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ANALYSIS OF THE LANDUSE/LANDCOVER CHANGES IN PARTS OF DISTRICT MAROWIJNE DURING 1987-2014

by

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A thesis submitted to the Anton de Kom University of Suriname, Faculty of Technology, Suriname, in fulfillment of the requirements for the degree of
Master of Science (MSc) in Sustainable Management of Natural Resources

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List of abbreviations

SBB	(Stichting Bosbeheer en Bostoezicht) Forest Management and Forest Surveillance Foundation
RGB	(Ruimtelijke Ordening, Grondbeheer en Bosbeleid) Ministry of Spatial Planning, Land and Forest management
ABS	(Algemeen Bureau voor de Statistiek) Institute of geography and statistics
LULC	Land Use and Land Cover
LCM	Land Change Modeler
FAO	Food and Agriculture Organization of the United Nations
Suralco	Surinam Aluminum Company
TM	Thematic Mapper
ETM	Enhanced Thematic Mapper
OLI	Operational Land Imager
ESRI	Environmental Systems Research Institute
FCMU	Forest Cover Monitoring Unit
USGS	United States Geological Survey
NMAS	National Map accuracy standard
GIS	Geographic Information System
DEM	Digital Elevation Model
MLP	Multi-Layer Perceptron
NIMOS	Nationaal Instituut voor Milieu en Ontwikkeling in Suriname
UNDP	United Nations Development Program
REDD+	Reducing emissions from deforestation and forest degradation
SPS	Stichting Planbureau Suriname

Executive summary

The objective of the research is to analyse the landuse/landcover changes of parts of district Marowijne (ressort Moengo, Moengotapoe and Albina) during 1987-2014. The analysis of Marowijne's past can tell what the landuse/landcover will be in the future. For this study, Landsat images with the software ArcMap and TerrSat were used. Arcmap was needed for clipping, image classification and accuracy determination (Kappa) of maps. TerrSatt was needed for Land Change Modeler (LCM) modeling of the future landuse/ landcover. The modeling was done to analyze the LULC change, potential transition and future prediction of the images. After analyzing the landcover maps, the greatest change happened in the forest class. The important landcover changes were from 'forest' to 'built-up' and from 'forest' to 'barren land'. The change analysis was conducted for three periods: from 1987-1997, from 1997-2008 and from 2008-2014. Between 1987 and 1997 there was no significant change, only deforestation was observed. The deforestation was caused by mining of bauxite, building of houses and agriculture shifting cultivation in the area. Between 1997 and 2008 a certain reforestation appeared, because of a halt in bauxite mining and a decline in built-up activities. Between 2008 and 2016 again deforestation appeared in the LULC maps. For the future prediction from 2016-2060 the transition trends of 2008 to 2014 were projected in the LCM. The prediction was done for a business as usual scenario. The major forest change in the predictions occurred in the north of Marowijne. Between 2008 and 2014 no major change in primary and secondary road development took place in Marowijne. The road developments did not change the predictions, but instead influenced the built-up location in the roads area. The results from this research indicate the importance of LULC data for future planning and policy making for sustainable forest management.

Keywords: land cover change, LULC, ArcMap, TerrSat, image classification, LCM modeling

1. Introduction

1.1 History and background information on parts of district Marowijne

Before the “discovery” of Albina, it was the residence of indigenous people. Most of them had a nomadic lifestyle. After the indigenous people had left, a well-known German soldier by the name of Kappler rediscovered the place through detachment. At the end of his detachment he decided to settle down in Suriname. Soon after Kappler and his wife, Albina, changed the area for settlement and work. After Kappler’ s wife died, he named the place Albina (Loor, 2014). On the other side of the river lies Saint Laurent, French-Guyana. Albina became important, because of its convenient location for transport, overnight stay and trade.. In 1879 Kappler abandoned Albina. Albina became the capital of Marowijne, gradually Moengo and Moengotapoe became part of the ressorts (Loor, 2014). A ressort is an administrative layout of a district.

During World War II in 1916 the Surinam Aluminum Company (Suralco) settled in Suriname looking for bauxite ore for aluminum for their war equipment. The village Moengo was born from Suralco that ousted Albina. Soon after, trading and traveling in Albina declined, because of no work. The district commissioner then transferred from Albina to Moengo. In 1945 Albina became the capital again, because of its geographic and strategic location for a stopping place, ferry connection and land connection with French-Guyana. In 1960, the east-west connection road from Moengo to the capital city Paramaribo was constructed. Soon after all utilities, hospital, police, and border control service came to Albina. Then came a dark period of domestic war, in July 1986, where nearly all buildings in Albina were laid in ashes. After the domestic war till recently, the government has tried to build Albina back to its glory days (Loor, 2014).

Figure 1.1 shows the location of parts of district Marowijne in the north-east of Suriname. The area lies between latitude $5^0$3’0’’N- $5^0$5’0’’N and longitude 54°0′0″ W-54°4′0″ W according to Stichting Planbureau Suriname (SPS, 2014). Albina is the capital, Moengo and Moengotapoe are ressorts of Marowijne. The study area has a total area of 1969 km^2 (SPS, 2014) and lies around 3 meter above sea level. In the north lie the ressorts Wanhati and Galibi, and the Atlantic Ocean. In the east, the Marowijne river and French-Guyana. In the south the ressort Patamacca and to the west with the district of Commewijne.

