud Aerosols	1	0.62 - 0.67 µm	250 m
	2	0.84 - 0.87 µm	250 m
	3	0.46 - 0.48 µm	500 m
	4	0.54 - 0.56 µm	500 m
	5	1.23 - 1.25 µm	500 m
	6	1.63 - 1.65 µm	500 m
	7	2.10 - 2.15 µm	500 m
Ocean Color Phytoplankton	8	0.40 - 0.43 µm	1000 m
	9	0.44 - 0.45 µm	1000 m
	10	0.48 - 0.49 µm	1000 m
	11	0.52 - 0.53 µm	1000 m
	12	0.54 - 0.55 µm	1000 m
	13	0.66 - 0.67 µm	1000 m
	14	0.67 - 0.68 µm	1000 m
	15	0.74 - 0.75 µm	1000 m
	16	0.86 - 0.88 µm	1000 m
Atmospheric Water Vapor Cloud	17	0.89 - 0.92 µm	1000 m
	18	0.93 - 0.94 µm	1000 m
	19	0.91 - 0.96 µm	1000 m
Thermal Bands	20	3.66 - 3.84 µm	1000 m
	21	3.93 - 3.99 µm	1000 m
	22	3.93 - 3.99 µm	1000 m
	23	4.02 - 4.08 µm	1000 m
	24	4.43 - 4.49 µm	1000 m
	25	4.48 - 4.54 µm	1000 m
	26	1.36 - 1.39 µm	1000 m
	27	6.53 - 6.89 µm	1000 m
	28	7.17 - 7.47 µm	1000 m
	29	8.40 - 8.70 µm	1000 m
	30	9.58 - 9.88 µm	1000 m
	31	10.78 - 11.28 µm	1000 m
Thermal Bands Cloud Height&Fraction	32	11.77 - 12.27 µm	1000 m
	33	13.18 - 13.48 µm	1000 m
	34	13.48 - 13.78 µm	1000 m
	35	13.78 - 14.08 µm	1000 m
	36	14.08 - 14.38 µm	1000 m

Table 3.1: MODIS bands

3.2 Preprocessing

Before the MODIS products are ready to be downloaded, several effects are edited in the raw data sets. Usually all MODIS data are available for download only a few days after acquisition. These preprocessing steps influence the results of all applications carried out with MODIS products. In the following sections a brief summary of these preprocessing steps is given. A general grasp of these steps is necessary to be able to use MODIS data sets in a scientific context. Nevertheless no detailed algorithm description is given, just a brief summary to get an overview of preprocessing steps.

There is a hierarchy of processing levels in the generation of the products. The raw Level 0 data sets are received on the earth. Processing at Level 1 involves unpacking and verifying the raw datasets, organizing and storing them into a standard data-format (HDF), adding metadata information like ephemeries, calculating earth locations parameters and processing radiometric calibration. Level 2 processing uses the cloud mask algorithm. The results of this algorithm are attached to MODIS data sets like the surface reflectance (MOD09). Level 3 processings like the BRDF algorithm (MOD43) or the preprocessed Vegetation Indices (VI) are based on level 2 data. A flow diagram is given in figure 3.2.1. It contains only the data sets concerning this work.

3.2.1 MODIS Earth Location

The MODIS earth location algorithm is part of the level 1A processing system. A complete description is given in the Algorithm Theoretical Basis Document (ATBD) [30]. This system converts the raw data sets received from the satellites into scan oriented data structures. It generates the earth location system and adds further other meta data information. The eight earth location data fields are geodetic latitude and longitude, height above the Earth ellipsoid, satellite zenith angle, satellite azimuth, range to the satellite, solar zenith angle and solar azimuth. Of course, accurate information of earth location is one of the basic requirements for all satellite data sets in order to perform multi-temporal analysis and to be able to relate these data sets to other spatially referenced data sets. Several ancillary input data are needed for the earth location algorithm:

- Digital Elevation Model (DEM)
- Instrument constants

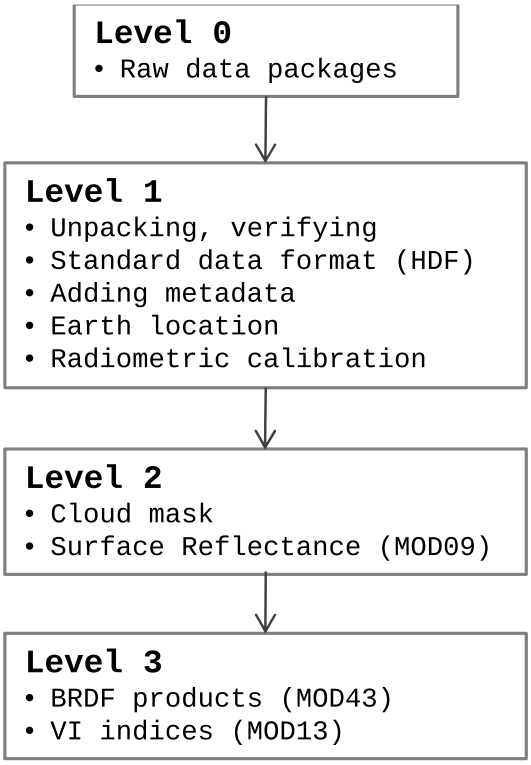


Figure 3.2.1: MODIS processing, diagram

- Ground control points
- Orbital ephemeris
- Spacecraft's attitude

The DEM is derived from a global database of terrain information provided by the EOS project. No detailed information on the DEM could be found in the corresponding MODIS document [30]. Three different types of instrument constants are required. The first type includes the focal plane, band and detector location. The second type includes different optical parameters, like focal lengths, the relationship between the optical axis and the instrument alignment axes and some others. Basically it is required to transform the Focal Plane Coordinate System into the Instrument Coordinate System. The third type of constants describes the spatial relationship between the MODIS instrument alignment axes and the EOS spacecraft. The ground control points are used to validate the performance of the algorithm. Although they are referred to as constants, these values can be intentionally adjusted, change with time or may be updated as better knowledge of their true values becomes available. They are constant when generating a particular data product. It consists of image windows containing well-defined features with known ground locations.

3.2.1.1 Accuracy and Details of MODIS Earth Location Algorithm

In the following section a brief description of geometric correction of the MODIS data sets is provided. All details are taken from the ATBD [30] and from a paper by Wolfe [40]. The pre-launch accuracy specification, which is needed for higher MODIS products is opposed to the real achieved accuracy, validated by error analysis, including several ground validation points, distributed over the globe. Perturbations in the motion of the sensor, the curvature of the Earth, surface relief and the instruments sensing geometry make geometric corrections necessary. Improvements of the interior satellite parameters after launch improved the geolocation accuracy tremendous.

For a hypothetical ideal band 0, the MODIS geolocation calculation is performed. From this band the positions of the other four bands are calculated by adding predefined offsets. The exterior orientation is estimated from star tracker and inertial gyro, the interior orientation is definded prior to launch. The geolocation is a sequence of transformations as listed below:

- A line of sight vector for the center of each detection unit is generated in the focal plane coordinate system
- This vector is rotated to the telescope coordinate system and to the instrument coordinate system
- A key element is the mirror model due to the impossibility of manufacturing a perfectly two sided mirror with parallel sides and perfect alignment with the mirror rotation axis. So the mirror is modeled by three angles to define the normal to the mirror surface, needed for the transformations
- Satellite position and velocity are defined in the Earth Centered Inertial (ECI) coordinate system and the satellite attitude is defined in the spacecraft reference frame
- The line of sight vector is rotated though the spacecraft, orbital and ECI coordinate system to the Earth Centered Rotating (ECR) coordinate system.
- The line of sight vectorand the satellite position in the ECR system are intersected with the terrain surface represented by a Digital Elevation Model (DEM). This is done in an iterative process. In a first approximation, the earth is represented as a unit sphere, followed by more detailed models.
- The result are eight parameters: height over ellipsoid, geodetic latitude and longitude, slant range to the sensor, sensor zenith angle, sensor azimuth, solar zenith angle and solar azimuth angle.

Considering errors in all of these transformations, as well as in the DEM, leads to a one sigma geolocation error of 117 m at nadir, increasing to 385 m at maximum 55° scan angle. The geolocation algorithm does not model refraction or aberration of the signal. To improve these errors, ground control points from Landsat scenes are used. According the NASA informations, the accuracy of geocoded Landsat-data is known to 30 - 50 m, using precise ephemeris for caculating the position of the satellite. These ground control points are represented by image windows, which are down sampled to the MODIS spatial resolutions of 250 m^2 to 1000 m^2. Using correlation techniques the MODIS scenes are matched to the ground control points. With a least square adjustment the sensor orientation parameters are recalculated. This is necessary due to the strong forces the sensor is exposed to on its journey from the earth to its orbit and which changed some pre-launch defined geometric properties of the satellite. This parameter update was done three times, leading to a mean along-track residual of 18 m and a mean along-scan residual of 4 m. Corresponding standard deviations are around 38 m and 40 m (1σ). So the MODIS geolocation goal of 50 m (1σ) at nadir is successfully met.

3.2.2 Radiometric calibration and atmosphere

Corrections for atmospheric effects are part of the Level 1B processing system. Earth observation-satellites aim to get pure signals from the earth's surface. Therefore, effects of the atmosphere on the signal have to be taken in account. Every signal measured by the satellite is affected by it. The MODIS atmospheric correction consist of several parts:

- One part is responsible for real atmospheric correction describing the actual constitution of several important parameters of the atmosphere and converting them into a correct scattering and absorption model
- Another feature is atmospheric point spread function
- And one part couples the surface BRDF with atmosphere affects.

The MODIS atmospheric correction scheme covers effects caused by thin cirrus clouds, gases and aerosols. Many other MODIS products are based on its results, like the Vegetation Indices (MOD13) or BRDF data (MCD43).

3.2.2.1 Real Atmospheric Correction [39]:

- Rayleigh scattering: It describes the scattering of electromagnetic waves by particles which are small in relation to the wavelength λ. Scattering through the atmosphere depends on the wavelength of the radiation, air pressure and temperature profiles. These profiles are known for different regions and seasons on the earth. In addition, surface altitude information for each pixel is needed. This is taken from a digital elevation model at the resolution of 5 minutes (ETOPO5).
- Tropospheric aerosol: These particles strongly influence the quality of surface reflectance. The algorithm treating this effect makes use

of the MODIS aerosol product. This product provides daily informations about the aerosol thickness and the aerosol size over the whole globe [10]. These data enable the MODIS team to make corrections for aerosol loading directly for a specific day and location.

- Stratospheric aerosol: The stratosphere can have heavy aerosol load due to volcanic eruption, which may persist for years. Of course, more common aerosol sources like any kind of smoke, pollen and dust influence the aerosol content of the stratosphere as well. The actual aerosol thickness is determined from MODIS algorithms using the 1,38 µm Band (MODIS band NR. 26)
- Gaseous absorption: Some gases in the atmosphere absorb radiation of certain wavelengths. These gases are O2, O3, CO2 and water vapor transmission. These effects are well-established. As inputs for the corrections serve special MODIS gas and water vapor products.
- Cirrus correction: This correction also relies on MODIS band Nr. 26. This correction is uniformly applied to all all surface reflectance bands.

3.2.2.2 Point spread function:

The signal of a target pixel, as received by the satellite, is a combination of the signal of the desired pixel and of the signal of the surrounding pixels. This effect is minimized by the point spread function. Physically, the signal at the top of the atmosphere is treated as a uniform Lambertian surface. A Lambertian Surface is isotropic, therefore it does not matter at which angle of view a certain point is viewed. The surrounding pixels of a target pixel are weighted according to their distance from the target [11]. Another name for this effect is adjacency. In addition, the influence of the angle of view is taken into account, because the signal as well as the adjacency effect vary in relation to view angles. The adjacency affect correction is possible up to a distance of 10 pixels in the case of MODIS.

3.2.2.3 BRDF atmosphere coupling correction:

In reality we are not dealing with Lambertian surfaces. Therefore the point spread function is inexact because of coupling effects between the surface BRDF and atmosphere BRDF, which the equation does not take into account due to its assumption of a Lambertian surface. The anisotropy of target on the surface leads to four different effects on top of the atmosphere:

- Photons are directly reflected form the target to the sensor.
- Photons are scattered by the atmosphere before being reflected by the target.
- Photons are scattered by the atmosphere after being reflected by the target. .
- Photons are scattered by the atmosphere before as well as after being reflected by the target. This is probably the most common case

3.2.3 Cloud and Cloud Shadow Masking

This paragraph is based on the Algorithm Theoretical Basis Document (ATBD) [29]. Clouds have generally higher reflectance and lower temperature than the underlying surface of the earth. Thus cloud detection algorithms work with different threshold approaches. The detection of clouds above ice and snow, as well as the detection of thin cirrus clouds require more sophisticated approaches. The cloud mask algorithm uses 20 of the 36 MODIS bands listed in table 3.1 and produces one 48 bit information for each 1km pixel, also containing cloud masks for the 16 included 250 m pixels. The 48 bit information for each pixel gives much more detailed information on the cloud conditions than a simple yes/no cloud mask. Many applications use this product. For some of them, more detailed information is needed. Therefore the 48 bit cloud mask output also includes results from certain cloud detection tests. However, bit number 2 represents a single bit cloud mask with a yes/no statement. The following data sets serve as input for this algorithm:

- Calibrated reflectance data with corrections for atmospheric effects
- Geolocation data sets including height above mean sea level
- Land/water map
- Daily snow/ice map
- Weekly surface temperature map from NOAA
- Mean NDVI maps

The cloud masking algorithm is divided in several individual tests optimized for certain types of clouds. Depending on the height of the clouds, the thickness and the type of surface below, specific tests are used for cloud detection. All tests rely on thresholds for reflected and emitted energy which make use of certain MODIS bands. Different bands have different detection qualities for certain types of clouds. The approaches are explained in detail in the ATBD.

After the cloud detection, the filter for pixels containing cloud shadows is performed. Areas of water and areas of clouds are excluded from the filter. The remaining pixels, adjacent to cloudy pixels are compared to a clear sky image. If the reflectance of the investigated pixels is beyond 80% of the clear sky pixel, the pixel is flagged as a pixel of cloud shadow.

In the MODIS surface reflectance data set MOD09, the cloud informations is included as an additional layer. The MOD09 data set serves as primary input for the MODIS BRDF (MCD43) product, which has also been used for this thesis. The BRDF algorithm uses only cloud free observation for its calculations. Therefore, it requires the cloud information layer of MOD09.

3.2.4 BRDF

Land surface albedo is related to land surface reflectance and its directional integration. The bidirectional reflectance distribution function (BRDF) describes how the reflectance depends on the two directions of solar and view angles. Albedo is the reflecting power of a surface. It is defined as the ratio between the reflected radiation of a surface and the incoming radiation. In passiv remote sensing systems, the incoming radiation comes, of course, from the sun. BRDF and albedo are determined by optical properties and the structure of land surface. For example surface structure influences the BRDF by shadow-casting and the spatial distribution of vegetation elements. Surface optical characteristics influence the BRDF, for example, through optical attributes of certain canopy elements. In consequence, the land surface as seen in BRDF reflects a variety of natural and human influences on the surface that are of interest to global change research. The phenological cycle of vegetation or deforestation are two examples of influences on the surface.

The BRDF consists of a linear combination of terms (the so-called kernels) characterizing different scattering modes of the surface. It is semi-empirical. It is based on physical models of reflectance and the coefficients are calculated empirically. The linearity of the model is a big advantage in large-scale operational data processing and analysis. The down-welling radiative flux from the sun to the earth's surface can be described as the sum of a direct and a diffuse component. The so-called Black-sky albedo is the direct albedo in absence of the diffuse component and is a function of solar zenith angle. White-sky albedo refers to only the diffuse component and it is constant.

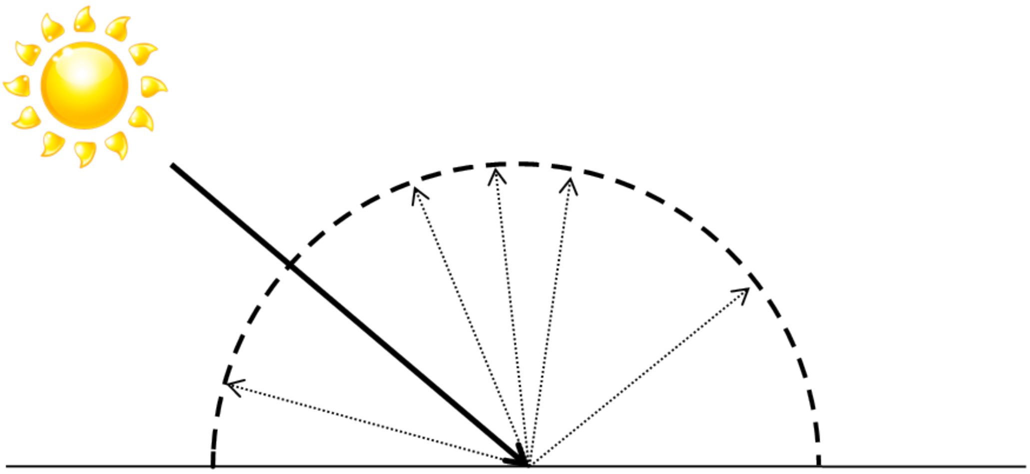


Figure 3.2.2: Isotropic scattering

Black-sky and white-sky albedo mark the extreme cases of completely direct and completely diffuse illumination of the surface. Actual albedo is interpolated between these two, depending on the aerosol optical depth.

The BRDF Algorithm details are provided in the Algorithm Theoretical Basis Document of MODIS. [37] The BRDF model of MODIS, which converts multiangular reflectances to albedos, includes three kernels, representing basic scattering types:

- ≻ isotropic scattering
- ≻ volumetric scattering
- ≻ geometric-optical scattering

There is a fundamental difference between isotropic and anisotropic scattering, illustrated in figures 3.2.2 and 3.2.3. Isotropic scattering is equal in all directions. In the context of remote sensing, it is therefore called hemispherical scattering. Anisotropic scattering is different in all directions. It is therefore called directional hemispherical.

The volumetric-scattering term was described by Roujean [33]. The model consists of a Lambertian background and a layer of small scatterers with uniform leaf angle distribution. In the case of reflectance of forest, it expresses the effects of small inter-leaf gaps in a canopy. The mathematical idea is given by J. Ross. The kernel is therefore called Ross-Thick kernel. It assumes a dense leaf canopy. The geometric-optical term was described by

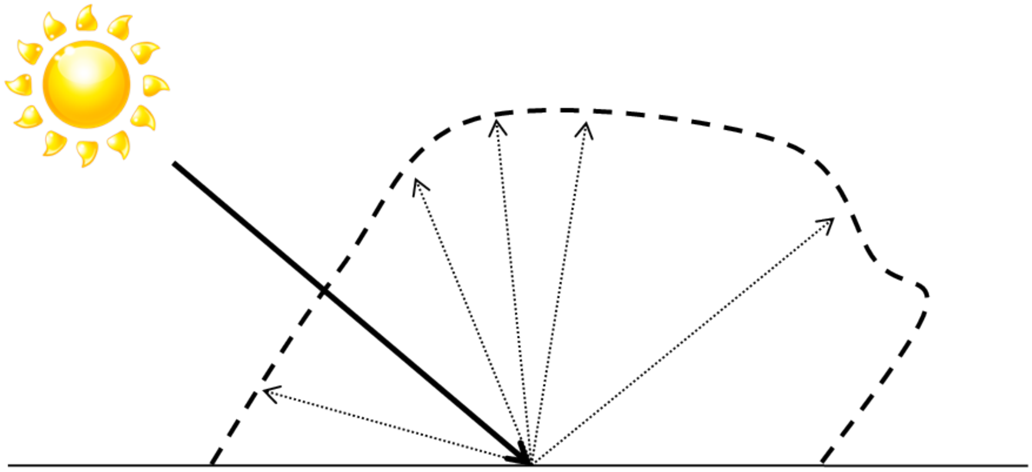


Figure 3.2.3: Anisotropic scattering

Li and Strahler [27]. In this context, it is referred to as the Li-Sparse kernel for its assumption of a sparse ensemble of surface objects casting shadows on a background, which is assumed to be Lambertian. It expresses the effects caused by larger inter-crown gaps in the forest. A Lambertian background is a surface with equal density of reflection in all directions. The power of reflection only decreases with lower angles of reflection. The direction of maximum reflection is the normal direction to the Lambertian surface. The surface objects of the Li-Sparse kernel are modeled by randomly located spheroids. The combination of the Ross-Thick and the Li-Sparse kernel is called Ross-Li BRDF model in this context.

This algorithm has been intensively validated. It is also summarized in the work of Strahler[37]. For a wide variety of situations, including barren and densely vegetated cases, the Ross-Li BRDF albedo values were compared to field-measured albedo data sets. The residual deviation between modeled and observed albedos was between 15 and 20 percent in all bands and for white sky-albedos as well as for black-sky albedos. This result is not as exact as desired, but due to the simple form of the model and its linearity, which makes it easy to use, the result is satisfactory. So this simple BRDF model is capable of representing all kind of naturally occurring BRDFs, without adapting the algorithm for different types of landcover.

3.3 Products

The MODIS team provides a huge number of data products, which are processed out of the 36 channels. Some products are normal surface reflectances in different bands, correct for several effects. In addition, precalculated Vegetation Indices (EVI, NDVI) in different spatial resolutions are provided, as well as the very often used MODIS BRDF product. It will be explained in one of the following sections. All these products can be downloaded for free. As mentioned before, the MODIS mission involves two satellites, Terra and Aqua. Data sets are available for both of them. Data from Terra are named with the prefix MOD- and data from Aqua use the prefix MYD-. Some products like the BRDF reflectance make use of both, Terra and Aqua data. These data sets are named with the prefix MCD-. In the following section of product descriptions, the prefix MOD- stands for both Terra and Aqua data, and the prefix MCD- stands for combined data, using Terra and Aqua.

3.3.1 MOD09

This group of products provide surface reflectances for the bands 1-7 for each of the two satellites. Data sets are available in different spatial resolutions and also in different temporal distances. In principle, the reflectances are measured daily by the satellites and they are also provided daily. An 8-day product is calculated, which assembles for each pixel the value of best quality within the 8-day period to one image. An example of the product is given in figure 3.3.1. It represents an area of 220 x 220 km around the village Ouesso. This settlement is situated in the project area of this work, in the North of the Republic of Congo. Date of acquisition is December 29, 2009.

3.3.2 MOD13

Vegetation Indices (VI) are computed by simple transformations of at least two spectral bands. The VI products of MODIS aim to provide data sets for temporally and spatially consistent comparisons of global vegetation [21]. MOD13 data product includes two VIs, the normalized difference vegetation index (NDVI) and the enhanced vegetation index (EVI). The NDVI is designed for chlorophyll sensitivity whereas EVI is better suited for canopy structural variations [17]. The two Vegetation Indices are produced at 500 m and 1 km resolutions in a 16 day composition period. Again the VIs are calculated separately for Aqua and Terra. Furthermore, the data sets of the two satellites are shifted by 8 days. Thus in an interval of 8 days, preprocessed VIs are available, each representing a composition period of 16 days. The VIs

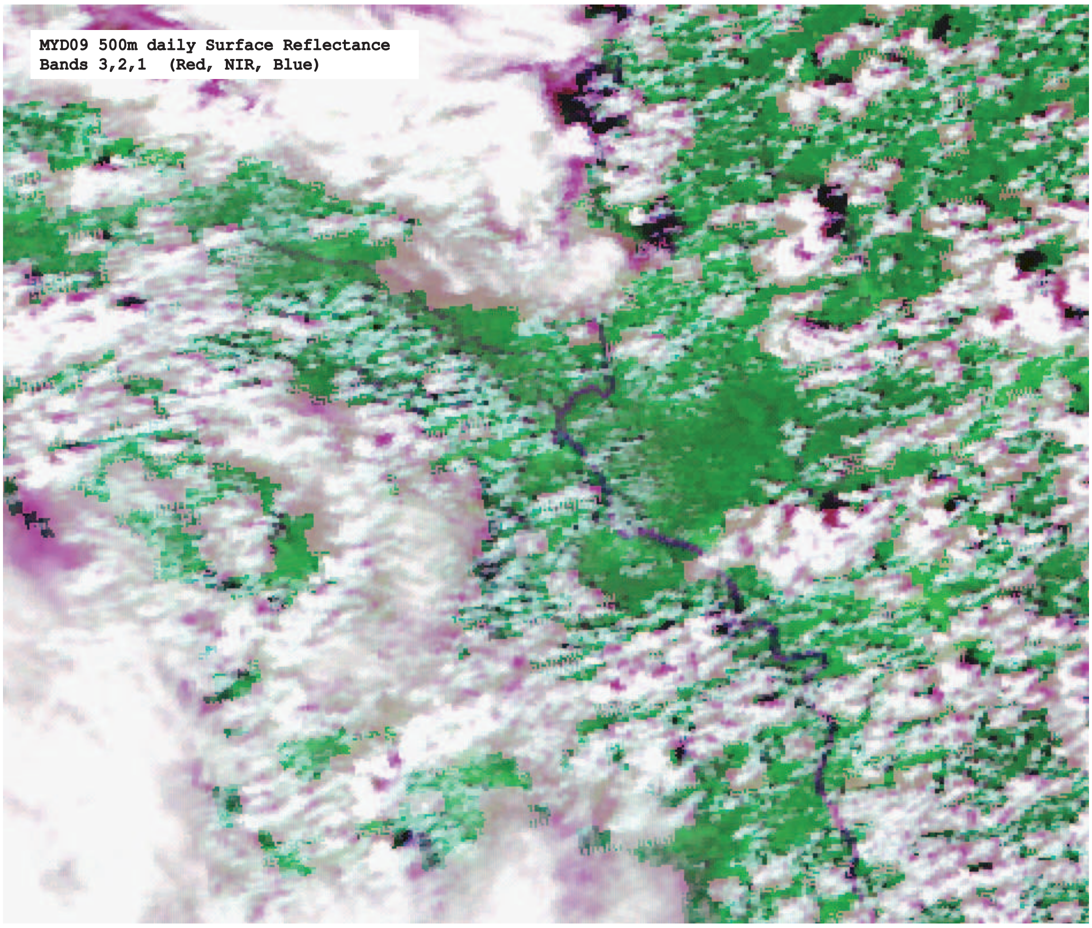


Figure 3.3.1: MOD09 example

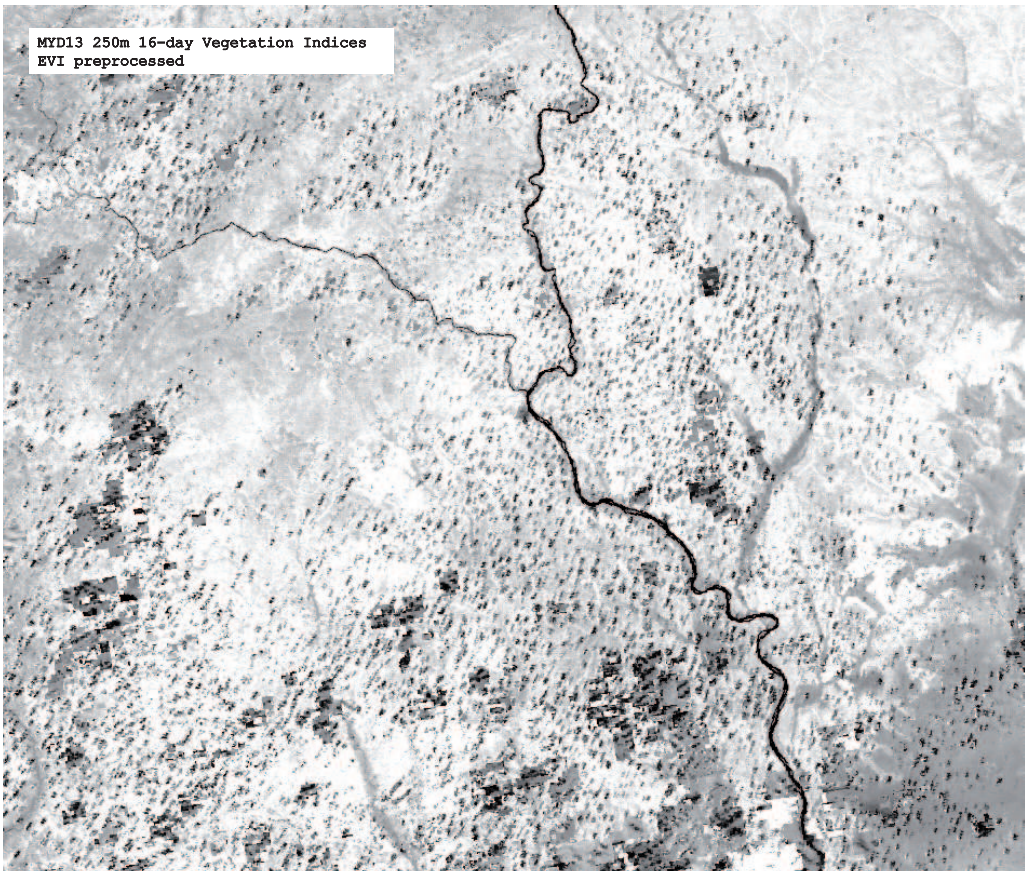


Figure 3.3.2: MOD13 EVI example

are calculated for each day of the 16 day period. For the 16 day product, the values of best quality within that period are picked out and assembled. The quality is mainly influenced by the cloud and aerosol conditions of each day. However, this information is available and attached to each data product. A visual example is given in figure 3.3.2. It shows preprocessed EVI of the same area and date than as example of MOD09.

3.3.3 MCD43

The MODIS BRDF product combines multidate, multiband and atmospherically corrected surface reflectance from Terra and Aqua to fit a Bidirectional Reflectance Distribution Function (BRDF) in seven spectral bands at 500m spatial resolution on a 16-day cycle. The algorithm performs an angular integration to derive real land surface albedos for each spectral band. The BRDF algorithm is explained in section 3.2.4. A visual example is given in figure 3.3.3. It shows the same area and date as the examples of MOD09 and

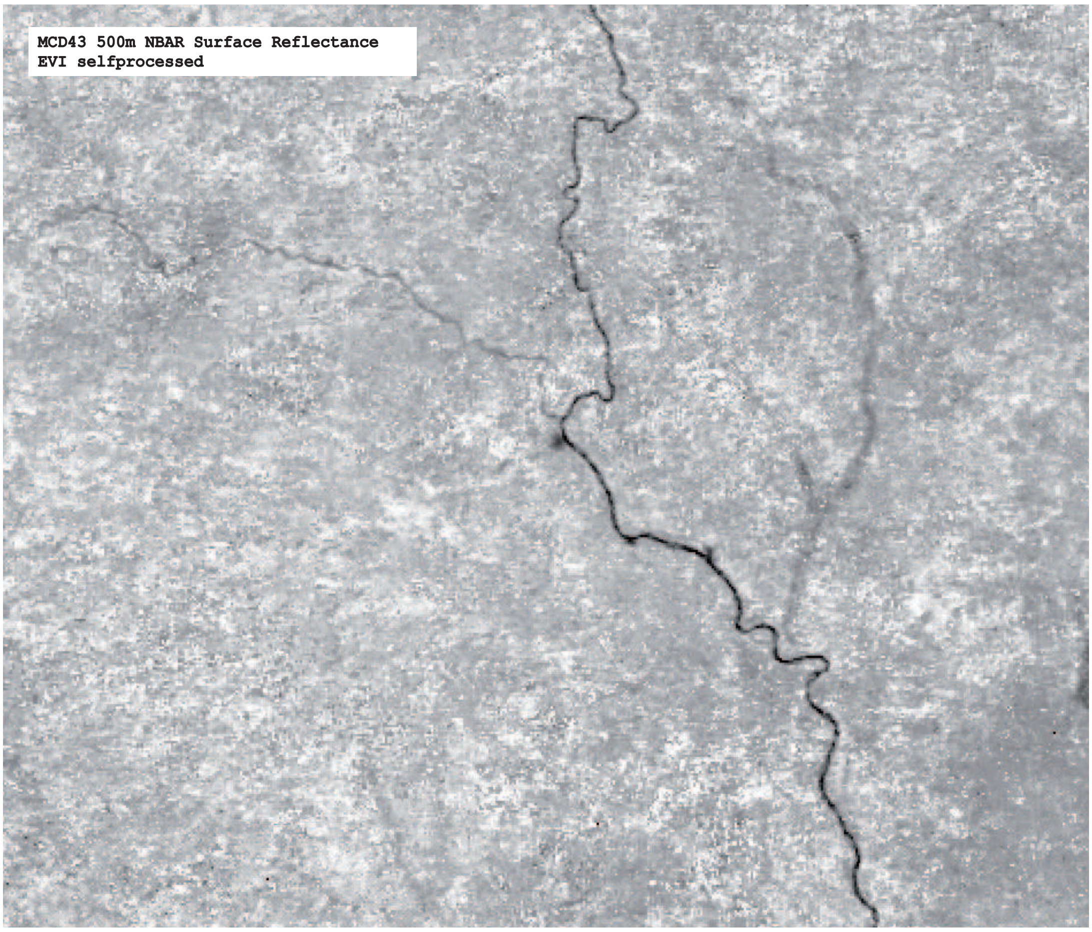


Figure 3.3.3: MCD43 EVI example

MOD13.

3.4 Conclusion

The MODIS BRDF product MCD43 is the only ready-to-use product of the satellites processing team. Bad quality pixels, caused by clouds, aerosols as well as view angle effects are minimized. It only provides data sets of highest quality. The BRDF needs at least seven cloud-free observations within the 16 day period for the full algorithm. If this is impossible, the concerning pixel in the image is empty, marked by a fill-value. The deviation between modeled BRDF albedos and observed ones is 15 - 20%. It is unknown if the difference between the BRDF values of logged and unlogged forests disappear in this deviation. The present thesis shell investigate wether there are differences or not. If there are no differences, this deviation of 15 - 20% may be a reason for it. The other data packages (MOD09, MOD13) contain, in most of the cases, clouds, through common tropical weather conditions. One would have to detect and mask the clouds or use the metadata product of MODIS to eliminate these effects. Several studies have declared the MCD43 data sets as very suitable for several scientific applications. This will be demonstrated in chapter 4.

Chapter 4

State of the Art

4.1 Introduction

For the theoretical background at this work several works on tropical forest, degradation and the general use of MODIS data have been analyzed. In the following chapter a summary of the most relevant studies is given. For better understanding, the reviewed works are grouped into three different temporal approaches too. Afterwards, a summary of the reviewed studies is provided. There is only a very small number of studies using MODIS data in the context of deforestation and degradation of tropical forest. To give a basic idea of the general use and possibilities of MODIS data, studies from very different application fields are reviewed and summarized in this chapter. As the use of Vegetation Indices (VI) is very common when analyzing different types of vegetation with remote sensing methods, first of all a brief introduction to VIs is given in the following section.