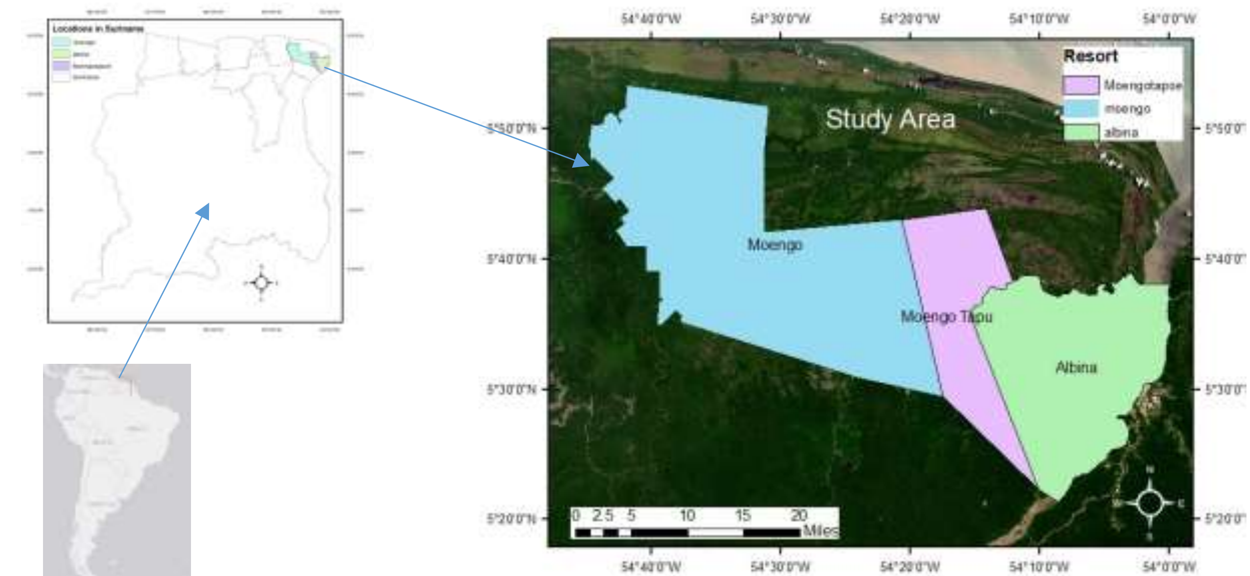


Figure 1.1: Location of the parts of district Marowijne in Suriname.
Source from " (ArcGIS, 2017)" [Maps and Data] Districten van Suriname. *GISsat_content 5/26/2017* Using: *ArcGIS* [GIS-software]. Version 10.2.2. Paramaribo. Copyright ©1999-2014 ESri Inc.

Most of the villages in the study area are settled along the Marowijne River, see figure 1.2.

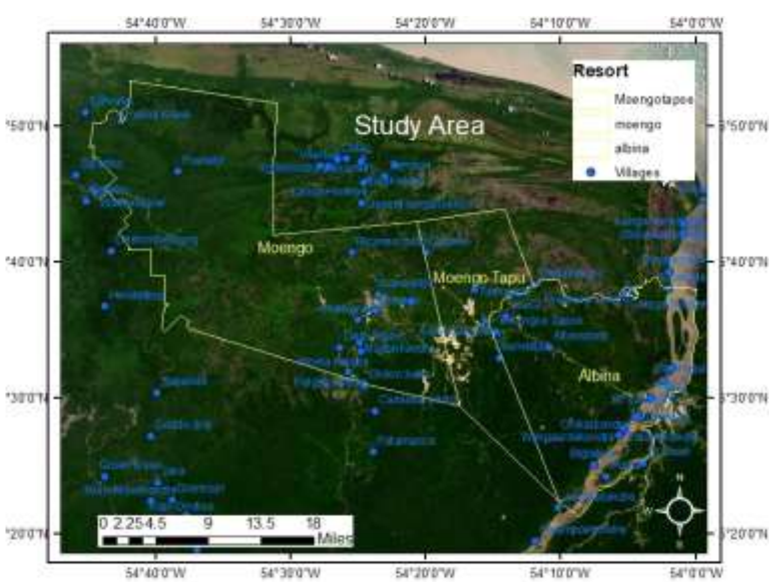


Figure 1.2: The different villages (presented in dots in the map) in the study area.
Source from " (ArcGis, 2018)" [Maps and Data] Dorpen in Suriname. *GISsat_content 08/20/2018* Using: *ArcGIS* [GIS-software]. Version 10.2.2. Paramaribo. Copyright ©1999-2014 ESri Inc.

There are also several creeks that flows through Albina, such as the Wanekreek, Powisiekreek, Anjoemarakreek, Awarakreek, Moi Wannakreek and the Montekreek. Because of the geography of the area, large scale agriculture is not in favor (Loor, 2014). Along the Marowijne River lie a lot of sand beaches. In the east, the landscape is sloping. In the south there are a lot of untouched forests on high ground, while in the north there are wetlands, forest, and in some areas a lot of savanna (SPS, 2014). According to statistics of the study area, Moengo (10.000) and Albina (5000) have the most habitants of Marowijne (ABS-Suriname, 2019).

1.2 Problem description

Population growth often leads to increase use of natural resources. According to statistics, the population growth in Suriname from 2000 to 2011 was 16% (ABS-Suriname, 2019). The activities of population growth can be: agriculture, mining, logging, housing, energy use and tourism for example. These activities can lead to deforestation, permanent loss of forest cover, land pollution or land cover transition if uncontrolled (FAO, 2015), (NIMOS, SBB, & UNIQUE, 2017).
Suriname is a tropical country with a High Forest Cover and Low Deforestation (HFLD) status. This means that Suriname Forest area covers about 90% of the country (FAO, 2010). The forest and services are important at local and global levels. The forest and services they provide food and income security for forest communities, climate mitigation and biodiversity preservation for society at large. In order to keep the country HFLD-status and services, the activities that leads to deforestation must be managed. This can be done through land use planning by the government. For land use planning it is important to analyze the past LULC changes to indicate what the future LULC changes will be. This will in turn, help make important decisions for future land use and plans.

1.3 Previous studies of LULC change in Suriname

There have been a number of studies done in Suriname using LULC, such as for forest cover monitoring (Svensson, 2014) and for analyzing and modeling changes in the Upper Suriname river basin (Fung-Loy, 2014) for example. Other LULC studies in Suriname were about the impact of roads (Jolly, 2010), the drivers of deforestation (Ramirez-Gomez, 2011), (NIMOS, SBB, & UNIQUE, 2017) and planning and policy of major infrastructural work (Van Dijck & Wallis, 2013).

1.4 Research objectives and questions

The research objectives of this study are to analyze and model LULC changes in parts of district Marowijne by using TerrSet 18.31 and ArcGIS 10.2.2 software with remote sensed data.

The research questions for the study area that were interesting were:

- How did the LULC change of the study area take place between 1984-2000 and 2000-2015?
- What were the drivers for LULC change?
- What will the predicted LULC be by the years 2025, 2045 and 2060 in parts of Marowijne, under the business as usual scenario?

2 Materials and methods for the study area

With materials is meant, the images that were downloaded for the study area. In methods the following steps for classification, accuracy assessment, change analysis, transition potential and change prediction are discussed.

2.1 Materials for the study area

For this study, the time period 1984-2015 was split in 3 periods: 1987-1997, 1997-2008, and 2008-2014. The 3 time periods were chosen to easily identify the changes in the study area. The LCM with software TerrSet 18.31 used the last period in the study of the land cover maps history to predict the future. The images for the land cover maps were downloaded from the United States Geological Survey Earth Explorer (USGS, 2019) website free of charge. USGS is a scientific agency that study the landscape and its natural resources. The images were from Landsat 4-5 TM, Landsat 7 ETM+, and Landsat 8 OLI. Images with low cloud cover were selected; however, most of the images were not cloud-free. The downloaded images were insured with horizontal and vertical accuracy, systematic radiometric accuracy, geometric accuracy through ground control points, and topographic accuracy. All the accuracy statements are based on USGS image criteria (Lillesand, Kiefer, & Chipman, 2007). The images had a WGS_1984_UTM-21N reference system. The table 2.1 and table 2.2 shows the characters of the Landsat bands.

Table 2.1: Characteristic Landsat 5TM and Landsat 7 ETM+ bands

Bands	Wavelength (um)	Resolution(m)
Band 1 - Blue	0.45-0.52	30
Band 2 - Green	0.52-0.60	30
Band 3 - Red	0.63-0.69	30
Band 4 - Near Infrared	0.77-0.90	30
Band 5 - Shortwave Infrared	1.55-1.75	30
Band 6 - Thermal	10.40-12.50	60 * (30)
Band 7 - Shortwave Infrared	2.09-2.35	30
Band 8 - Panchromatic	0.52-0.90	15

* ETM+ Band 6 was acquired at 60-meter resolution, resampled to 30-meter pixels.
Adapted from (USGS, 2019). What are the best Landsat spectral bands for use in my research?" retrieved from https://www.usgs.gov/faqs/what-are-best-landsat-spectral-bands-use-my-research?qt-news_science_products=0#qt-news_science_products

Table 2.2: Characteristic Landsat 8 Operational Land Imager (OLI) bands

Bands	Wavelength (um)	Resolution(m)
Band 1 - Ultra Blue	0.435 - 0.451	30
Band 2 - Blue	0.452 - 0.512	30
Band 3 - Green	0.533 - 0.590	30
Band 4 - Red	0.636 - 0.673	30

Band 5 - Near Infrared	0.851 - 0.879	30
Band 6 - Shortwave Infrared	1.566 - 1.651	30
Band 7 - Shortwave Infrared	2.107 - 2.294	30
Band 8 - Panchromatic	0.503 - 0.676	15
Band 9 - Cirrus	1.363 - 1.384	30
Band 10 - Thermal Infrared	10.60 - 11.19	100 * (30)
Band 11 - Thermal Infrared	11.50 - 12.51	100 * (30)

* TIRS bands were acquired at 100 meter resolution, but resampled to 30 meter in delivered data product.
Adapted from (USGS, 2019). What are the best Landsat spectral bands for use in my research?" retrieved from https://www.usgs.gov/faqs/what-are-best-landsat-spectral-bands-use-my-research?qt-news_science_products=0#qt-news_science_products

In table 2.3, the downloaded low cloud cover Landsat images for the study area are shown. It starts with 1987, because images of 1985-1986 were not available.

Table 2.3: Landsat images with low cloud cover from USGS website

Year	Path/row 228/56	Year	Path/row 228/56
1987	LM52280561987204AAA03	2001	LT05_L1TP_228056_20011017_20161209_01_T1
1992	LT05_L1TP_228056_19920922_20170121_01_T1	2008	LT05_L1TP_228056_20080817_20161030_01_T1
1997	LT05_L1TP_228056_19970803_20161230_01_T1	2014	LC08_L1TP_228056_20140903_20170420_01_T1
2000	LT05_L1TP_228056_20000912_20161214_01_T1	2016	LC08_L1TP_228056_20161111_20170318_01_T1

Source: U.S. Geological Survey (USGS, 2019). Landsat land cover maps [Data file] Retrieved from https://earthexplorer.usgs.gov/

Maps of Suriname were also downloaded from the ArcGIS online website through the ArcMap 10.2 software. These maps also had a WGS_1984_UTM-21N reference system. Shapefiles of table 2.4 were also downloaded from (DIVA-GIS, 2014) a website where geographic spatial data at the country level can be downloaded free of charge, as administrative areas, altitude, roads, and inland water maps.

Table 2.4: Digital Maps of Suriname, created in year 2017

2017	Districten van Suriname (districts of Suriname)
2017	Dorpen in Suriname (villages in Suriname)
2017	Percelen Suriname (plots in Suriname)
2017	Primaire Wegen van Suriname (primary roads of Suriname)
2017	Ressorten van Suriname (ressorts of Suriname)
2017	Scholen in Suriname (schools in Suriname)

Source: (DIVA-GIS, 2014) [Data file] Retrieved from https://www.diva-gis.org/gdata

2.2 Methods for analyzing and predicting change of LULC-data maps

2.2.1 Input and data images processing

In Figure 2.1, input of low cloud cover LULC-image of 2016 was downloaded from the USGS-website. The Landsat image (Path/row: 228/056) was then opened in ArcGIS 10.2.2, for cutting, clipping.