4.2 Vegetation Indices

Vegetation Indices are remote sensing techniques to amplify certain characteristics within image bands. This is done by combining different bands of a satellite. The result is a one-dimensional band, which is suitable for a certain application. Generally, the reflectance of vegetation is negatively correlated in the red and in the NIR channel. Healthy vegetation tries to absorb red light, it is needed for photosynthesis. Therefore, the absorption rate is high and reflectance is small. In the band of near-infrared (NIR), the reflectance of light is significantly higher, whereas the absorption rate is lower. This is illustrated in figure 4.2.1. Green vegetation is characterized by an increase of reflectance at the boundary of red and NIR radiation. Red light shows

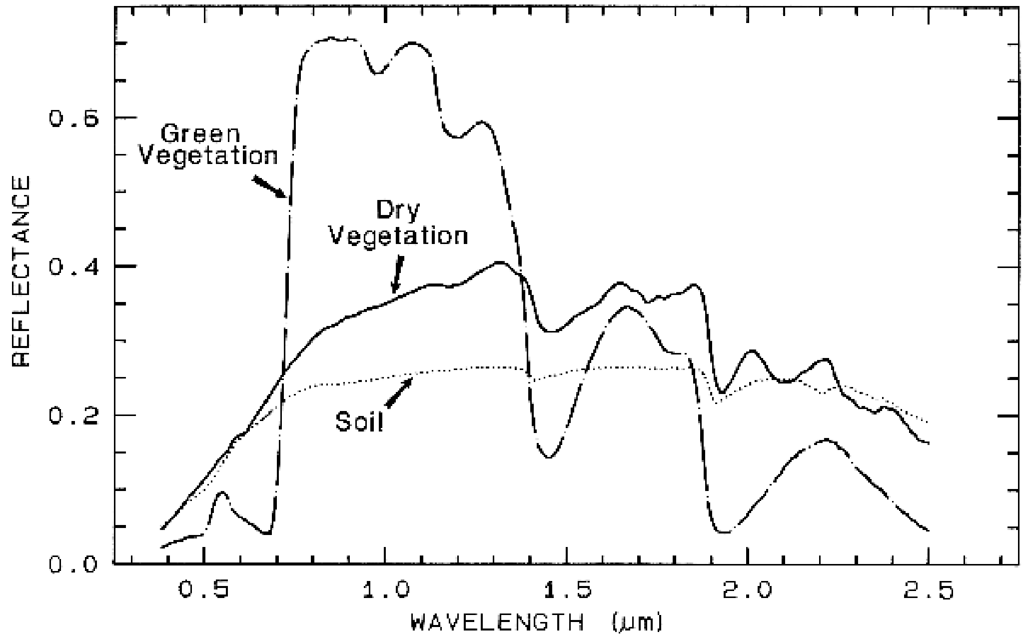


Figure 4.2.1: Spectral signature,

figure source: http://speclab.cr.usgs.gov/PAPERS.refl-mrs/refl4.html#section4.3

a bandwith from 650 to 750 [nm], whereas near-infrared light shows wavelengths from 750 up to 1400 [nm]. In comparison to this, the reflectance of soil and dry vegetation reacts different. There is no rapid increase of the rate of reflection between the band of red light and the band near-infrared light.

4.2.1 Enhanced Vegetation Index (EVI)

The basic idea of this index is the amplification of the reflectance difference between red and NIR light. Furthermore, EVI is designed to optimize the vegetation signal in high biomass regions. It has improved sensitivity in high biomass regions and has been developed for vegetation monitoring through a de-coupling of the canopy background signal and a reduction of atmosphere influence. This is achieved by introducing the aerosol sensitive blue band into the equation of the EVI [21]. EVI is responsive to canopy structural variations, canopy type and canopy architecture analysis [17]. The formula of the EVI is given in equation 4.2.1.

$$EVI = 2.5 * \frac{(NIR - Red)}{(NIR + 6 * RED - 7.5 * Blue + 1)} \tag{4.2.1}$$

4.2.2 Normalized Difference Vegetation Index (NDVI)

The idea of NDVI is basically the same as of EVI. Chlorophyll strongly absorbs visible light, especially red light, and the cell structures of leaves strongly reflect near-infrared light. If there is more reflected radiation in near-infrared wavelengths than in visible wavelengths, vegetation is likely to be dense. If there is only little or no difference in the intensity of the two bands, the vegetation is sparse and old, or may probably consist of other vegetation types like desert or tundra. The result is a quantification of plant growth. NDVI values can range from -1 to 1. High values, close to 1, indicate a high density of green leaves, low values, down to zero, indicate areas of little or no leaf coverage. The formula of NDVI is given in equation 4.2.2.

$$NDVI = \frac{NIR - Red}{NIR + Red} \tag{4.2.2}$$

4.3 Review of methods and temporal approaches

When using MODIS data, the main advantage in comparison to other satellite data sets is the high temporal availability. For this reason, the structure of this work is thought to be a comparison of different temporal approaches in the use of satellite data. Consequentely, the reviewed studies are also grouped according to these approaches. The first approach is monotemporal approach, investigating processes at one date. The second one is multitemporal approach, comparing circumstances between two dates and the third one is the approach of time series analysis, working with several consecutive data sets to observe the dynamic and short time behavior of a certain process. Some of the studies, described below, are more related to the present thesis due to their thematic content and some studies due to their methodical approach. However, this cannot be separated totally.

4.3.1 Monotemporal

Definition:

This refers to studies observing a process at exactly one date, with no comparison to other dates. An example for this is the classification of a forest into several wood classes.

For mapping degradation in tropical rain forests, monotemporal approaches are not very common. The question of how much area has been degraded in what period of time cannot be answered with this approach. The spectral mixture analysis (SMA) can be applied in a monotemporal approach. The idea behind this algorithm is that every pixel reflectance cannot only be interpreted as one single cover type. In fact, it represents a mixture of different cover types, the so called endmembers. The inputs for SMA are the spectral signatures of each endmember. The outputs of the SMA are basically gray scale images representing a percentage of appearance for each endmember. Common endmembers in the field of tropical forest applications are soil, shadow, green vegetation (GV) and non-photosynthetic vegetation (NPV). When rainforests are disturbed by selective logging, bare soil remains at the former places of powerful trees. Because of that, the endmember soil can be associated with the amount of disturbance due to logging. Thus, the result of SMA applied to a logging area of tropical forest is a percentage of logging areas in relation to the total area of forest. In comparison to analyzing a forest with common Vegetation Indices, the SMA method has advantages.

Field studies by Gregory Asner [5] have shown, that a single forest structural pattern, like soil through logging gaps, cannot be extracted directly from VI maps. From SMA features this can be deduced. In addition SMA can give a quantification of the amount of soil within an area, leading to direct information of degradation intensity. Jeffrey Gerwing [18] did a comprehensive field study in the region of Paragominas, Brazil, which is in the Amazon basin. On several study plots, he investigated the amount of above ground biomass in a plot of intact forest by counting and measuring all trees within the plot. In comparison to this, he analyzed the reduction of biomass in plots of different logging intensity. Post-logging forest fires arised as a serious problem for this study. Opening up the canopy and removing the natural protection of the surface drys out the vegetation and soil leading to an increased risk of fire. The study proposes four years for a logged forest to regain its fire resistance. Fire in moderately logged forests result in a total biomass reduction equal to intensive logging.

A study from Jieying Xiao [41] uses MODIS data in a monotemporal approach. This work used a mosaic of MOD 43 data sets for one date. The topsoil grain size index (GSI) was developed as a result of laboratory analysis and field studies. The spatial distribution of the grain size was correlated with the reflectance of topsoil data sets, and the correlation proved highly significant. The result of this work was a desertification map of a certain date for Central Asia, including the countries China, Mongolia, Kazakhstan, Uzbek, Turkmen, Afghan, Pakistan, Tajikistan and Kyrgyzstan. The desertification was divided into several classes. However, data gaps within the used MODIS MCD43 images were found. This is normal due to excess cloud obstruction within the 16-day processing period of the data set. The BRDF algorithm needs at least 7 cloud-free observations within 16 days to be fully applied 3.2.4. These data gaps were excluded from the study. The next step of this work could be a multitemporal approach of observing the change of desertification between several points of time.

4.3.2 Multitemporal

Definition:

This is the approach of studies, which observe a certain a process at two or more points in time. Comparisons and analyses of what occurred between these dates are conducted. The change of forest classes from one year to another is an example. Also common feature space analyses between two dates belong to this approach. Mathematical instruments used in this approach can be several separability techniques like the Jeffrey Matusita distance. The remote sensing software ERDAS, used for the present thesis supports three separability techniques: Divergence, Transformed Divergence and Jeffrey Matusita distance. According to a well known book on digital image processing by Jensen [25] these techniques perform quite similar. So for the present thesis the Jeffrey Matusita distance is chosen.

Several multitemporal approaches dealing with deforestation and degradation can be found in the scientific literature. When the public and the scientific community started to recognize the amount of selective logging, first visual approaches were performed by Stone and Lefebvre [36]. They quantified selective logging by digitizing Landsat images. The logging patterns proved much more difficult to detect than normal deforestation patterns. Stone and Lefebvre detected that logging reduces the total amount of forest by more than 10% in certain areas of the Amazon basin. Furthermore, they made a comparison between logging areas in 1986 and logging areas in 1991. There was not a single overlap between the areas of these two points in time, separated by around seven years. This means that selective logging can only be detected for a few years out of medium resolution satellite data, although it disturbs the forest for a much longer time.

Again, a team around Gregory Asner [6] applied the method of SMA to

Year	Author	Application	Data set	Time span	Method
2002	Jeffrey Gerwing [18]	Degradation of forests through logging and fire in the eastern Brazilian Amazon	Field study	2000	Building up field inventories in intact and degraded forests. Degradation by logging and post-harvest fires.
2003	Gregory Asner [5]	Per-pixel analysis of forest structure: Spectral Mixture analysis.	Landsat		SMA in logged forests, in comparison to common VIs
2005	Jieying Xiao et al. [41]	Mapping soil degradation	MODIS MCD43	2004	Calculating Grain Size Index (GSI) for Central Asia, leading to a desertification map

Table 4.1: Reviewed studies: Monotemporal

Landsat images in the Amazon basin in a multitemporal approach. For the years 1999 – 2002 they calculated the percentage of Soil endmember, which is associated with the amount of logging. Having this value for every year available, they showed the logging rates for every year for several states in the Amazon basin. The automated Carnegie Landsat analysis system (CLAS) is introduced. Based on the SMA method, it provides measurements of forest-canopy damage at Landsats spatial resolution of 30m x 30 m. It does so over millions of square kilometers of forest. CLAS was applied to several states of the Amazon basin. The result was that selective logging doubles previous estimates of the total amount of foreset degradation. The approach of SMA for logging quantification was also applied in Joanneum research's framework on REDD in Cameroon [20].

Douglas Morton [31] made a comprehensive work with different MODIS data sets. With reference of Landsat images, annual deforestation mapping was investigated by using four different change detection algorithms:

- Two-date image differencing, values exceeded certain thresholds classified as deforestation
- Single-date image threshold
- Combined single-date threshold
- NDVI difference with NDVI threshold

These algorithms were applied to the following MODIS data sets: MOD09 and MOD13. The algorithms performed differently in detecting a minimal size of deforestation. Non-ideal MODIS pixels were eliminated by MODIS quality informations. The NDVI differences performed best, detecting 60 % of the deforestation clusters of 3 ha (30.000 m^2), which is half the size of one MODIS pixel of 250m x 250m. More than 90% correct detections could be performed with all four methods for deforestation clusters $>$20 ha. This area is a few times bigger than a single MODIS pixel. The study proposes MODIS data sets for the rapid identification of the location of deforestation. But the MODIS data sets are no replacement for high-resolution analysis that estimate the exact area of deforestation.

4.3.3 Time Series Analysis

Definition:

Year	Author	Application	Data set	Time span	Method
1998	T.A. Stone et al. [36]	Quantification of logging in amazon rainforest	Landsat	1986 - 1991	Digitizing Landsat images
2005	Asner et al. [6]	Carnegie Landsat Analysis System (CLAS) in Amazon basin	Landsat	1999 - 2002	CLAS for quantification of logging
2009	Stefan Haas [20]	Forest Degradation for REDD in Cameroon	Landsat	1990 - 2005	SMA
2005	Douglas Morton [31]	MODIS and deforestation in Amazon basin	MODIS MOD09, MOD13	2001 - 2002	Change detection algorithms, Landsat groundtruth

Table 4.2: Reviewed studies: Multitemporal

This refers to studies which use sequences of consecutive data sets with constant temporal spacing. Data sets are taken daily or weekly, long-time or short-time dynamics are displayed and can be investigated. An example of this approach would be the phenological curve of a certain forest class through a year. Data sets based on this approach can be analyzed using various mathematical techniques. For example mean values, standard deviations and regression lines can be calculated and used.

This capability for time series analysis is one of the main advantages of MODIS data sets, due to the high temporal resolution. A lot of studies use MODIS images in this way. However, only one study was found which maps forest degradation with MODIS data sets. The vegetation phenology in parts of North America was monitored by Xiaoyang Zhang [45]. He used MODIS NBAR data sets at a ground resolution of 1 km x 1 km. EVI was computed and a logistic model was fit to the time series. The study aimed to identify four key phenological transition dates: green-up, maturity (plant green maximum), senescence (date of rapidly decreasing photosynthetic activity), dormancy (no physiological activity of the plant). These four dates were derived from maximum and minimum rates of change of the phenological curves. This was done for each pixel. The date of green-up and dormancy was correlated with the geographic latitude of the pixel. It could be shown that green up started later in the season at more northern latitudes, as well as dormancy started earlier in more northern areas. However, no comparisons have been made between ground observations and the remote sensing-based results.

An extension of this work was done six years later [44]. The same four transition dates were tried to calculate. In addition, typical land-cover types for North America were introduced and compared. From daily MODIS09 surface reflectances, EVI was calculated. The data sets showed big variations due to residual clouds, shadows and view angle effects. So the work was continued with MODIS NBAR data sets. The MODIS NBAR algorithm needs 7 cloudfree observation during the 16-day observation period. If these 7 observations are not available, due to frequent cloud obstruction, for example, the MODIS NBAR algorithm can not be executed. In fact some pixels showed too frequent cloud obstruction, so missing data points arised as a problem. The whole study based on one pixel of full data availability for each vegetation. Again the four transition dates green-up, maturity, senescence and dormancy were calculated. The study was done with pixel of full data availability. Several other pixel have missing data values in the time series of MODIS NBAR data, because of too less cloud free observations. For these incomplete time series, the four transition dates were calculated as well and the difference to the complete time series was investigated.

A similar study uses another MODIS data set, MOD15 Leaf Area Index (LAI) [8]. Time series of different land-cover types were modelled and it was attempted to make a prediction about future LAI values. Another study by Xiangming Xiao [42] investigated the amount of gross primary production (GPP) in a tropical rainforest, especially during the dry seasons. GPP is the rate at which plants capture and store chemical energy, derived from CO_2, as biomass in a certain length of time. Vegetation indices were calculated from MODIS NBAR data sets. NDVI time series of the rainforest showed significantly different seasonal dynamics in comparison to EVI. Obviously NDVI does not reflect the subtle changes in leaf and canopy structure of tropical evergreen forests. Working with MOD13 data sets, Swedish scientists tried to map insect defoliation in Norwegian pine forests [12]. Smoothed time series of NDVI during spring and summer were taken. These values represent the growing period of pine trees. A regression line was calculated for these points and the slope of these lines were compared between the observed seasons. The slope dropped significantly in a year of insect defoliation.

Among the reviewed studies, the one most closely related to the present thesis is the one by Alexander Koltunov [26]. His work tries to characterize the phenology of a regenerating forest, after a selective logging event. The study takes place in the Brazilian Amazon basin and works with a time series approach using MODIS data at a spatial scale of 1 km^2. As Groundtruth the Area-Integrated Gap Fraction (AIGF) derived from Spectral Mixture Analysis (SMA) using Landsat Scenes was used. The AIGF is representative index for the intensity of selective logging because represents the percentage of the SMA – endmember Soil within a certain area. High AIGF values indicate larger areas of bare soil in a forest and thus greater disturbances by selective logging activities. Koltunov used a AIGF map for the year 2000 to discover the amount of logging. In addition, he knew the areas of logging in the period of 2000 – 2002. The corresponding maps are provided by the INPE PRODES (Program for Monitoring Deforestation in the Brazilian Amazon). Areas which were logged after the reference year 2000 were excluded from the study because Koltunov only investigated the regeneration of selective logging disturbance over several years. Therefore, new logging events, after the initial logging events in 2000 would disturb the analysis. The AIGF show the selective logging disturbance from 0 - 100 %, where as 100% indicated deforestation. The values were split into nine disjoint groups, the first class concerns disturbance from 5 - 10 %, the second from 10 - 20 % and so on. For each pixel (which will not be disturbed within two years) the Enhanced Vegetation Index (EVI) and the Normalized Difference Water Index (NDWI) is calculated out of MODIS NBAR data. Differences between the measured reflectance value of the disturbed forest and the estimated value of the undisturbed forest were calculated. This differences were considered instead of the VI themselves. There are two ways to estimate the undisturbed forest reflectance value for an actually disturbed forest at a certain point in time. The first one is to consider earlier reflectance measurements for this place, when the forest was still undisturbed. This was not possible in this case, because of missing MODIS data. MODIS data are not available before 2000. The second one is to take surrounding undisturbed reflectance values for the same point in time, to calculate a mean value and use it as an estimation of undisturbed forest reflectance. Investigating impacts instead of vegetation indices should minimize confounding effects of environmental factors, which are only caused by the geographic location. Then the impact time series are parametrized with orthogonal polynomials, leading to two coefficients for EVI and NDWI time series. For MODIS EVI, they are called Intra-Seasonal Greenness Impact (SGI) and Intra-Seasonal Greenness Impact Trend (SGIT). For MODIS NDWI times series they are called Intra-Seasonal Moisture Impact (SMI) and Intra-Seasonal Moisture Impact Trend (SMIT). For unlogged forests, these impact parameters are expected to be zero. Forest phenology is strongly varying with time. To minimize this effect, the same interval is taken for each dry season from 2000 – 2002. It is assumed that the forest phenology is similar in dry seasons and therefore comparable at same intra-annual dates in different years. This assumption will be also made in the present thesis. Due to frequent clouding during the wet season, only the dry seasons were analyzed. Further on, only pixels which were not clouded or had missing values in any of the NBAR images of the seasonal interval were tested. Therefore, many pixels are excluded from the study. With statistical analyses, it was confirmed that SGI, SGIT, SMI and SMIT of selectively logged forests are significantly different to those of unlogged forests. The greenness impact parameters are significant even up to the 5 – 10% disturbance class level, and up to the third year after selective logging. Within this time period the regeneration of tropical forests, after a selective logging event, can be separated from intact forests.