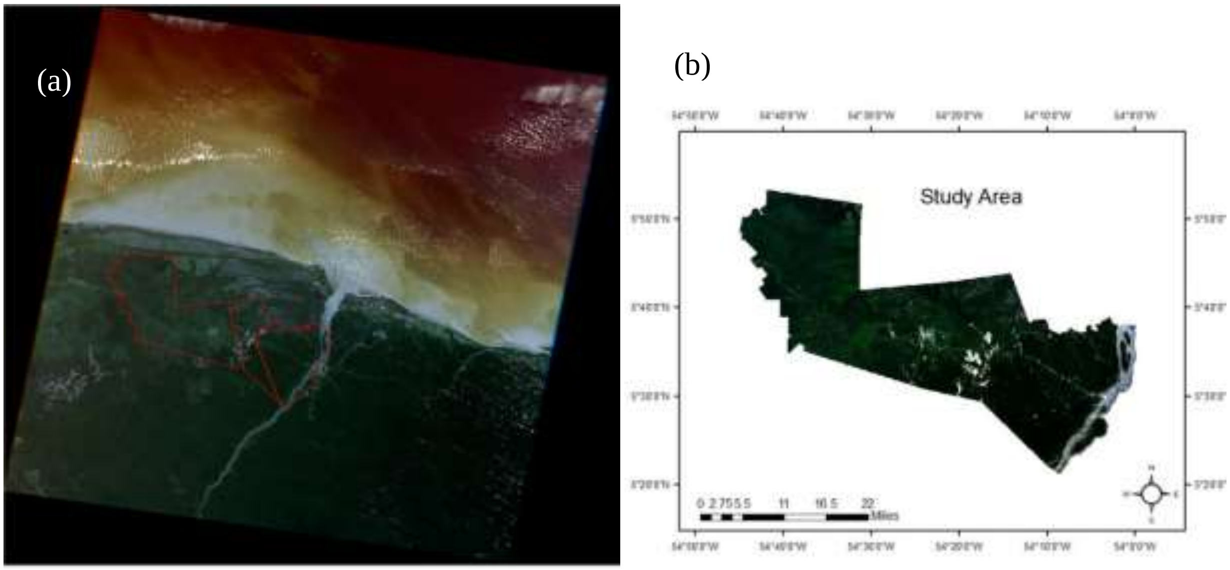


Figure 2.1: Downloaded Landsat image (a) and the study area after cutting/clipping (b)
Source from (USGS, 2019) [Maps] Landsat and land cover map,2016. Retrieved from https://earthexplorer.usgs.gov/
Using: *ArcGIS* [GIS-software]. Version 10.2.2. Paramaribo. Copyright ©1999-2014 ESri Inc. All Right Reserved

For cloud removal see figure 2.2(a,b,c,d). The image with clouds was first resampled to a raster image with X and Y-resolution of respectively 30x30m with a WGS_1984_UTM-21N reference system. Resampling was needed for comparison of the satellite images. Images without clouds were directly used for further analyses. Most of the images that were downloaded have clouds in the study area. These clouds can result in an inaccurate classification of the image if not removed. The land cover under the clouds can make a difference in the accuracy of the supervised. That is why these clouds were removed from the images.

The cloud removal was done in ArcMap 10.2.2 software. First the raster image in figure 2.2a was clipped, then it was classified into 5 classes, according to a supervised classification method (figure 2.2b). Supervised classification is done by selecting sample pixels in the image that represent specific classes, training sites in the ArcMap software, and then use it as reference of all other pixel in the image (Lillesand, Kiefer, & Chipman, 2007). Classes are: blue for water, green for forest, yellow for built-up, red for mining and rose for barren land. The images were then converted from raster to polygon, so it made it easy to remove the clouds. For example when removing the clouds, Google earth satellite image from the same year of classification (figure 2.2c) was being consulted to pinpoint the exact land cover under the clouds. After the clouds were removed the polygon image was then again converted back to its raster image for further analyzing (see figure 2.2d).

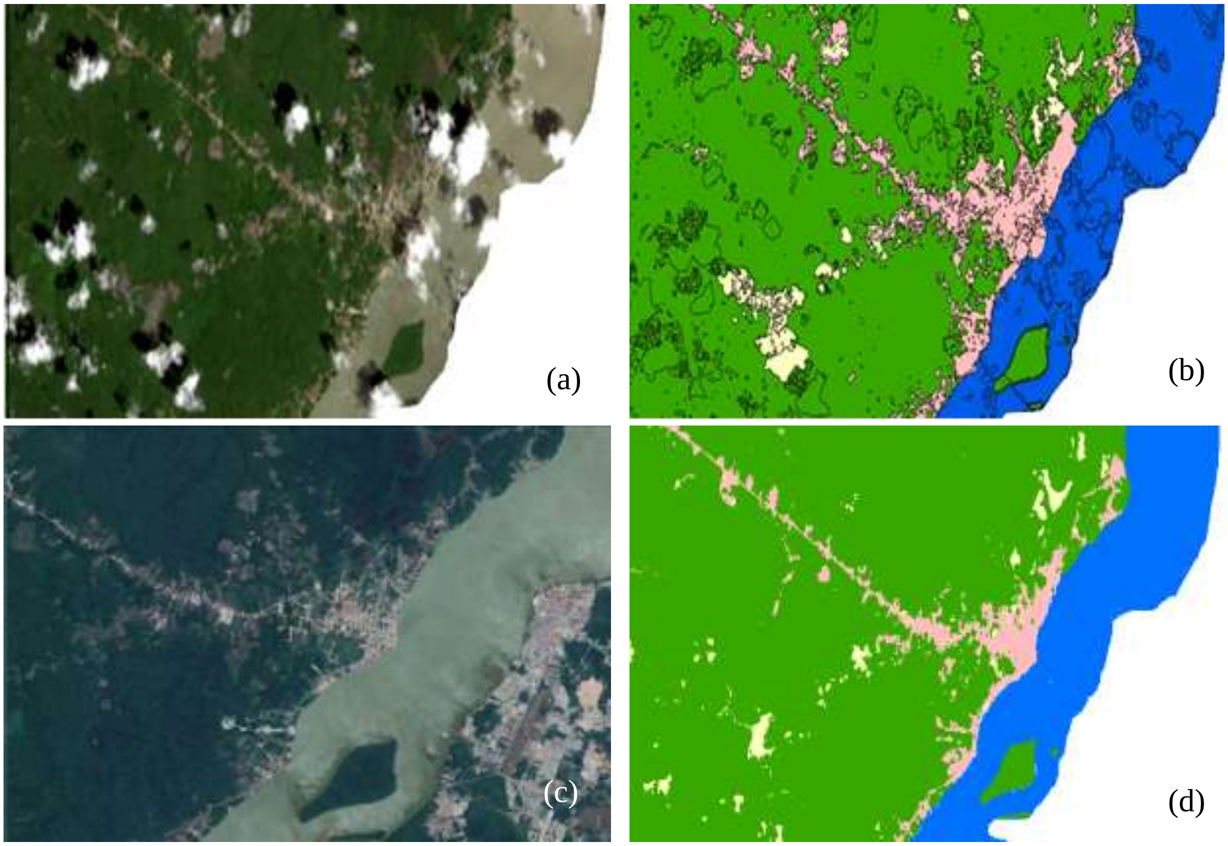


Figure 2.2: Cloud removal procedure with software ArcMap and Google earth
(a) Study area with clouds (raster image in multispectral view)
Source from " (USGS, 2019)" [Maps] Landsat and land cover map,2000. Retrieved from https://earthexplorer.usgs.gov/
Using: *Cut/Clip Tools for ArcGIS* [GIS-software]. Version 10.2.2. Paramaribo. Copyright ©1999-2014 ESri Inc
(b) The raster image converted to a polygon image for cloud removal
Source from " (USGS, 2019)" [Maps] Landsat and land cover map,2000. Retrieved from https://earthexplorer.usgs.gov/
Using: raster to *polygon Tools for ArcGIS* [GIS-software]. Version 10.2.2. Paramaribo. Copyright ©1999-2014 ESri Inc
(c) Google map of the study area was used to locate the land cover under the cloud
Source from ",Google earth pro" [Maps] Map data ©2000. Screenshot by author. Using: Google earth pro [software]. Version 7.3.2. Paramaribo. Copyright ©2019 Google LLC. All Right Reserved
(d) After cloud removal the polygon image was converted back to its raster format for further analyzing. Source from " (USGS, 2019)" [Maps] Landsat and land cover map,2000. Retrieved from https://earthexplorer.usgs.gov/ Using: *polygon to* raster *Tools for ArcGIS* [GIS-software]. Version 10.2.2. Paramaribo. Copyright ©1999-2014 ESri Inc.

2.2.2 Image classification

After the study area image was made or downloaded cloud free, it was ready for classification. The study area was classified with the USGS LULC classification system for remote sensing (Lillesand, Kiefer, & Chipman, 2007). The classification of LULC changes was done at level II with a 30m resolution. The classification for the study area is shown in table 2.5.

Table 2.5: LULC classification system for the classes in Marowijne

Classes	Description
1. Water	Classification of streams, rivers and reservoirs
2. Built-up	Classification of residential areas for villages and settlements, roads that are paved and unpaved
3. Mining	Mining locations that are active and inactive
4. Forest	landcover with primarily trees, palm, bamboo, herbs, grass with a minimum crown tree cover of 30%, with potential to reach canopy height of minimum 5meter and a minimum area of 1.0 ha
5. Barren land	Open area occurring naturally by landchange/climate consisting of sand, rocks and loam. Can also be man made by deforestation or Slash and burn agriculture (ArcGIS, 2014, July).

Adapted from (Anderson, 1976). *A land use and land cover classification system for use with remote sensor data* (USGS Numbered Series No. 964). Retrieved from http://pubs.er.usgs.gov/publication/pp964

The study area was classified according to a supervised method in ArcMap software. The instructions on supervised classification in ArcMap were done with help of the website for remote sensing support (Virginia, 2009).The website was made to support the educational community in remote sensing in collaboration with USGS Earth Explorer. The United States Geological Survey has developed a multilevel classification of LULC based on remote sensing. For detail of level classification see the table 2.1 and table 2.2 (Anderson, 1976).

The different levels of Image size and interpretation are:

I : Low to moderate resolution data, e.g. Landsat TM and MSS images

II: Small-scale aerial photograph; moderate resolution data, e.g. Landsat TM, ETM, OLI data

III: Medium-scale aerial photograph; moderate/high resolution data, e.g. IKONOS data

IV: Large scale aerial photograph; high resolution data, e.g. Quikbird data

Level I and II are suitable for information on nationwide and statewide. Level I has a 20-100 m and Level II a 5-20 m image resolution. Level III and IV provide information of regional (district), province, local and management activities. Level III has a 1-5 m image resolution and Level IV an image resolution of 0.25-1m (Anderson, 1976). The classification of LULC changes was done at level II with images or data of Landsat 5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper (ETM) and Landsat 8 Operational Land Imager (OLI) bands. There are a number of studies that have used level II using remote sensing and GIS (Kaliraj, Srinivas, Ramachandran, & Saravanan, 2017), (Gadrani, Lominadze, & Tsitsagi, 2018) and (Cheruto, Kauti, Kisangau, & Kariuki, 2016). Other level II study was to assess climate change (van Minnen, Strengers, Eickhout, Swart, & Leemans, 2008), for a comparative study (Ali, Qazi, & Aslam, 2018), for Land use and Cover Changes (Aroengbinang & Kaswanto, 2015) and (Nasihin, Prasetyo, Kartono, & Kosmaryandi, 2016). LULC maps were created and analyzed for changes over time. With the changes in the past, the future LULC of the study area is predicted (Fung-Loy, 2014).