4.4 Conclusion

Douglas Morton [31] suggested the use of MODIS data sets for the rapid detection of deforestation clusters. This is comparable to the hot spot map-

Year	Author	Application	MODIS data set	Time span	Method
2003	Zhang et al. [45]	Modeling phenological curves of different land cover types and calculating 4 transition dates.	MOD43	2000 - 2001	Calculating EVI from MODIS NBAR channels, transition dates found by minimum and maximum rated of change in the phenological curve
2005	Xiao et al. [42]	Correlation of surface reflectance data and other biological parameters, like rainfall	MOD09, MOD43	2000 - 2002	visual analysis and correlation of the models calculated
2009	Koltunov et al. [26]	Change of forest phenology due to selective logging in the Amazon basin	MOD43	2000 - 2002	Temporal and spatial difference in reference to Landsat derived AIGF
2009	Zhang et al. [44]	Phenological curves for different land cover types in the USA, difference daily and 16 day data	MOD09, MOD43	2004	Modeling the phenological curves with logistic model. Influence of missing data
2009	Eklundh et al. [12]	Mapping insect defoliation in Norway	MOD13	2000 - 2006	Smoothed Time Series, Slope of regression line in growing period
2010	Jiang et al. [8]	Modeling phenological curves of different land cover types	MO15, MOD13	2001 - 2005	Trends and intra-annual variations for modelling future dynamics
2010	Linderman et al.[28]	Different aspects of fAPAR(fraction of Absorbed Photosynthetically Active Radiation) Variability	MOD13	2001 - 2008	Correlation of NDVI and fAPAR values
2010	Ferreira et al. [14]	Correlation of fragmentation and VI values	MOD13	2005 - 2006	Seasonal response of MODIS VI

Table 4.3: Reviewed studies: Times Series Analysis

ping approach of REDD described in 1.4. Degradation normally affects areas smaller than one MODIS pixel, however, the practicability of MODIS data sets for hot spot mapping of degradation shall be investigated in this study. The most promising method was employed by Alexander Koltunov [26]. Koltunov introduced a great number of pixels to the analysis and excluded automatically missing NBAR values. This will not be possible in the present study, because the project area in the north of republic Congo is quite small with only a limited amount of logged pixels. According to the satisfying results of several studies [43, 41, 26, 42, 34] with MODIS MCD43 data sets, this kind of MODIS data will be also used for the present thesis. According to Xiangmin Xiao [42] as well as Koltunov [26] the EVI index will be used for the present application. Landsat images will be used as groundtruth, as proposed by several studies [6, 7, 20, 31, 26].

Chapter 5

Satellite data

5.1 Reason for selecting MODIS

MODIS data sets are used because of the high temporal resolution. The decision to use MODIS MCD43 data product was made after investigating the different MODIS data sets and reviewing scientific work on this subject. MCD43 is the most stable and accurate product of MODIS and was used in lot of studies related to the present study. This has been described in detail in the preceding chapters. Every study on remote sensing data needs some kind of ground truth. Fieldstudies are suitable for this, or data from other, more accurate sensors, like Landsat. Since 2008, Landsat scenes can be downloaded at no charge from the internet (http://glovis.usgs.gov). Each scene is available in intervals of 16 days. The spatial resolution of 30m can be perfectly used for visual detection of logging patterns.

5.2 General Information

The primary focus of this study lies on the MODIS data sets, and the Landsat data sets serve as a visual groundtruth for all investigations done in this work. Details on MODIS data are given in chapter 3, details for Landsat and comparison between these two missions are given in the present section. Technical specifications of the missions are given in table 5.1.

5.3 Landsat for Ground Truth

This mission of the United States is the longest serving earth observation mission in the world. It started in 1972 and is now in its 7th generation. The

Satellitemission	MODIS	Landsat
Sensor	MODIS	Enhanced Thematic Mapper (ETM+) at Landsat 7
Operator	NASA	NASA
Launch	1999 (Terra), 2002 (Aqua)	1999 (Landsat7), 1972 (Landsat 1)
Orbit	Sun-sync.	Sun-sync.
Altitude [km]	705	705
Spacial resolution [m]	250, 500, 1000	30
Swath width [km]	2330	185
Repeat orbit [days]	1 - 2	16

Table 5.1: MODIS and Landsat specifications

images are distributed at no charge on the internet (http://glovis.usgs.gov). A description of Landsat bands is given in table 5.2. The main instrument of the current 7th generation Landsat satellite is the Enhanced Thematic Mapper Plus (ETM+). According to the Landsat Internet Platform, the geometric accuracy of the images is around 40m.

5.4 Table of Data Sets

All cloud-free Landsat scenes from 2006 to the end of 2010 were ordered and downloaded from the download portal for NASA's satellite images, . In addition, some cloud-free scenes from 2000 - 2005 were used. An overview of the scenes can be seen before ordering, so the cloud-status is known. For the MODIS scenes, the cloud-status is unknown before downloading. Therefore, all data sets within the dry season of interest have been downloaded and compiled. A detailed list is given in figure 5.4.

Band	Bandwidth	Spatial Resolution	Nr. of comparable MODIS Band	MODIS Bandwidth
1 Blue	0.45 - 0.52 µm	30 m	3	0.46 - 0.48 µm
2 Green	0.52 - 0.60 µm	30 m	4	0.54 - 0.56 µm
3 Red	0.63 - 0.69 µm	30 m	1	0.62 - 0.67 µm
4 NIR	0.77 - 0.90 µm	30 m	2	0.84 - 0.87 µm
5 SWIRa	1.55 - 1.75 µm	30 m	6	1.63 - 1.65 µm
6 Thermal	10.40 - 12.50 µm	60 m	31, 32	10.78 - 11.28 µm, 11.77 - 12.27 µm
7 SWIRb	1.08 - 2.35 µm	30 m	no SWIR channel with that bandwidth	
8 PAN	0.52 - 0.90 µm	15 m	no panchromatic MODIS channel	

Table 5.2: Landsat bands in comparison to MODIS

Landsat	2000: 18. Sept 2001: 02. Sept, 08. Nov 2002: 01. April, 13. Dec, 29. Dec 2003: 15. Feb 2004: 21. March, 18. Dec 2006: 07. Feb, 15. June, 01. July, 24. Dec 2007: 09. Jan, 25. Jan, 18. June, 11. Dec, 27. Dec 2008: 13. Feb, 29. Feb, 24. Oct, 13. Dec 2009: 14. Jan, 30. Nov, 30. Dec 2010: 01. Jan, 31. Jan, 18. Feb, 04. March
MODIS MCD43	dry season 2006/07 (Nov. - Feb.) 8 images, 16day interval dry season 2007/08 (Nov. - Feb.) 8 images, 16day interval dry season 2008/09 (Nov. - Feb.) 8 images, 16day interval dry season 2009/10 (Nov. - Feb.) 8 images, 16day interval dry season 2000/01 (Nov. - Feb.) 8 images, 16day interval *(results not shown in this work)* dry season 2001/02 (Nov. - Feb.) 8 images, 16day interval *(results not shown in this work)* dry season 2002/03 (Nov. - Feb.) 8 images, 16day interval *(results not shown in this work)* dry season 2003/04 (Nov. - Feb.) 8 images, 16day interval *(results not shown in this work)* dry season 2004/05 (Nov. - Feb.) 8 images, 16day interval *(results not shown in this work)*

Table 5.3: Table of data sets used for this study

Chapter 6

Methodology

The methodology for this thesis is explained in the present chapter, the methods as well as the reasons for using specific kind of satellite data sets have been extracted from the State of the Art analysis summarized in section 4.4. The results are discussed in the following chapter. The investigations are divided into three groups:

- Preliminary studies: Monotemporal
- Preliminary studies: Multitemporal
- Time Series Analysis

6.1 Preliminary studies: Monotemporal

There are two intentions in a monotemporal context for this work.

First, Landsat scenes of the project area are interpreted visually for logging activities. If such activities are found, they serve as reference for the following MODIS analysis, which is the central concern of this study. The MODIS satellites Terra and Aqua are producing data since 2000. Therefore, Landsat scenes, from 2000 up to February 2010 have been prepared to serve as ground truth for the logging activities within that time span. Searching for logging patterns in Landsat scenes can be done fast, cheap and unambiguously. For better understanding, a visual example of typical logging patterns in Landsat data is given in figure 6.1.1 on the next page. The most important pattern is the one of logging roads. By investigating satellite scenes in a chronological way they can be detected very easily and clearly. First, there

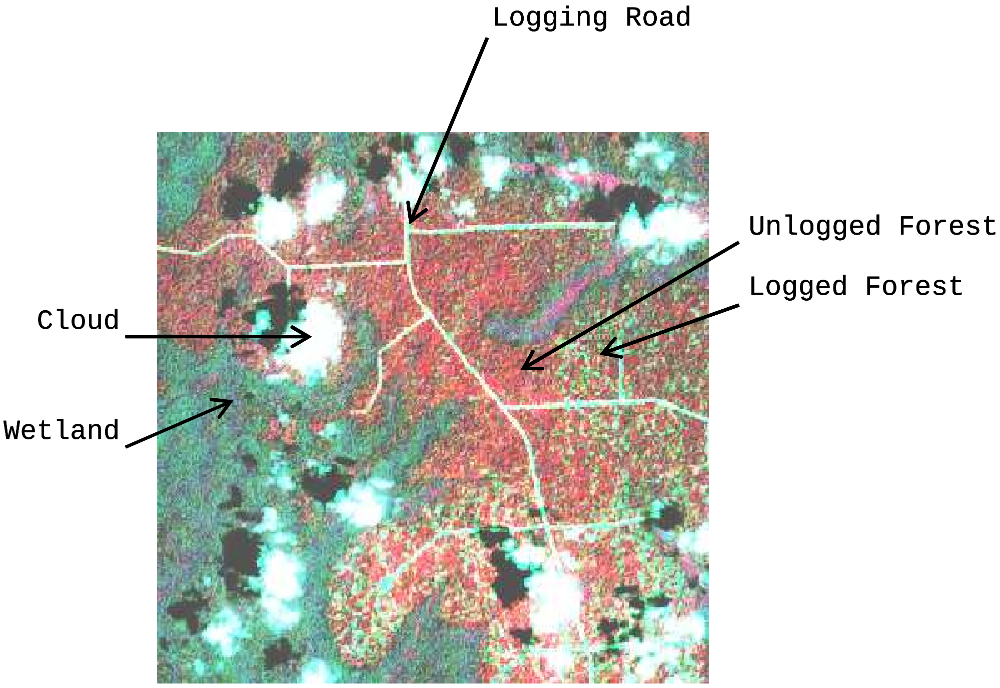


Figure 6.1.1: Logging Example: Subset of Landsat scene P182R059 08/11/2001 Bands 432

is an area of homogeneous forest and in the next scene logging roads are cut into the forest. The bare soil of these roads reflects in a very different way than the surrounding forest.

The main intention concerns the MODIS data sets. They are analyzed in order to find out whether clear logging patterns are also detectable visually in the optical bands of MODIS at all. In addition a basic correlation test for a MODIS scene from 26/02/2010 between red and NIR band is performed.

6.2 Preliminary studies: Multitemporal

According to the definition of the multitemporal approach, relations between two points in time are shown. If a certain forest area is degraded by selective logging from one point to another, the separability of this logged forest in comparison to an unlogged forest is investigated. This is done by a simple separability test within the feature space between two scenes. With support of the remote sensing software ERDAS this can be done.

6.2.1 Extraction of logged and unlogged Pixel

Logged and unlogged areas within the period of two certain dates found in the visual monotemporal approach are saved as by Area of Interests (*.aoi). This means that the UTM coordinates of a certain area are stored in such a file. Due to the uniform coordinate system of Landsat and MODIS data sets (Projection: UTM, Zone 33N; Ellipsoid: WGS 84) areas of interest can be transferred directly from Landsat to MODIS and vice versus. The optical bands of Landsat have a ground resolution of 30m, the same bands of MODIS have a ground resolution of 500m, which means that there are many Landsat pixels within one MODIS pixel. This fact is paid attention to when transforming an area of interest from Landsat to MODIS. 5 x 5 km may be considered as normal size of a logged forest. Such an area includes around 28.000 Landsat pixels, but only 100 MODIS pixels. When defining an area of interest, it is unavoidable that the surrounding polygon intersects pixels. To exclude these border pixels, only pixels completely inside the Area of Interest are defined by Points of Interest and introduced to feature space analysis.

6.2.2 Feature Space and Jeffrey Matusita Distance (JM)

A feature space analysis is a standard method in remote sensing. In the case of the present thesis it is 2-dimensional, because one channel of MODIS is analyzed at two dates. Each axis represents one date. For example, it can be used to Analise the separability of two land cover types. Area of interests, representing the two land cover types are located within the feature space according to its reflectance values at the two observed dates. In the resulting diagram, the reflectance values of these land cover types form clusters. Now the separability of these clusters can be investigated with certain mathematic methods. The result is evidence about separability of two observed land cover types in one satellite channel at two dates. In the feature space analysis of the present thesis, the separability between logged and intact forest is investigated.

The Jeffrey Matusita distance (JM) is used to make a mathematical valid deposition concerning the separability of the features. To compute their separability, it uses the Battacharyya (B) distance [16] between two features, calculated from the mean vectors as well as from the standard deviation of the single samples within one feature. JM has a range from 0 to $\sqrt{2}$, whereas

0 means “not separable” and $\sqrt{2}$ means “separable”. The JM formula is given below.

$$JM = \sqrt{2(1 - e^{-B})} \tag{6.2.1}$$

$$B = \frac{1}{8}\left(\mu_1 - \mu_2\right)^2 \frac{2}{\sigma_1^2 + \sigma_2^2} + \frac{1}{2}\ln\left(\frac{\sigma_1^2 + \sigma_2^2}{2\sigma_1\sigma_2}\right) \tag{6.2.2}$$

6.3 Time Series Analysis

The main advantage of MODIS data is its high temporal resolution. This allows the introduction of several methods of time series analysis into the field of logging detection. Reflectance differences between total deforestation and intact forest are supposed to be obvious, even more obvious than the differences between logged and intact forest. First the scenario of deforestation is investigated in detail. Afterwards selective logging, which still leaves some trees is discussed. This is done in the way proposed by Alexander Koltunov [26]. He describes two characteristics to separate logged and unlogged forest. These are temporal differences and spatial differences. A fundamental fact is that single pixels values are treated when working with differences. No area features are introduced to this analysis. The reason for this is the huge surface area of 500 x 500 m which is represented by one MODIS pixel.

Time series analyses in the present thesis are only conducted during the dry season of each year. In tropical rain forests, there is usually a periodical transmission between rainy seasons and dry seasons. During rainy seasons, clouds prohibit ground reflectance measurements most of the time. For every time series analysis, data sets without gaps are desired. Scanning visually through data sets over one year in the project area, it has become obvious that the best data sets are available from November to February. Therefore, only these periods at each year are analysed.

6.3.1 Preliminary study: Deforestation

There is no deforestation within the project area in the Republic of Congo. Deforestation occurred in the south of Cameroon between 2000-2004. Deforestation can be made in short periods for large areas using heavy machines. Deforestation can also be made in long periods for small areas using small machines or even hand tools. This type of slow deforestation is investigated in the present thesis. The area is located in the surrounding of a small village.

The two vegetation indices NDVI and EVI are used. Comparisons are done between areas of deforestation and areas which remained unchanged within the period of investigation.

6.3.2 Time Series of Spatial Differences - Selective Logging

A spatial difference in the context of the present thesis is a difference between the reflectance value of a logged pixel and the reflectance value of an intact, unlogged pixel. This difference is calculated with reflectance values of the same date. The logging areas are known from the visual search in Landsat scenes. For calculating the spatial differences, the nearest piece of forest, representing the same forest type than the logged one is taken. This piece of forest was also found in a visual search in Landsat scenes and transferred to the investigated MODIS scenes. The mean reflectance of all unlogged pixels is calculated and subtracted from each logged pixel. This approach is called spatial difference in the present thesis. It is applied to each logged pixel. This is done at several consecutive dates for all pixels, resulting in time series of spatial differences. If the date of logging is known for a certain pixel and the spatial differences are calculated before and after this logging event, this logging event should be visible in the differences. Before the logging event the observed pixels are still intact, therefore the difference to the mean reflectance value of a nearby area of the same forest type should be around zero. After the logging event the differences are assumed to be unlike zero. The idea of this approach was found in the study by Alexander Koltunov [26] as described in section 4.3.3.

6.3.3 Time Series of Temporal Differences - Selective Logging

Basically, logged pixels and unlogged pixels are compared. A temporal difference of one pixel is calculated by subtracting its value at a certain intra annual date from its value at the same intra annual date but in a different year. The basic assumption for using same intra annual dates is, that the forest phenology is the same in each year. Therefore, the temporal difference should be free from phenological effects. If there are logging activities in the area of a certain pixel and a difference is calculated with one value before the logging event and another value after the logging event, this logging activity should be visible in this difference. This difference, representing logged forests, is then compared to a difference representing unlogged forests.

Of course, the difference of unlogged forests is calculated in the same manner and with the same dates of observation, only using pixels which remain unlogged during the observation period. Consequently, this comparison is scientifically valid. According to the definition of time series, the comparison of these two differences is made for several consecutive dates.

Chapter 7

Results and discussion

7.1 Preliminary studies: Monotemporal

First, the results of the visual scan for logging areas in Landsat scenes are shown. They later serve as ground truth input for the MODIS time series analysis. Second the comparison between Landsat and MODIS is shown, investigating the question if logging patterns are visually seen in MODIS data sets. Further on, a correlation test between two MODIS bands is shown. This is important to evaluate the usability of vegetation indices, which are necessary for the purpose of the present study.

7.1.1 Landsat Logging Areas

Scanning visually through landsat scenes of the project area (Landsat ID: P182R059) from 2000-2010 revealed several logging areas. The chronosequence of one of these areas shown in figure 7.1.1 is used for further analysis. It shows very clear logging patterns within the time span of a few months. With visual analyses of Landsat data it can be detected, that at the end (2009/01/14) of the dry season from November 2008 to February 2009 the forest is still unlogged, whereas to the beginning (2009/11/30) of the dry season from November 2009 to February 2010 the forest is definitely logged. This means that this logging event is represented for sure in the MODIS data sets of the fourth dry season and may also be represented in the last two scenes of the dry seasons from November 2008 to February 2009. The black&white dashed line in the pictures marks the borders of the area of interest. It is necessary in the software ERDAS to mark and define certain areas. The size of the marked logging area is approximately 8 x 4 km. One MODIS pixel represents 500 x 500m of surface reflectance. Due to its form, the area contains around 30 - 40 MODIS pixels. For the visual landsat analysis, band 4 is assigned to the red channel, band 3 to the green channel and band 2 to the blue channel. This band combination works well for visual vegetation analysis.