2.2.3 Accuracy assessment (Kappa)

After classifying the images, an accuracy assessment was done. An accuracy assessment was needed in order to know if the classified image was in correspondence with the real image/reference data. Accuracy assessment's purpose is to compare the created map pixels to a reference map for the correct land cover class (Lillesand, Kiefer, & Chipman, 2007). As a rule of thumb, samples 10 times the reference point were taken for each classes. This way areas on the Landsat image and Google earth map was clearly identified. For the study area, 5x10=50 reference point at random were manually selected for each class. For the accuracy assessment of the classified image ArcMap, Google earth and office Excel software's were needed. With ArcMap software, an error matrix table is made (Virginia V. , 2013). With the error matrix the overall accuracy and Kappa-value is calculated with Excel software for the classified map. Overall accuracy (Kappa) = Number of correct plots/ total number of plots (Lillesand, Kiefer, & Chipman, 2007).

Kappa =

$$K = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r}(x_i + Xx_{+1})}{N^2 - \sum_{i=1}^{r}(x_{ii}Xx_{+1})} \tag{1}$$

Where r = number of rows and columns in error matrix, N = total observations (pixels) ,
x_{ii} = observation in row i and column i, x_{i+} = marginal total observation of row i, and
x_{+I} = marginal total of column i.

Depending on the accuracy (Kappa-value) of the classified map, the classified map could be used for further analyzing. The Kappa value lies between 0 and 1. The value 0 means, the classified (modelled) image doesn't match the reference image (ground truth). The value 1(100%) means, the classified image matches the reference image (ground truth). For this study area Kappa smaller than 40 % (< 40%) means poor prediction, between 40 - 80% means a moderate prediction and between 80 -100% gives the best prediction. There is also the user's and producer's accuracy (Lillesand, Kiefer, & Chipman, 2007). A user's accuracy tells how accurate the map is, from the perspective of the user. How many pixel on the map respond with the reality. A producer's accuracy tells how accurate the map is, from the perspective of the maker. It usually tells how many reference point in reality corresponds to the map pixels. With the Excel program the user's and producer's accuracy wer calculated. The results were found in table 3.2 and in the appendix 2.

2.2.4 The Land Change Modeler (LCM)

The LCM is a tool in TerrSet 18.31, for modeling LULC-changes for maps after classification and accuracy assessment (Kappa). LCM has three sub modeling tools: for *Change Analysis, Transition Potentials* and *Change Prediction* of the study area (Eastman, 2016a). A complete overview of LCM for the study is shown in figure 2.3. The accurate classified maps were then modelled in TerrSat with LCM in three steps. First through the Change analysis, where analysis of land change over a certain time was analyzed. Secondly, through the Transition Potentials, where there can be 'forest gain' or 'land loss' in the study area. For the transition potential maps to be made, input of explanatory variables was needed. Thirdly, through the Change Prediction, input of planning of future transition change maps were added. A predicted LULC-map of 2016 was created to validate with a 2016 classified map. After validation LULC-maps of 2025, 2045 and 2060 were predicted as output.

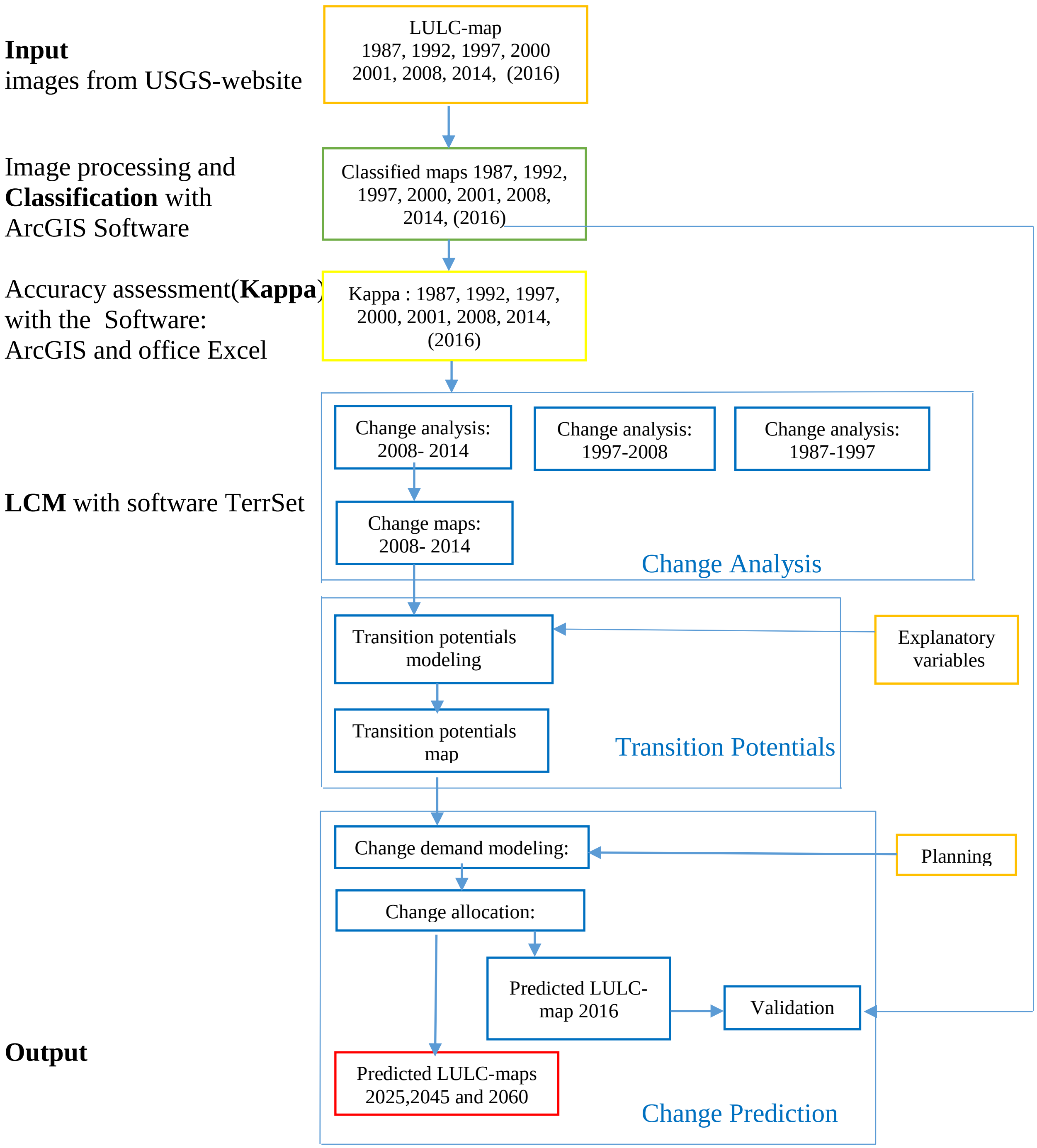


Figure 2.3: Overview for analyzing and change prediction of LULC-maps for the study area
Adapted from (Fung-Loy, 2014). "Analysis and modeling of land use and land cover change in the Upper Suriname river basin". *Paramaribo: Anton de Kom University of Suriname, Faculty of Technology*, 2014.

2.2.4.1 LULC Change Analysis

LULC change analysis is analysis of land change over certain time. Land use explains how the land was used for example as agriculture, residence or industry. Land Cover could tell us about the cover of an area. It could be evergreen, forest or lakes. LULC change analysis is a scientific field that is growing rapidly. Satellite images were mapped to analyze the change in geographic area to foresee future conditions. It was possible to identify the effect of humans on the environment. There were a variety of software developed for analyzing LULC change on the internet (Anderson, 1976). A few studies that have been done to analyze the LULC were in Kuningan (Nasihin, Prasetyo, Kartono, & Kosmaryandi, 2016) and Iraq (Hadi, Shafri, & Mahir, 2014).

In this study four types of software were used:

a) ArcMap 10.2.2, for cutting, clipping, creating supervise classification of the study area
b) Microsoft Excel 2013, for calculating the error matrix for each map created in ArcGIS
c) Google earth pro 7.3.2 and Google map, for monitoring and synchronizing the supervised maps with available maps in Google earth.
d) TerrSet 18.31. with LCM

ArcMap 10.2.2 is a free software available for download through registration at the Environmental Systems Research Institute (Esri, 2019) license website. Softwares like office Excel 2013, Google earth pro7.3.2 and TerrSet 18.31 are also free software for download. Google map is a free website on the internet for use.

To perform the LULC change analysis in TerrSet for the study area, images from the year 1987-2014 were used. In this study, the time periods for analysis were split in 3 periods, from 1987-1997, 1997-2008 and 2008-2014. The time periods that were frequently used, were for every 5 or 10 year (FAO, 2015). The periods were chosen unevenly, because of the limitation of cloud-free images available for the years 1987 to 2014. The interest was in the different changes in land uses of the study area. The study area consists of 85-89% forest. The changes that were analyzed were from built-up to forest, barren land to forest, forest to built-up and forest to barren land.

2.2.4.2 Modeling LULC Transition Potentials

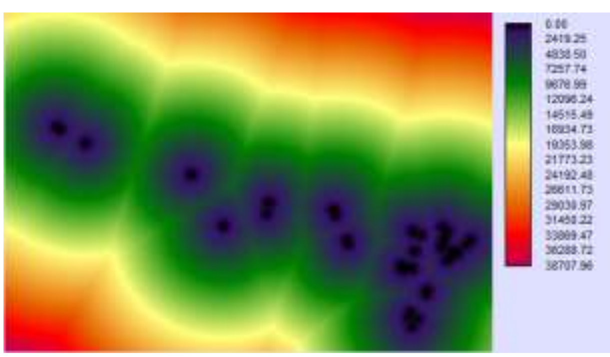
After the Change Analysis, the Transition Potential for the study area was modelled. The transition modeling was done in two groups. The first transition group was the ‘forest gain’: from built-up to forest and from barren land to forest. The second transition group was ‘forest loss’: from forest to barren land and from forest to built-up. When modeling ‘forest gain’ and ‘forest loss’ together the model accuracy was on the lower side (20%). For a higher accuracy, the modeling was done separately (Eastman, 2016a). Explanatory variables were introduced, for the transition modeling. The variables described the drivers of historical change between 1984 to 2014 through the Cramer’s V-test value (see the table 2.6). A high Cramer’s V was a good indicator for change, but does not assure a strong result. A Cramer's value of V>0.15 is useful, V>0.4 is good and lower than 0.15 can be discarded (Eastman, 2016a). The explanatory variables were modeled static or dynamic (table 2.6). Static means that the driver variables for the classes does not change over time. Dynamic means that it does change over time. For the study area a business as usual scenario with controlled deforestation, roads and future urban developments was modelled. The digital elevation model (DEM) and slope layers were downloaded from USGS website. The other driver variables were made by SBB on basis of changes in the LULC due to the development in the area. Table 2.6 shows which driver variables for the classes were used for the scenario. The DEM, 'Distance to mining 2014' and slope were static, because no change in elevation, mining and slope were noticed during the analysis.