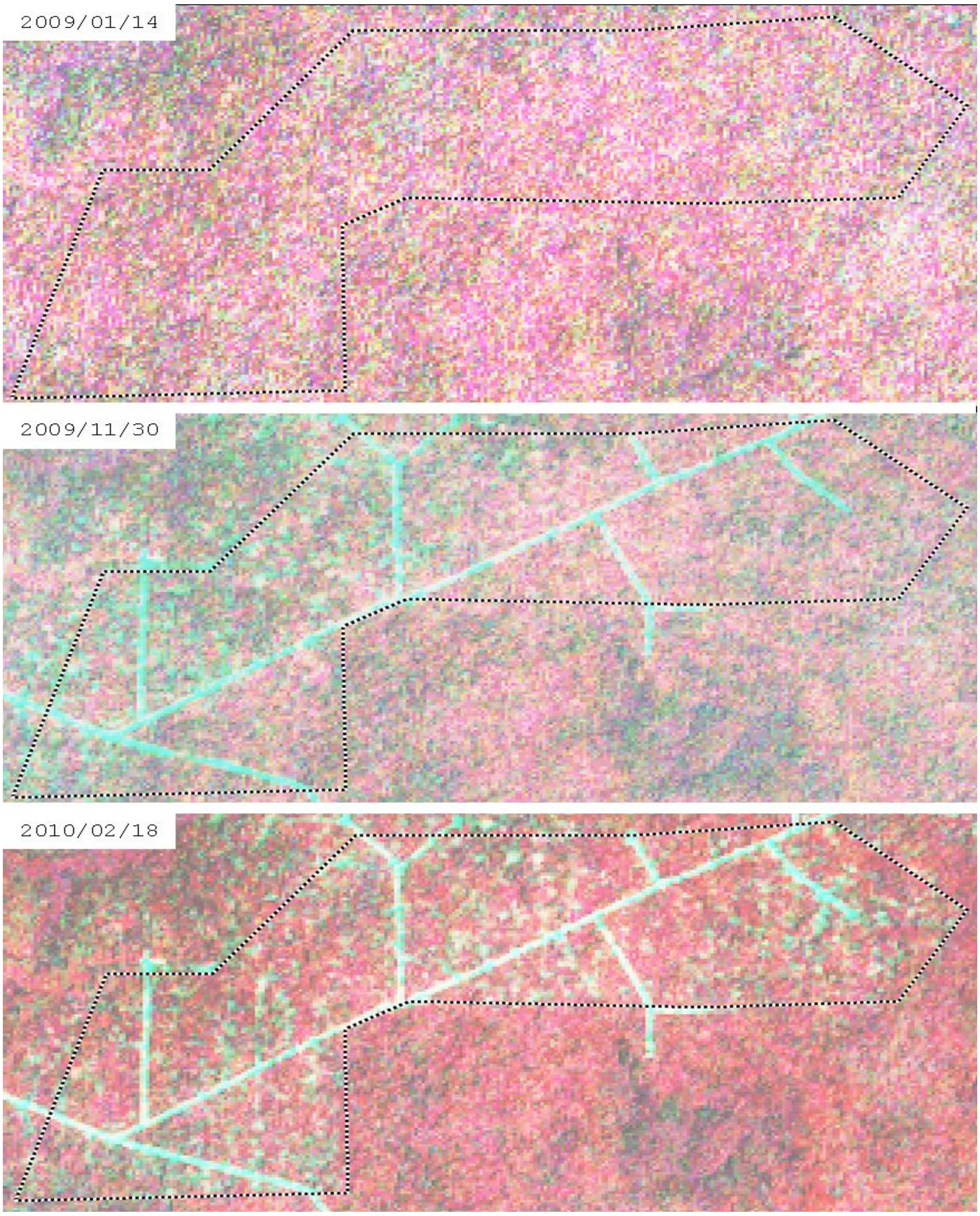


Figure 7.1.1: Chronosequence of a logging area in Landsat

7.1.2 MODIS Logging Areas vs. Landsat Logging Areas

Subsets of MODIS images are compared visually to a Landsat subset of logged forest in figure 7.1.2. All subsets show exactly the same area. Its size is approximately 11 x 10 km. The Landsat scene is from 28/02/2010 and the MODIS scene is from 26/02/2010. This difference of two days between the images does not prohibit a brief and correct visual comparison. Two days is a very short time in logging, and the large-scale patterns are not changed distinctly in such a short period of time.

The logging patterns of roads and equally distributed holes in the canopy are clearly visible in the Landsat image. In none of the MODIS bands subsets these pattern are visible. Even the distribution of brightness within the MODIS subsets does not correlate with the distribution of logging in the MODIS subsets. The central logging road, as seen in Landsat, may correlate with the light area seen in the NIR band of MODIS. But in this band subset the complete area in the lower right corner is very bright aswell, although this represents an area of unchanged forest, as seen in Landsat. Thus logging is not visually detectable in MODIS. The white pixel in the blue MODIS subset marks a missing value in the MCD43 data set. These relations are shown in figure 7.1.3.

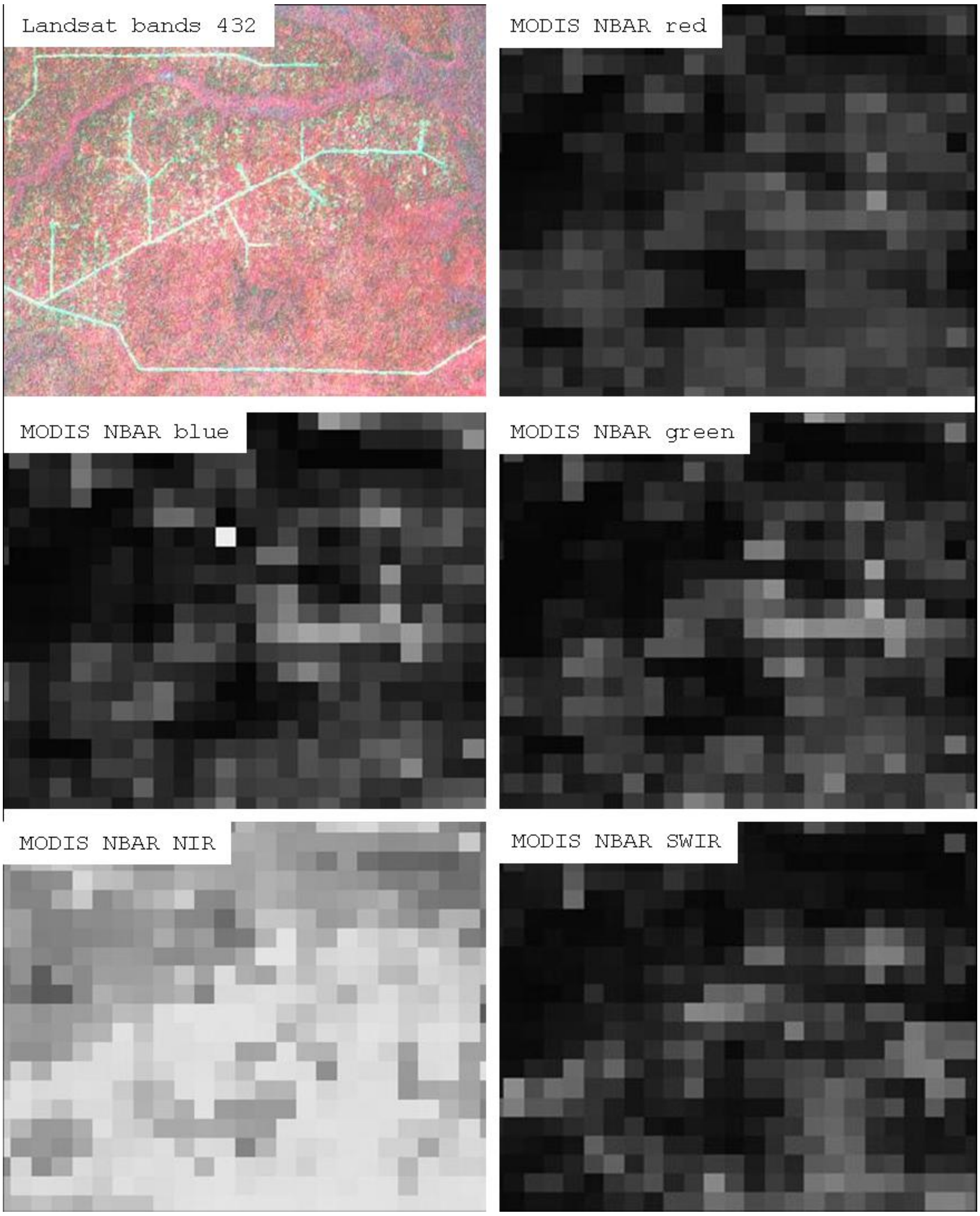
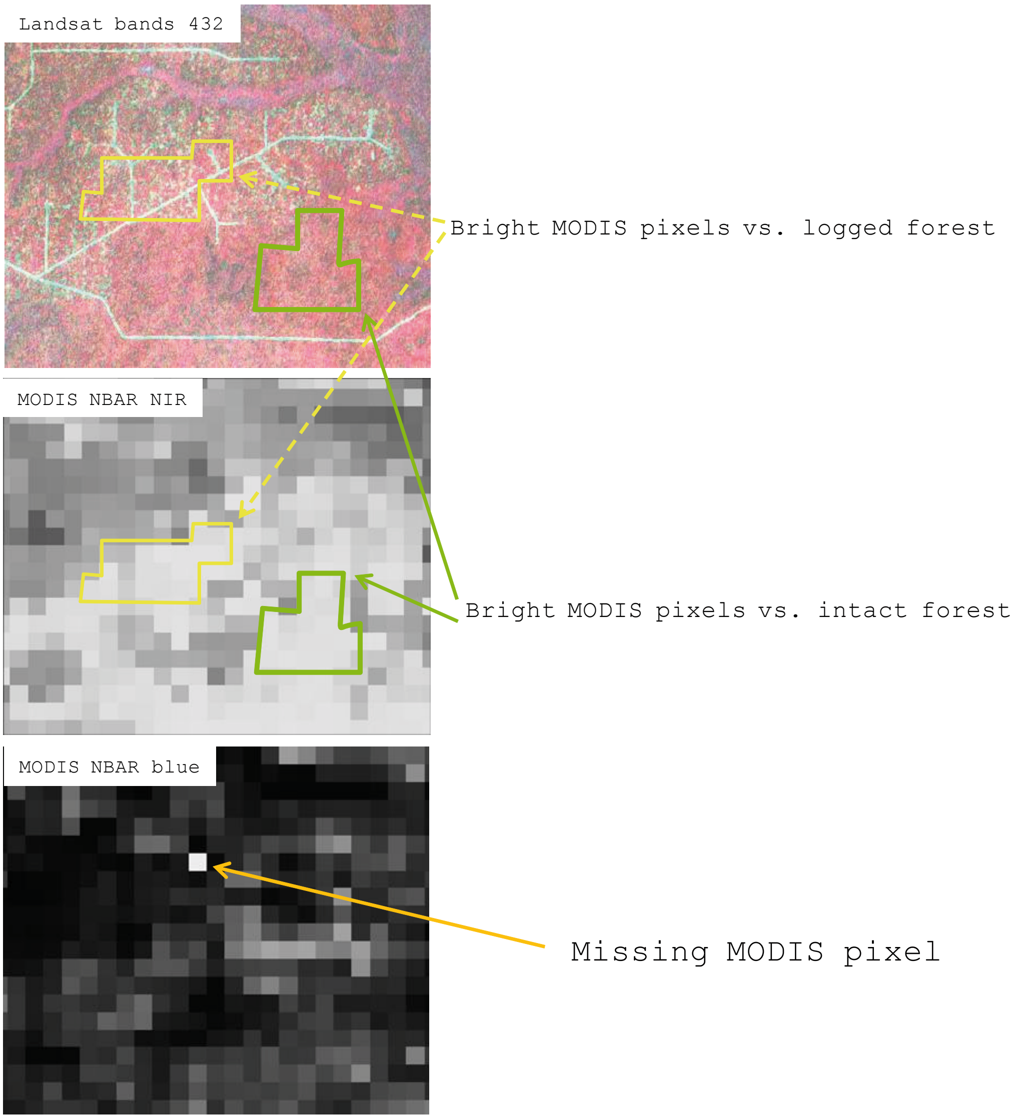


Figure 7.1.2: Comparison Landsat vs. MODIS

7.1.3 Correlation Test MODIS Bands

For the MODIS NBAR scene from 26/02/2010, a feature space for the bands 1 (red) and 2 (NIR) is presented. Pixels with logging (marked by a red cross)



Landsat bands 432

MODIS NBAR NIR

MODIS NBAR blue

Bright MODIS pixels vs. logged forest

Bright MODIS pixels vs. intact forest

Missing MODIS pixel

Figure 7.1.3: Detailed Comparison Landsat vs. MODIS

and pixels which remain unchanged (marked by a green cross) are drawn into the feature space. This is shown in figure 7.1.4. Logged and unlogged pixels show high reflectances in the NIR channel and low reflectances respectively high absorption in red channel. The reasons are given in section 4.2. The Jeffrey Matusita distance between these two types of pixel is 492. This is low value of separability making it difficult to distinguish them in monotemporal analyses. This circumstance will be dealed with in the following sections.

7.1.4 Discussion

The preliminary studies in a monotemporal approach delivered good results for the present thesis. Several instances of logging could be found through the visual scan of Landsat scenes. However, these logging areas could not be detected visually in MODIS MCD43 images. In none of the single bands, logging patterns could be identified. After the correlation test, MODIS channels red and NIR will be used later for VI calculations.

7.2 Preliminary studies: Multitemporal

After the detection of the logging areas, the separability of logged and unlogged pixels between two points in time is investigated. All analyses are based on the Enhanced Vegetation Index (EVI) as proposed by [42]. Pixels of logged forest and pixels of intact forest are plotted in multi-temporal feature spaces between the EVI images of two dates. The question is, whether change and no-change pixels can be separated with this kind of separability analysis.

7.2.1 Feature space Tests

The Phenology of a tropical rain forest has very dynamic intra-seasonal behavior. To minimize these effects, feature space tests are only done between images of the same intra-seasonal date. For example, a comparison between December 2009 and December 2010. MODIS NBAR images are available for the same dates each year, so it is possible to have an exact congruence of date. Pixels from the logging area presented in the monotemporal visual studies shown in figure 7.1.1 are used. The forest was degraded between 2009/01/14 and 2009/11/30 in this area. A nearby area of unchanged forest of the same type than the logged one, is used as a reference area. In this context, forests of the same type are forests with same reflections before the logging event. The variations in reflectance are caused from the moisture level and from

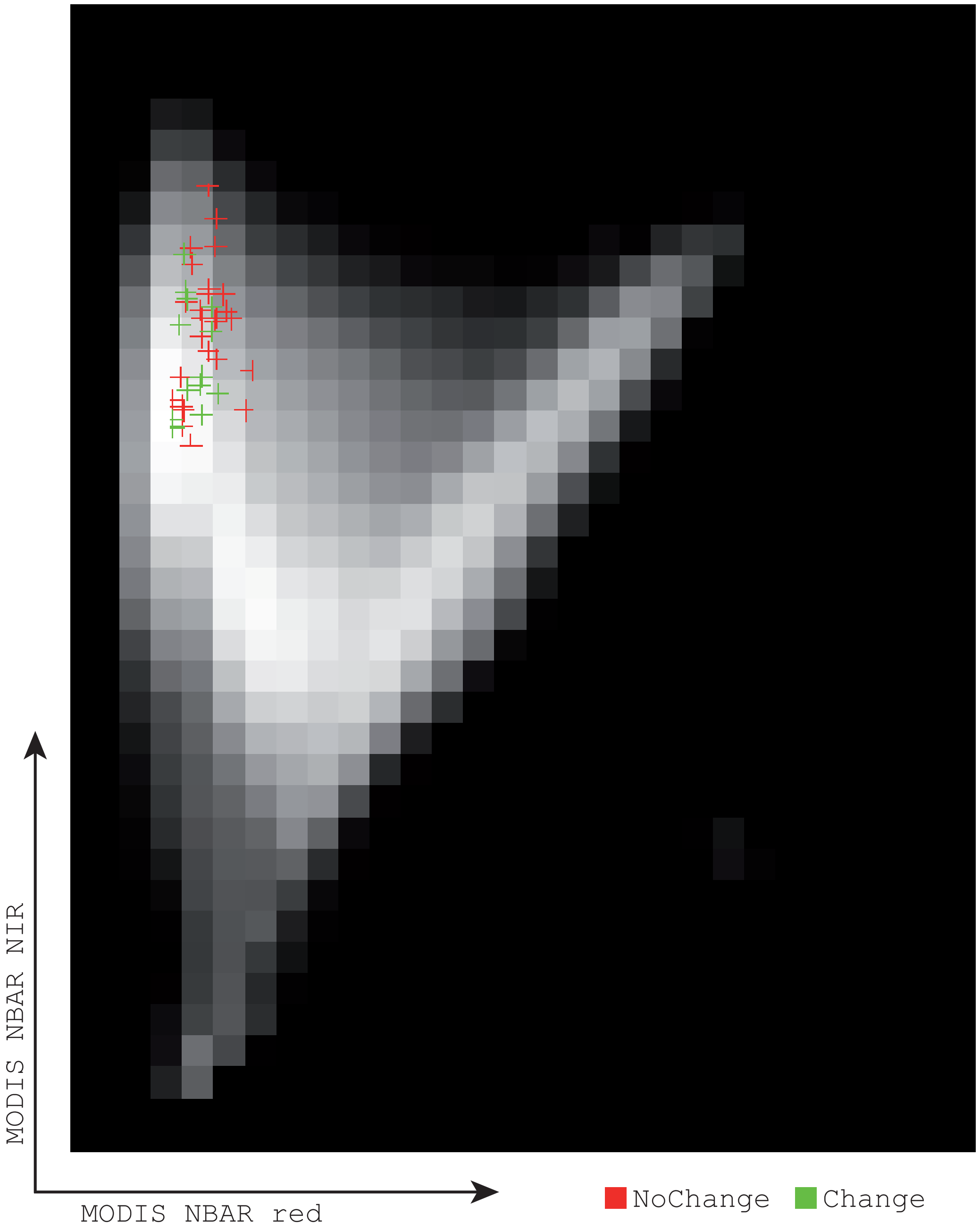


Figure 7.1.4: Feature space MODIS red and NIR

Date of first scene	Date of second scene	JM distance	Shown in figure
2007/02/26	2010/02/26	413	7.2.1
2006/12/27	2009/12/27	426	7.2.2
2007/12/27	2009/12/27	489	7.2.3
2008/01/25	2010/01/25	472	7.2.4

Table 7.1: Multi-date feature space analyses

the kind of tree species within an area of forest. Through analysing different bands of Landsat and also different band combinations, forerst of the same type can be detected. If one uses an area of forest of another type than the observed logged one, the pre-logging natural difference in reflectance will disturb all investigations.

This kind of multi-date preliminary study at equal intra-annual dates in different years was investigated exemplary. The separability between logged and unlogged pixels is tested. Therefore, all multi-date investigations of this section include one scene before and one scene after the observed logging activity from February 2009 to November 2009. An overview of these investigations, including the corresponding Jeffrey Matusita (JM) separability as well as the link to the related figure is given in table 7.1.

The JM separabilities are very low in all four cases. This can also be seen in the corresponding multi-date feature spaces.

7.2.2 Discussion

The preliminary studies in a multitemporal approach, have not been successful in this case. The investigated forest degradation by selective logging show too small or almost no changes in the MODIS EVI reflectance. One reason may be the deviation between modeled and observed BRDF values as described in section 3.2.4. These are unfavorable precondition for the outstanding approach of time series analysis which is basically a sequence of analyses between two dates as shown in this section. However, all preliminary studies in a multitemporal approach took place in the second part of the dryseasons. In addition, mathematical analysis techniques for time series, like the standard deviation will be introduced, to gain other possibilities of separability.

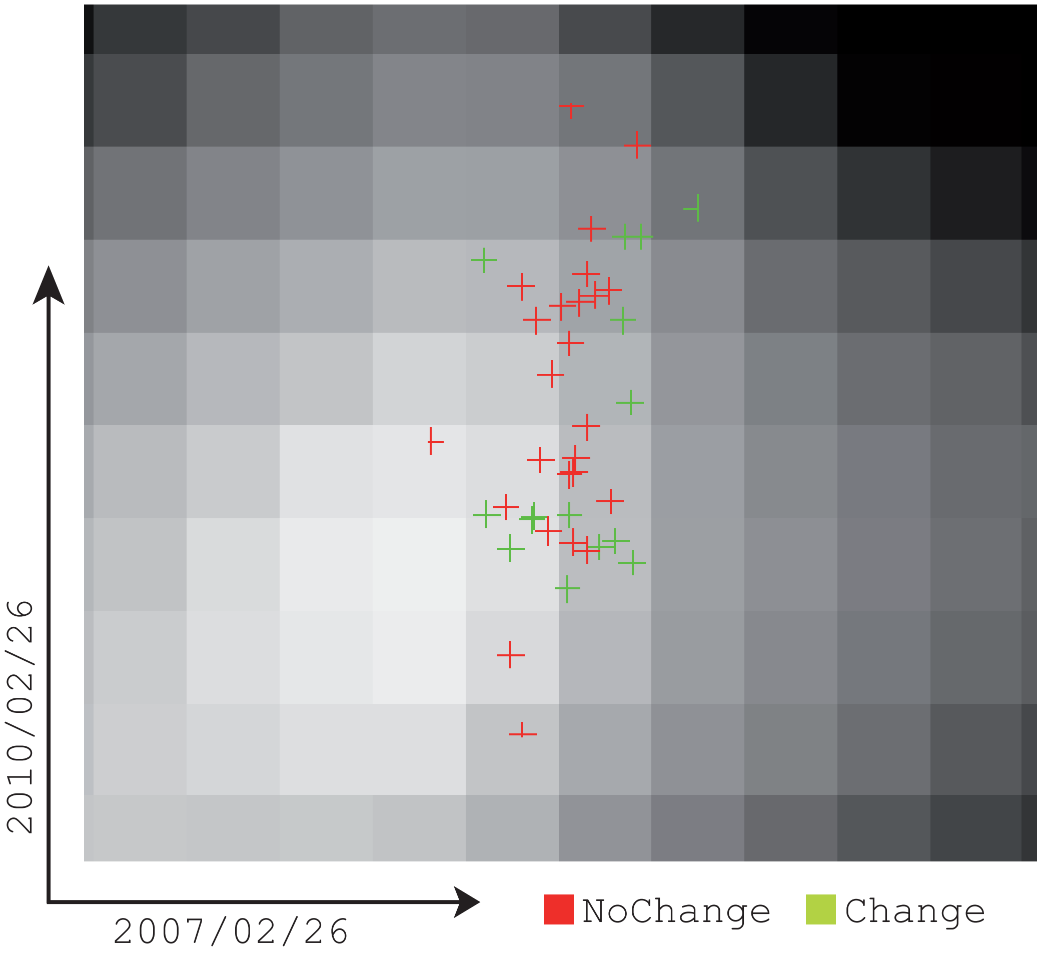


Figure 7.2.1: MODIS feature space 2007/02/26 and 2010/02/26

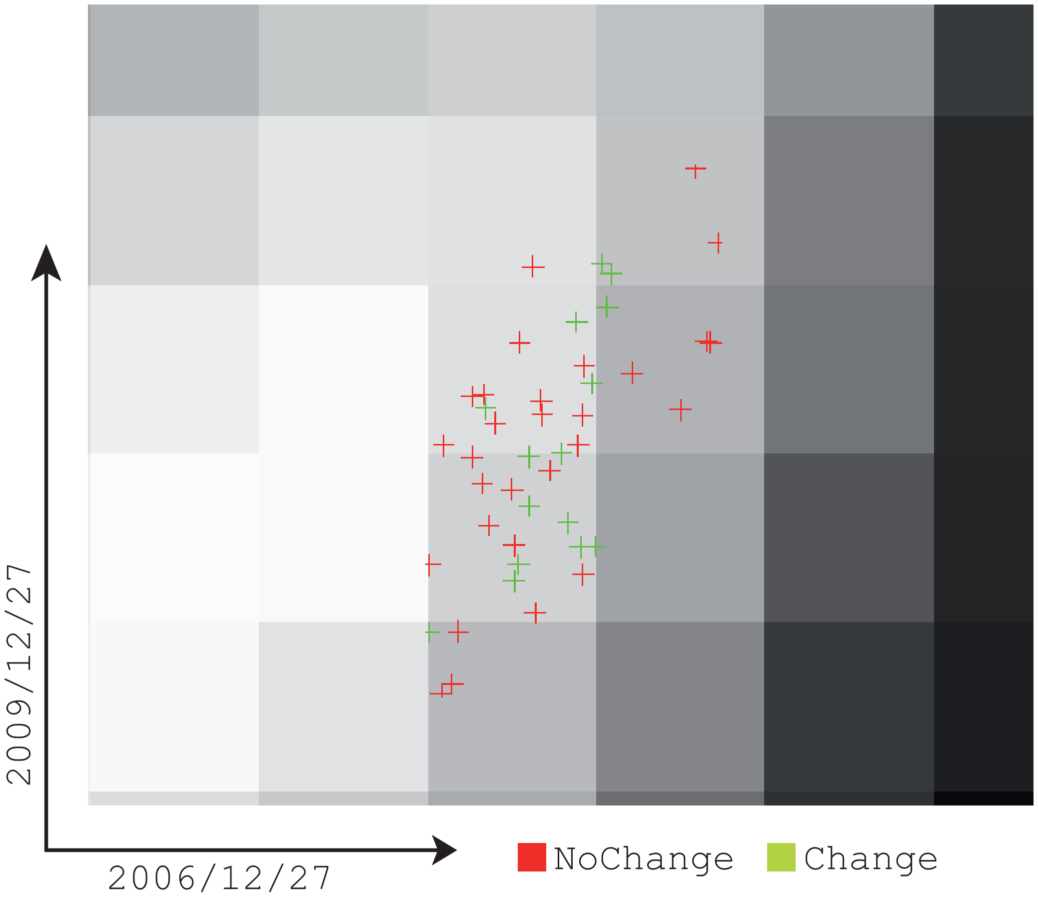


Figure 7.2.2: MODIS EVI feature space 2006/12/27 - 2009/12/27

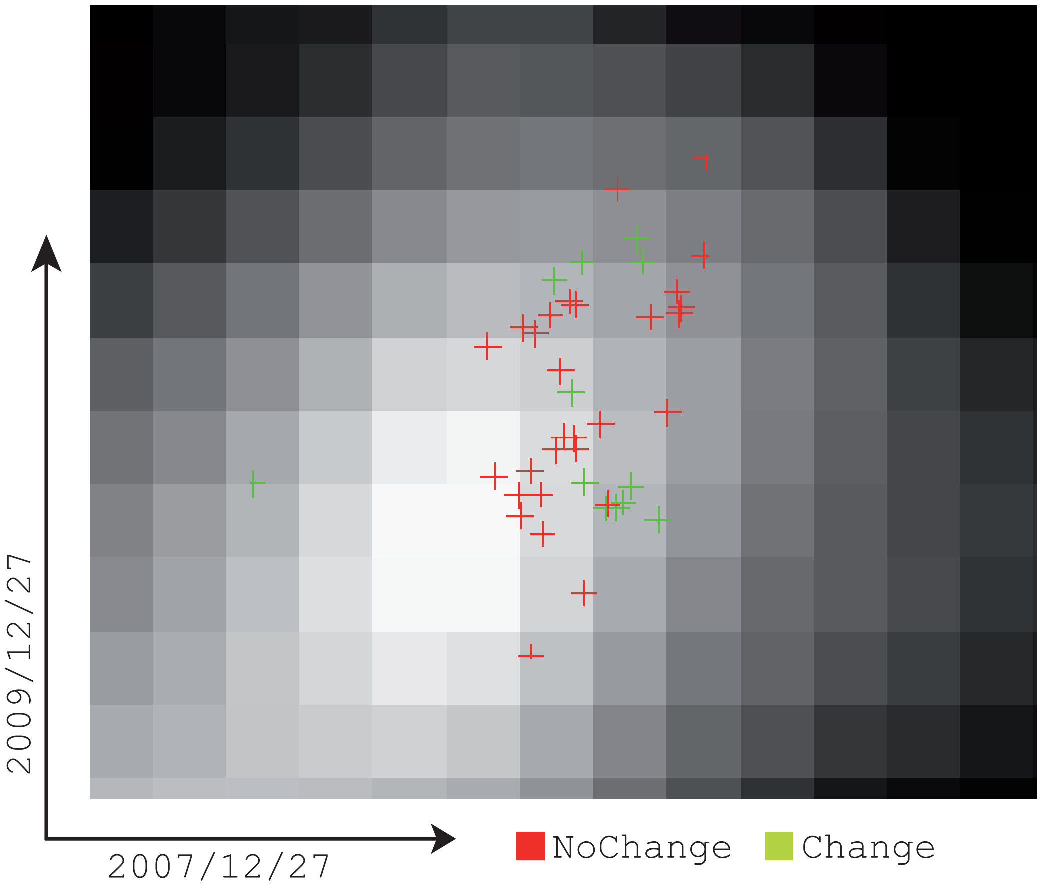


Figure 7.2.3: MODIS EVI feature space 2007/12/27 - 2009/12/27

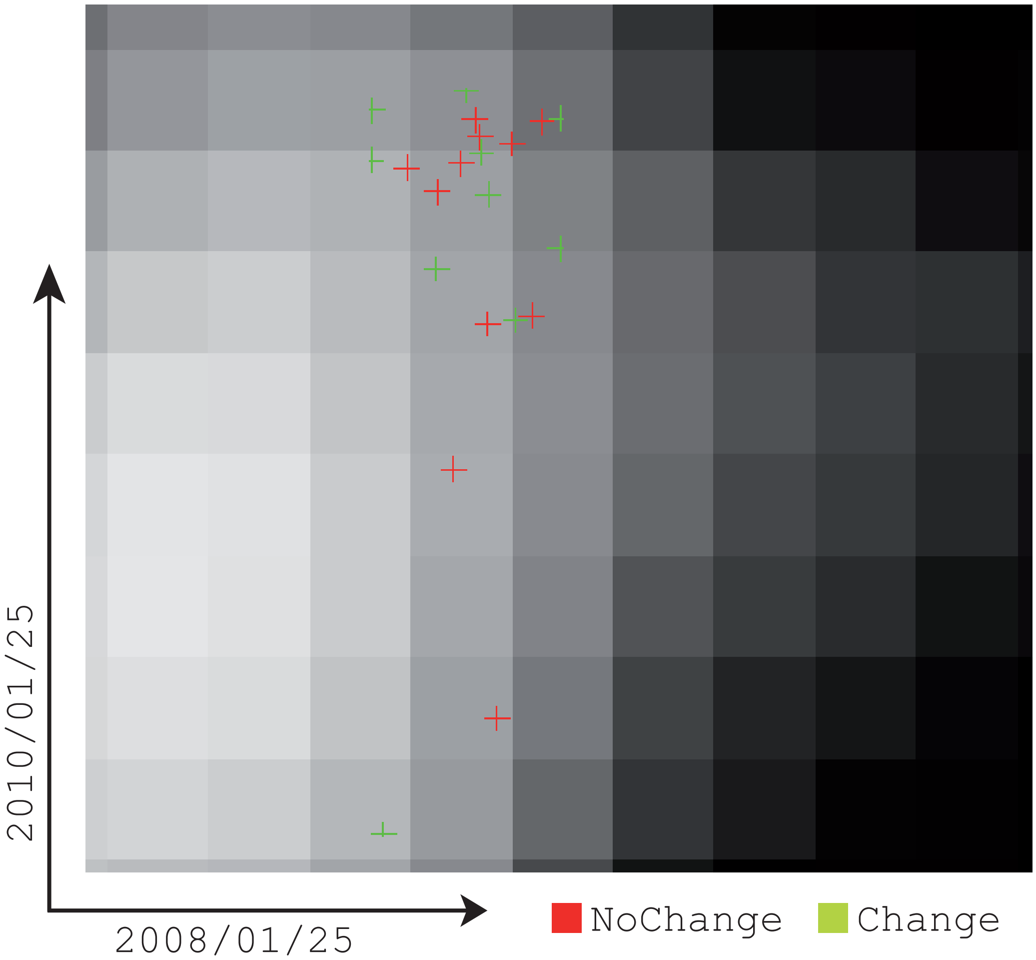


Figure 7.2.4: MODIS EVI feature space 2008/01/25 - 2010/01/25

Number	Period of time
First	Nov 2006 - Feb 2007
Second	Nov 2007 - Feb 2008
Third	Nov 2008 - Feb 2009
Fourth	Nov 2009 - Feb 2010

Table 7.2: Investigated dry seasons

7.3 Time Series Analysis

First, time series of deforestation are shown. The selected case is the most extreme case of forest degradation, which is supposed to produce significant patterns. This is done with EVI and NDVI. Working on the detection of selective logging, the two differences described by Koltunov [26], temporal and spatial differences, are calculated. The analysis is concerned with data from four consecutive dry seasons from 2006 to 2010. Each dry season is represented by 8 MCD43 images at an interval of 16 days. The dry seasons are numbered and named according to table 7.2.

7.3.1 Preliminary study: Deforestation

The phenology of intact forests and deforested areas can be seen. If the separability in this case should prove low, the separability of small-scale degradation activities will be even more difficult.

7.3.1.1 EVI

A comparison of intact forest pixels and pixels of continuous deforestation within the period of 4 years is shown in figure 7.3.1. MODIS data sets of the four dryseasons listed in table 7.2 are introduced. At the end of these 4 years, all change pixels are deforestated. This statement is based on visual investigations of Landsat scenes with a spatial resolution of 30m x 30m. Therefore, no evidence is given wether some trees are left or not in these areas. The result of the visual interpretation was a clear change of reflectance within the observed four years. Pixels which showed reflectance values of forests changed to pixels with very different reflectance values. It is obvious that the two kinds of pixels can be separated very well in the last dry season as seen in figure 7.3.1. In the first two seasons, some pixels can be separated and some not. The reason is the different date of deforestation. Some pixels are still intact after the first dry season In the subplot below the Jeffrey Matusita distance between all unchanged pixels and all changed pixels is plotted for each date.

The high variance of EVI within the specific years is attributed to the emergence of new leaves and to the fall of old leaves [42]. Generally, old leaves have less chlorophyll and water content in comparison with old leaves. The last dry season shows an especially interesting pattern between pixels of deforestation and unchanged pixels. At the beginning of the dry season, the deforested pixels show higher EVI values the unchanged ones. Due to the warm and humid climate, central Africa has a very fertile soils. In these climatic conditions, a piece of bare soil will be completely covered with all kinds of plants within a few weeks during the humid season. These plants may have a higher chlorophyll and water content than young leaves at the top of a tropical tree at the beginning of the dry seasons. Thus the EVI value of these pixels is higher than of pixels of unchanged forest. in addition, some of these plants may be crops, which are harvested after a certain time, changing a vegetated area of land into an area of bare soil. In this period, changed and unchanged pixels cannot be separated by JM distance at a single date. Later on in the dry season, the crop plants at the former places of clear cut trees are mostly harvested. The changes the area to bare soil, and leads to extreme variations in the values of Vegetation Indices. Intact tropical rain forest have evolved mechanisms to store water for the dry seasons. Deep root systems provide access to water and the dense canopy protects the ground from direct sun radiation. Without the canopy, the ground dries up very fast. Around the equator, the sun shines to the ground at an angle of around 90° at its zenith.

7.3.1.2 NDVI

A comparison between intact forest pixels and pixels of continuous deforestation within the period of 4 years is shown in figure 7.3.2. The result is similar to that based on EVI data. Again separability works best in the last dry season when deforestation reached its maximum extent in the observed period. As detected in EVI, also working with NDVI, the forest shows the ability to store water through the dry season. The young and fresh plants at former places of tropical forest do not have this ability. Because of this, the JM separability increases with the progressing dry season. It is also possible that the deforested areas are used for planting crops, which may be harvested in the dry season. This leads to bare soil and low NDVI values. A low water content of leaves is correlated with low NDVI values, this context is well known and is presented in detail in [9].

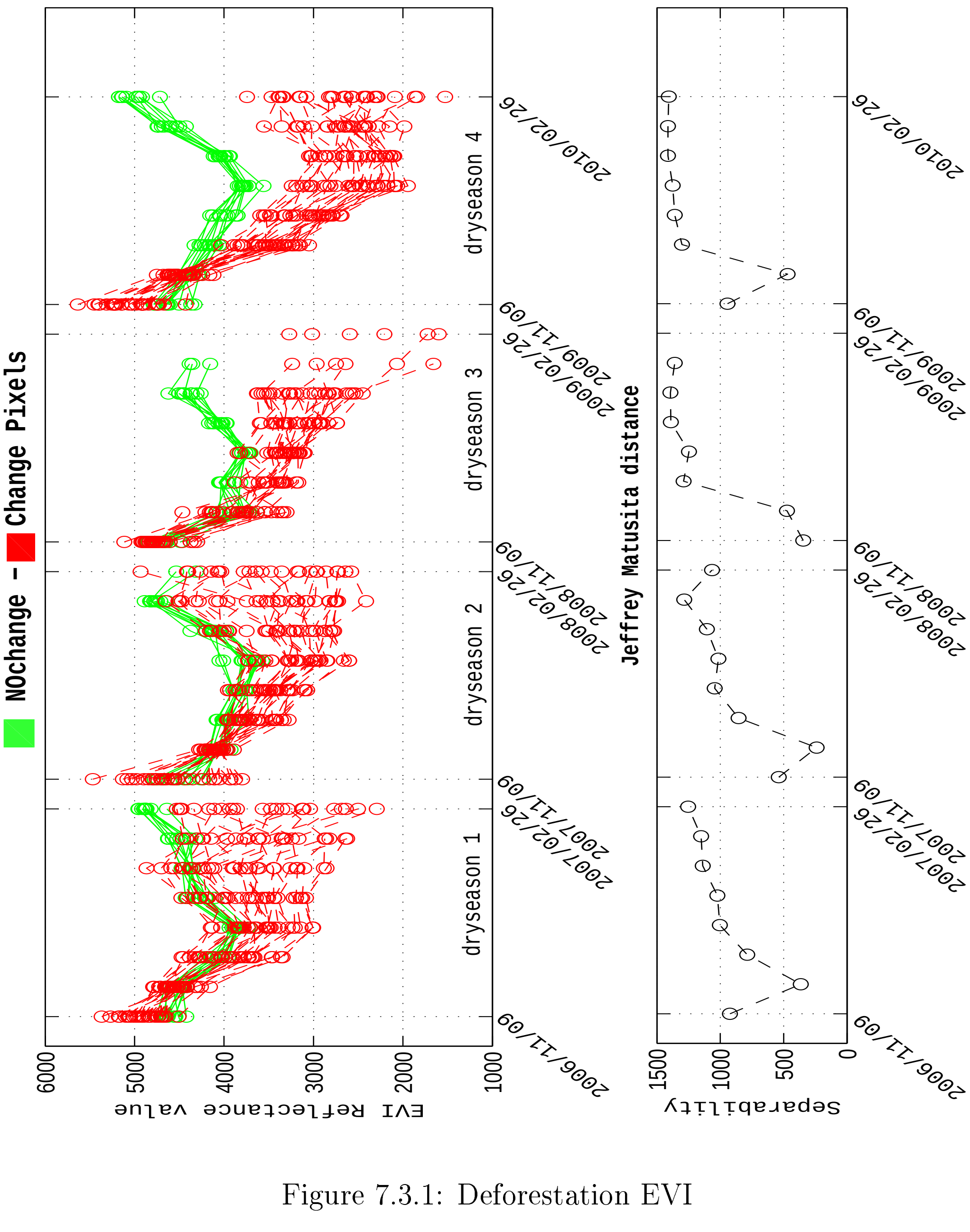


Figure 7.3.1: Deforestation EVI

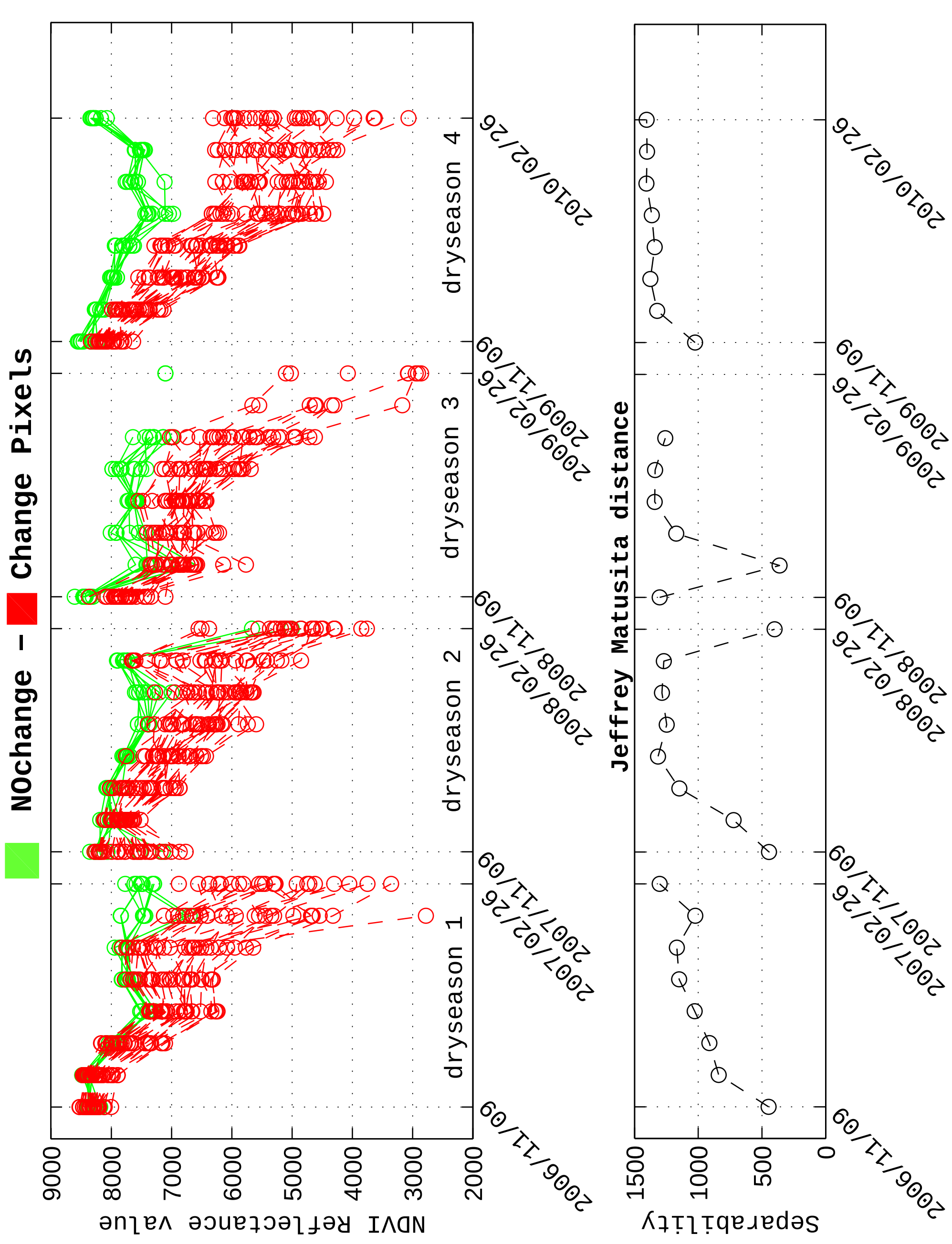


Figure 7.3.2: Deforestation NDVI

7.3.2 Selective Logging - Absolute Time Series

All analysis with absolute time series as well as spatial and temporal differences takes place in the logging area shown in figure 7.1.1. Again EVI index, calculated from MODIS BRDF data sets is used. This changing area is compared to a nearby unchanged area. Again, logging occurs in the fourth dry season from November 2009 to February 2010, possibly also in the last two dates of the previous, third dry season of the study. 30 pixels of logged forest and 15 pixels of intact forest are considered in this analysis, shown in figure 7.3.3. The number of intact forest pixels is smaller because no more pixels of the same type could be found. Each dot in the figure represents one pixel at one date. Unchanged and changed pixels behave similarly through the firest three dry seasons, most obviously in the first dry season. The fourth dry season is different because the change pixel show especially larger variations than in the dry seasons before. As described in section 3.3.3 the MODIS BRDF algorithm needs 7 unobstructed observations within 16 days to be completely calculated. Many data sets are missing. For example at the beginning of the third dry season there are almost no data values within three consecutive dates.

7.3.3 Selective Logging - Time Series of Spatial Differences

For each date a mean value of all unchanged pixels is calculated. This mean value serves as reference and is subtracted from each change pixel. The resulting difference should be around zero in the first three dry seasons, where there is no logging. In the fourth dry season, the difference is expected to not be zero due to the logging which is represented by these differences. The result is shown in figure 7.3.4. In the top subplot, the differences are plotted, in the subplots below, the standard deviation of the differences for each date and also the number of valid pixel for each date. There is logging in the fourth dry season. Either a clear offset from zero in this dry season or a difference from the first three dry seasons, or higher standard deviations in the fourth dry season could serve as mathematical instruments of separability. Missing data values make continuous analysis impossible, which is especially in the case of time series studies quite obstructive. The standard deviations are higher in the fourth dry season, but in the third dry season there is no single data value at some dates, which would enable comparisons and clear results. Therefore the only result for spatial differences is the assumption that in case of full data availability, logging pixels are separable by higher standard deviations.

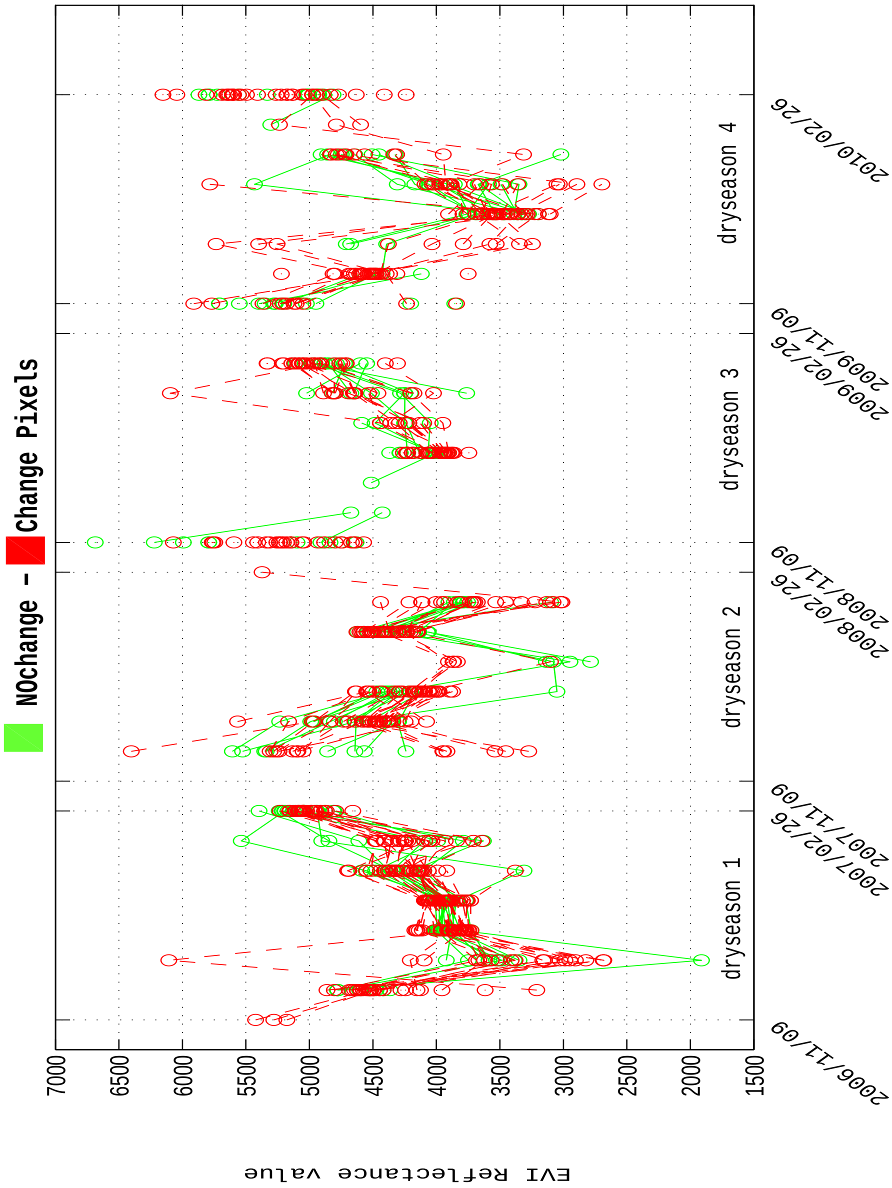


Figure 7.3.3: Change - No Change Absolute Time Series

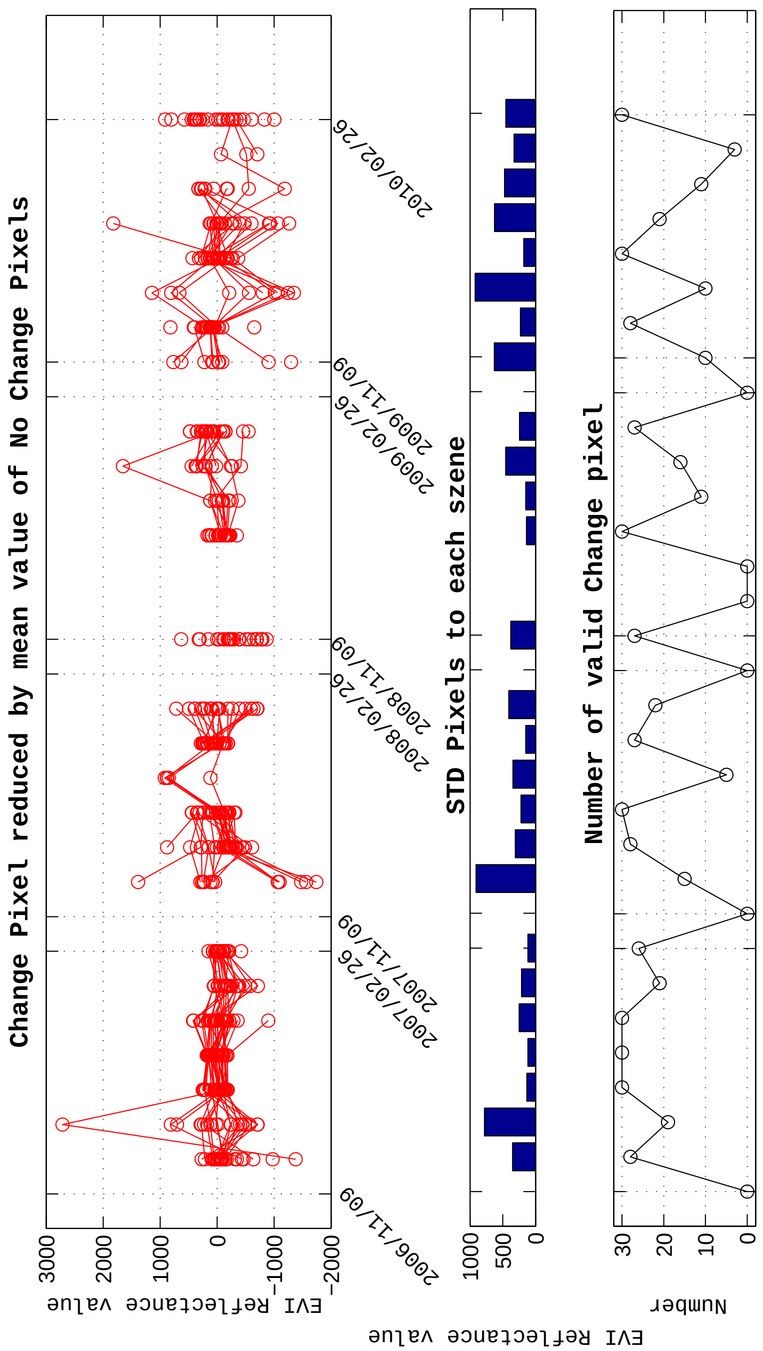


Figure 7.3.4: Spatial differences

7.3.4 Selective Logging - Time Series of Temporal Differences

All temporal differences are made with reference to the fourth dry season, which is the season where logging occurs. Differences are calculated between the fourth and the third, between the fourth and the second and between the fourth and the first dry season. Thus, the logging activity of the fourth dry seasons is included in all three differences. As described in the chapter on methodology, differences are calculated pixel-wise, at the same Intra-annual dates. Regarding the result shown in figure 7.3.5, the biggest problem of this kind of analysis is obvious. It is again the lack of continuous data. For temporal differences, one needs two valid data sets from the same intra-annual dates to get one resulting data value. Applying this technique to a data sets with many gaps, the result will have even more gaps. However, this problem arises in all application of remote sensing, regarding changes between two points of time. As a result in the case of temporal differences, not even an assumption about the utility of the method can be made in a scientific sense. Too many data sets are missing.

7.3.5 Other Logging Areas

The Time Series analysis of the most promising logging area has been not successful. With visual analysis, several other logging areas have been detected. This has already been mentioned in chapter 7.1.1. Furtheron, The data of another logging event between 2000 - 2004 was evaluated as shown before. But again, the lack of data was a problem. Even more data sets were missing. The only conclusion is, that MODIS data sets are not useful for these purposes.

7.3.6 Discussion

The most problematic fact that emerged in the course of this study is the low data quality of the MODIS MCD43 data sets. Seven cloud-free observations within a 16-day period are needed to perform the full NBAR algorithm which operates behind MCD43 data sets. In rainforests, which have high moisture levels through the whole year, it is normal and natural that the surface is frequently obstructed by clouds. Too many data gaps were found equally distributed over the investigated dry seasons between 2006 and 2010. These gaps make solid time series analysis impossible. In addition, the logging areas of this study are much smaller than logging areas in the Amazon basin. If logging areas with a similar size to the areas in the Amazon basin would have

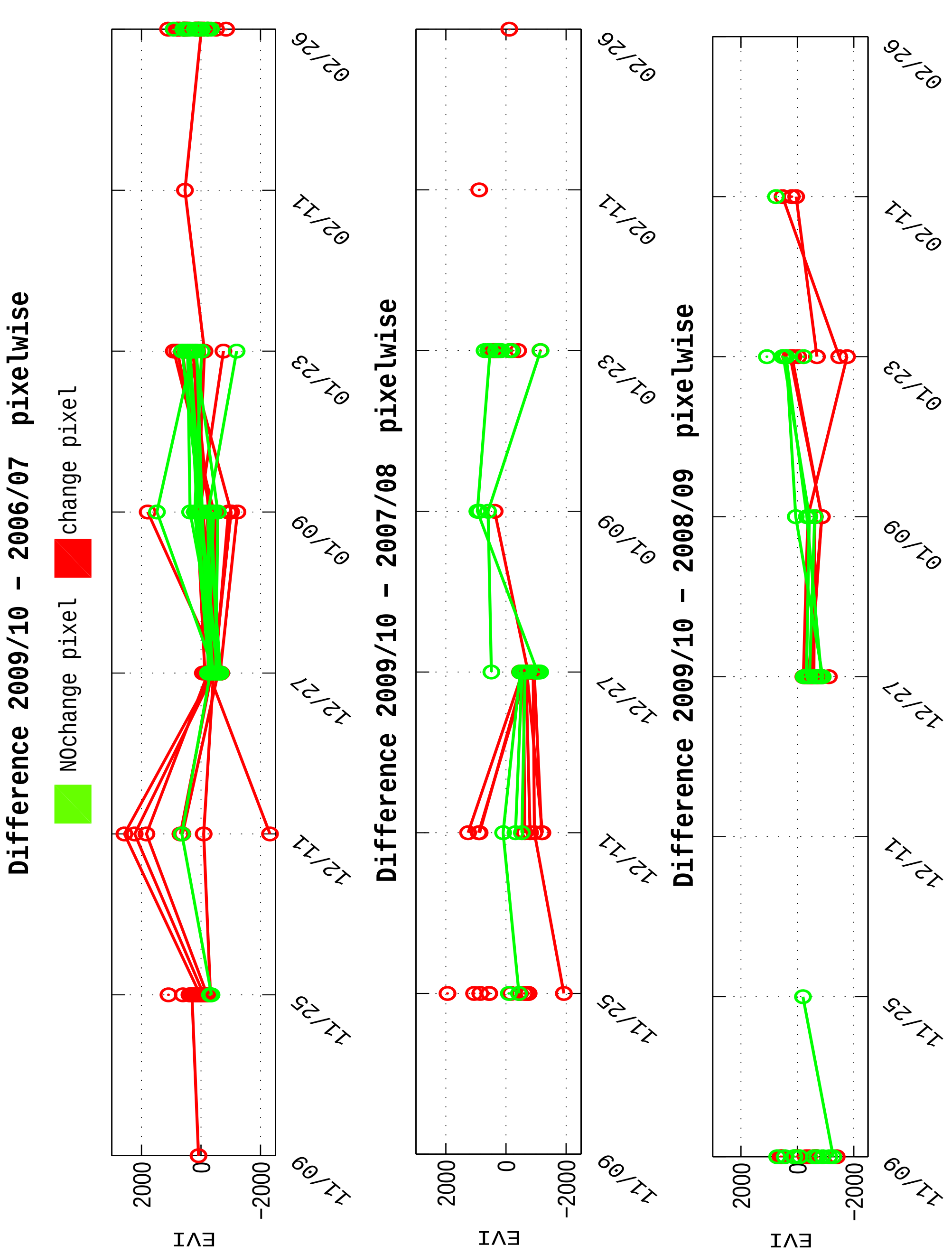


Figure 7.3.5: Temporal differences

served as project areas, one could probably have found pixels of good quality for the whole observation period. In that case, the suggested methods of this work could have been tested and maybe proved. However, for an operable REDD monitoring system, even if it is only used as the first step of a hot spot approach, comprehensive data sets of good quality are needed. One MCD43 pixel represents 500 m x 500 m of surface. It is therefore not possible to just exclude one pixel of missing observations from the whole monitoring process.

Even the MODIS team notes the problems of numerous data gaps in MCD43 data sets [34]. In case of clouds obstructing the surface, making reflectance measurements impossible, the scientist suggest the use of a prior knowledge of the likely surface reflectances, which could serve as an input for the MCD43 processing algorithm. Including these data sets into the monitoring system would falsify the whole process, because the main interest of a monitoring system is the status of the surface right at a certain point of time. This can not be provided by a prior estimation of the reflectance. In the work of Koltunov [26], which is the most closely related the present study from the reviewed works, no advice was found concerning how many data sets these scientists had to exclude due to low data quality. It is only mentioned that merely data sets of good quality are used, the exact number is not given. However, this work used an area of 65 MODIS scenes, testing thousands of logged pixels. Therefore pixels with complete time series of good quality must have been found.

Chapter 8

Conclusion and Outlook

8.1 Conclusion

The present thesis could not benefit from the main advantage of MODIS data sets, its high temporal resolution. Working with optical light, the well-known cloud obstruction of tropical forests has proved too limiting for acceptable results. Therefore, MODIS cannot serve as an adequate input for degradation mapping in an hot spot mapping approach, even on a first coarse level. In addition the design life time of the two MODIS satellites is 6 years. Both satellites are working at current date (March 2011) beyond their designated life time. Terra is operating since 1999 and Aqua since 2002. So for future operable REDD monitoring system, sensors are needed with ensured lifetimes of at least 5 years.

8.2 Requirements for Hot Spot Mapping

The ideal data set for the first level of hot spot mapping is void of data gaps. For an area of interest, a data set of comprehensive and good quality is needed for at least one date per year. For the first level of hot spot mapping, this data sets needs to have the capability to identify changes of degradation. Measuring and mapping the amount of this degradation can be done with other data sets of medium or fine spatial resolution.

8.3 Evolving Technologies

8.3.1 Synthetic Aperture Radar (SAR)

Radar is an active remote sensing system. This is its fundamental difference to optical remote sensors, which are passiv sensors measuring reflected or reflected electromagnetic energy of the earth. Radar sensors operate in the microwave region (λ = 3 - 70 cm). This fact is one of the main advantages of theses sensors, its autonomy of weather conditions for obtaining good measuring results. The microwaves penetrate through surface-obstructing features (aerosols, clouds, smoke), which are especially common above tropical forests. In the case of measuring a forest with radar sensors, different radar bands provide different useful information on the the forest structures. Longer radar wavelengths are scattered by forest structures deeper inside whereas the scattering of shorter radar wavelengths is more dependent on canopy features such as top crown leaves. The amount of backscattered energy gives information on the different forest structures like leaves, branches, stems and the underlying soil. Due to advancements in SAR technologies, an increasing number of SAR sensors has been recently built and sent to space [19]. With the intention of producing globally-consistent radar image data sets the KYOTO AND CARBON SCIENCE TEAM was formed. It is originally a Japanese initiative, however other space agencies, like JAXA, ESA and NASA plan to contribute and cooperate with their radar data sets to ensure and develop a long-time and worldwide coverage of radar data sets. Once established, this may be a used for REDD monitoring, especially through its independence of atmospheric conditions. Maybe it can serve as global input for REDD hot spot monitoring. However, the information content in SAR data sets is much lower than in optical data sets. This circumstance may limit degradation mapping.

8.3.2 Light Detection and Ranging (LIDAR)

This is an active measurement system which can be carried on an aircraft. In the case of a forest, first pulse measurements provides information about the canopy properties, whereas last pulse measurements provide information about the underlying topography. For estimations of biophysical parameters, these data sets have been found to be similarly or even more accurate than corresponding field-based methods. GLAS is a LIDAR sensor on board of the satellite ICESat. This satellite provides data sets from over the whole globe. A recent study used these data sets for estimating biomass and carbon stocks for the Canadian province of Quebec [19]. The only spaceborne laser, GLAS on board of ICESat is currently out of work. There are efforts to restart the system. The United States are developing three other spaceborne LIDAR systems. However, there are bound to be data gaps between the missions. But future missions promise to give data samples at 5 m ground resolution, which may serve as input for the whole REDD carbons stocks estimations, making the hot spot approach with different types of data sets unnecessary.

8.3.3 MERIS

MERIS stands for Medium Resolution Image Spectroradiometer. This sensor is on on board of ESA satellite ENVISAT and offers 12 channels between 390 and 1040 nm at a ground resolution of 300m x 300m. MERIS data sets have been used for global applications like GLOBCOVER. Especially the spatial resolution is seen as an improvement in comparison to the use of MODIS data [4]. These data sets may serve in the first coarse level, for mapping forest degradation in an hot spot approach.

Bibliography

[1] Abholzung. http://de.wikipedia.org/wiki/Abholzung. accessed 28 Feb 2011.

[2] Logging Companies Profile. http://www.forestsmonitor.org/en/reports/540539/549958. accessed 19 Feb 2011.

[3] F. Achard. Deforestation in tropical countries: Use of satellite remote sensing in detecting and monitoring forest area changes. presentation, June 2008. accessed 16 Feb 2009.

[4] F. Achard, R. DeFreis, H. Eva, M Hansen, P Mayaux, and H-J Stibig. Pan-tropical monitoring of deforestation. *Environmental Research Letters*, 2, 2007.

[5] G. P. Asner, J. A. Hicke, and D. B. Lobell. Per-pixel analysis of forest structure: Vegetation indices, spectral mixture analysis and canopy reflectance modeling. *Remote sensing of forest environments: Concepts and case studies*, pages 209–254, 2003.

[6] G. P. Asner, D. E. Knapp, E. N. Broadbent, P. J. C. Oliveira, M. Keller, and J. N. Silva. Selective Logging in the Brazilian Amazon. *American Association of the Advancement of Science*, 310:480–482, 2005.

[7] G.P. Asner, E.N. Broadbent, P. J. C. Oliveira, M. Keller, D. E. Knapp, and J. N. M. Silva. Condition and fate of logged forests in the Brazilian Amazon. *National Academy of Sciences of USA*, 103(34):12947–12950, 2006.

[8] B.Jiang, S. Linag, J. Wang, and J. Z. Xiao. Modeling MODIS LAI time series using three statistical methods. *Remote s*, 114:1432–1444, 2010.

[9] C.C.Hardy and R. E. Burgan. Evaluation of NDVI for Monitroing Live Moisture in Three Vegetation Types of the Western U.S. *Photogrammetric Engineering and Remote Sensing*, 65, No.5:603–610, 1999.

[10] D.A.Chu, Y.J.Kaufman, C.Ichoku, L.A.Remer, D.Tanré, and B.N.Holben. Validation of MODIS aerosol optical depth retrieval over land. *Geophysical Research Letter*, 29 No.12, 2002.

[11] E.F.Vermote, N. Saleous, C. O. Justice, Y. J. Kaufman, J. L. Privette, L. Remer, J. C. Roger, and D. Tanre. Athomsperic correction of visible to middle-infrared EOS-MODIS data over land surfaces: Background, operational algorithm and validation. *NASA Publications*, 1997.

[12] L. Eklundh, T. Johansson, and S. Solberg. Mapping insect defoliation in Scots pine with MODIS time-series data. *Remote Sensing of Environment*, 113:1566–1573, 2009.

[13] FAO. Global Forest Resources Assessment 2005. http://www.fao.org/DOCREP/008/a0400e/a0400e00.htm, 2006. accessed 2 Mar 2011.

[14] N.C. Ferreira, L.G. Ferreira, and A.R. Huete. Assessing the response of the MODIS vegetation indices to landscape disturbance in the forested areas of the legal Brazilian Amazon. *International Journal of Remote Sensing*, 31 No. 3:745 – 759, 2010.

[15] Forestmonitor. Country Profiles - congo(Brazzaville). http://www.forestsmonitor.org/en/reports/540539/549939. accessed 19 Feb 2011.

[16] K. Fukunaga. *Introdution to Statistical Pattern Recognition*. Academic Pr Inc, 1990.

[17] Gao, Huete, and Ni. Optical - biophysical relationships of vegetation spectra without background contamination. *Remote Sensing of Environment*, 74:609 – 620, 2000.

[18] J. J. Gerwing. Degradation of forests through logging and fire in the eastern Brazilian Amazon. *Forest Ecology and Management*, 157(1-3):131–141, 2002.

[19] GOFC-GOLD. A sourcebook of methods and procedures for monitoring and reporting anthropogenic greenhouse gas emissions and removals caused by deforestation, gains and losses of carbon stocks in forests remaining forests, and forestation. GOFC-GOLD Project Office, Natural Resources Canada, Alberta, Canada, 2010. GOFC-GOLD Report version COP16-1.

[20] S. Haas. Monitoring forest degradation for redd in cameroon. Master's thesis, Universtity of Karlsruhe, 2009.

[21] A. Huete, K. Didan, T. Miura, E.P. Rodriguez, X. Gao, and L.G. Ferreira. Overview of the radiometric and biophysical performance of the MODIS vegetation indices. *Remote Sensing of Environment*, 83:195–213, 2002.

[22] M. Hulme, R. Doherty, T. Ngara, M. New, and D. Lister. African climate change: 1900-2100. *Climate Research*, 17:145–168, 2001.

[23] IPCC. Climate Change 2007 - Impacts, Adaptation and Vulnerability, Working Group II contribution to the Fourth Assessment Report of the IPCC. http://www.ipcc-wg2.org, 2007. accessed 2 Mar 2011.

[24] IUCN. Forests and livelihoods, Reducing emissions from deforestation and ecosystem degradation (REDD), 2008. accessed 18 Mar 2011, Briefing Paper.

[25] J.R. Jensen. *Introductory Digital Image Processing: A Remote Sensing Perspective 2d ed.* Englewood Cliffs, New Jersey, 1996.

[26] A. Koltunov, S.L. Ustin, G. P. Asner, and I. Fung. Selective logging changes forest phenology in the Brazilian Amazon: Evidence from MODIS image time series analysis. *Remote Sensing of Environment*, 113:2431–2440, 2009.

[27] X. Li and A.H. Strahler. Geometric-Optical Bidirectional Reflectance Modeling of the discrete Crown Vegetation Canopy: Effect of Crown Shape and Mutual Shadowing. *IEEE Transactions on Geoscience and Remote sensing*, 30 No. 2:276–292, 1992.

[28] M. Linderman, Y. Zeng, and P. Rowhani. Climae and Land-Use Effects on Interannual fAPAR Variability from MODIS 250 m Data. *Photogrammetric Engineering & Remote Sensing*, 76(7):807–816, 2010.

[29] MODIS. *Discriminating Clear-sky from cloud with MODIS; Algorithm Theoretical Basis Document (MOD35).*

[30] D. Solomon MODIS Science Data Support Team: M. Nishihama, R. Wolfe. *MODIS Level 1A Earth Location: Algorithm Theoretical Basis Document Version 3.0.*

[31] D. C. Morton, R. S. DeFries Y. E. Shimabukuro, L. O. Anderson, F. Del Bon Espírito-Santo, M. Hansen, and M. Carroll. Rapid Assessment of Annual Deforestation in the Brazilian Amazon Using MODIS Data. *earth interactions*, 9(8):1–22, 2005.

[32] Reducing Emissions from deforestation and degradation. What is REDD. accessed 28 Feb 2011.

[33] J. Roujean, M. Leroy, and P.-Y. Deschamps. A Bidirectional Reflectance Model of the Earth's Surface for the Correction of Remote Sensing Data. *Journal of Geophysical Research*, 97:20455 – 20468, 1992.

[34] C.B. Schaaf, F. Gao, A. H. Strahler, W. Lucht, X. Li, T. Tsang, N. C. Strugnel, X. Zhang, Y. Jin, J. Muller, P. Lewis, M. Barnsley, P. Hobson, M. Disney, G. Roberts, M. Dunderdale, C. Doll, R. P. d'Entremont, B. Hu, S. Linag, J.L. Privette, and D. Roy. First operational BRDF, albedo nadir reflectance products from MODIS. *Remote Sensing of Environment*, 83:135–148, 2002.

[35] C. M. Souza, D. A. Roberts, and M. A. Cochrane. Combining spectral and spatial information to map canopy damage from selective logging and forest fires. *Remote Sensing of Environment*, 98(2-3):329–343, 2005.

[36] T. A. Stone and P. Lefebvre. Using multi-temporal satellite data to evaluate selective logging in Para, Brazil. *International Journal of Remote Sensing*, 19(13):2517–2526, 1998.

[37] A.H. Strahler and J.P. Muller. MODIS BRDF / Albedo Product: Algorithm Theoretical Basis Document V5.0. 1999.

[38] UNFCCC. The Marrakesh Accords and the Marrakesh Declaration, 2001. accessed 16 Mar 2011.

[39] E.F Vermote and A. Vermeulen. Athomspheric correction Algorithm: spectral reflectances. *NASA publications*, 1999.

[40] R.E. Wolfe, M. Nishihama, A.J. Fleig, J.A. Kuyper, D.P. Roy, J.C. Storey, and F.S. Patt. Achieving sub-pixel geolocation accuracy in support of MODIS land science. *Remote Sensing of Environment*, 83:31–49, 2002.

[41] J. Xiao, Y. Shen, and T. Ryutaro. Mapping soil degradation by topsoil grain size using MODIS data.

[42] X. Xiao, Q. Zhang, S. Saleska, L. Hutyra, P. De Camargo, S. Wofsy, S. Frolking, S. Boles, M. Keller, and B. Moore III. Satellite-based modeling of gross primary production in a seasonally moist tropical evergreen forest. *Remote Sensing of Environment*, 94:105–122, 2005.

[43] C. Zhang, W. Li, and D. J. Travis. Restoration of clouded pixels in multispectral remotely sensed imagery with cokriging. *International Journal of Remote Sensing*, 30(9-10):2173–2195, 2009.

[44] X. Zhang, M. A. Friedl, and C. B. Schaaf. Sensitivity of vegetation phenology detection to the temporal resolution of satellite data. *Int. Journal of Remote Sensing*, 30:2061–2074, 2009.

[45] X. Zhang, M.A. Friedl, C.B. Schaaf, A.H. Strahler, J.C.F. Hodges, F. Gao, B.C. Reed, and A. Huete. Monitoring vegetation phenology using MODIS. *Remote Sensing of Environment*, 84:471–475, 2003.