Table 2.6: Driver variables with Cramer's value for the classes

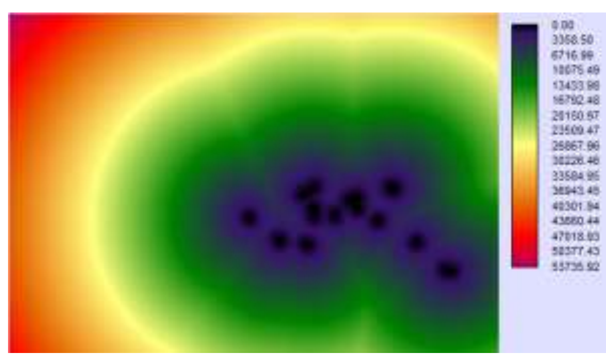
	Water	Built-up	Mining	Forest	Barren land	Overall	
Explanatory variable	Cramer's value *						type
DEM	0.630	0.1160	0.2746	0.5190	0.2880	0.3806	static
Slope	0.5426	0.0376	0.0385	0.3197	0.0511	0.2737	static
Distance deforestation 2014	0.134	0.2267	0.1588	0.1222	0.0499	0.0499	dynamic
Distance to mining 2014	0.1715	0.1396	0.2302	0.1715	0.1427	0.1745	static
Distance to roads 2014	0.1369	0.1859	0.0561	0.0965	0.0515	0.0515	dynamic
Distance to urban 2014	0.1255	0.2877	0.1376	0.2038	0.1479	0.1877	dynamic

* Source data: from " (USGS, 2019)" [Maps] Landsat map,2014. Retrieved from https://earthexplorer.usgs.gov/ Using: *LCM Tools for TerrSet* [GIS-software]. Version 18.31. Paramaribo. Copyright ©1987-2017 Clark Labs, Clark University.

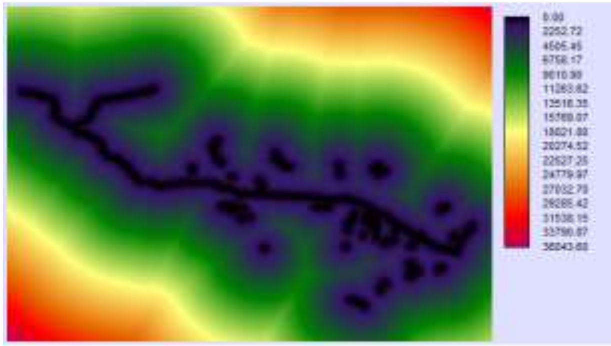
The variables of figure 2.4, (a) 'Distance to deforestation 2014' was dynamic, because of deforestation in the area. Variable figure 2.4(c) 'Distance to roads 2014' and figure 2.4(d) 'Distance to urban 2014' were also dynamic because of land cover change through built-up. The distance of the area were shown in colors of black to red. The red was the furthest and blue the closest.



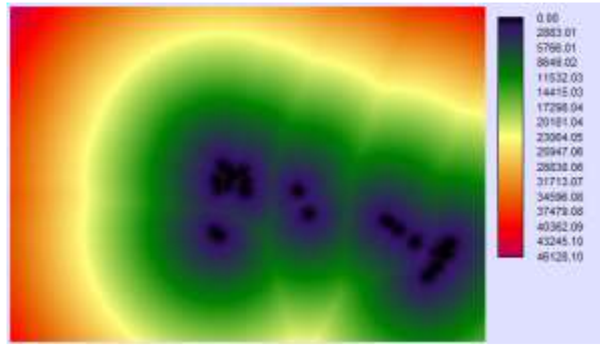
a. Distance to deforestation 2014



b. Distance to mining 2014



c. Distance to roads 2014



d. Distance to urban 2014

Figure 2.4: Explanatory variables: a,b,c,d for study area between 1984 and 2014
Source data: from (SBB, 2014). De Stichting voor Bosbeheer en Bostoezicht , department FCMU 2017.Using: *distance Tool in TerrSet* [GIS-software]. Version 18.31. Paramaribo. Copyright ©1987-2017 Clark Labs, Clark University.

After the sub-model group (‘forest gain’ or ‘forest loss’) and explanatory variables had been chosen, TerrSet offers three transition sub-model types:

1. MLP Neural Network
2. Simweight and
3. Logistic Regression

Simweight can model one transition at a time for a sub-model; it uses modified K-nearest neighbor based on machine learning algorithm. MLP Neural Network can model multiple transitions at a time for a sub-model, based on the training samples of pixels. Logistic Regression can model one transition at a time for a sub-model, based on default samples of 10% (Eastman, 2016a). The MLP Neural Network was used, because it automatically gives the best result in a short time with no user intervention. It also explains the roles of the variables. After the MLP Neural Network transition modeling was done running, a report was presented with accuracy and skill of the sub-model. There was also an option to create a sub-model transition map after running the model. For a good MLP Neural Network result an accuracy of greater 80% should be achieved. When the accuracy is under 80%, the model must be repeated.
The Skill varies between -1 and 1. A skill of 0 means no significant change in prediction, a skill of 1 means a perfect prediction and a skill of -1 means the model was the opposite of prediction.
If the best accuracy result is under 75% and the skill too low, the sub-model should be analyzed if it can be used (Eastman, 2016a).

2.2.4.3 Change prediction and Model Validation 2016

The change prediction predicts the effect on the future change by the explanatory variables. Based on the transition potentials of 2008-2014, the future prediction for 2016, 2025, 2045 and 2060 can be made. The years of prediction were chosen, because of the recalculation stages in the future prediction. The transition of future prediction was modeled through a Markov Chain analysis in recalculation stages (Eastman, 2016a). For an example see the paragraph 2.2.5.1.

For validation of the predictions, the classified map of the year 2016 was used. Validation was done by making a LULC map prediction for 2016 and comparing this with the classified reality map of 2016, (Eastman, 2016a). A clear Landsat image of 2016 was downloaded from USGS-website and classified for the reality map of 2016. The LULC map prediction of 2016 was made with the LCM-model. The steps for making change prediction maps for the future were explained in paragraph 2.2.5. Table 2.7 shows the validation that happened in a three-way tabulation between 2014 LULC map, the 2016 LULC predicted map, and the reality map 2016 to test how accurate the maps were predicted. The result after validation was a Hits, Misses and False alarm map to show how accurate the prediction map was.

Table 2. 7: Validation in a three-way tabulation

2014	2016 Predicted	2016 Real	
4	2	2	: Hits (green), model predicted change and it change
1	1	0	: Misses (red), model predicted persistence and it changed
2	4	2	: False Alarm (yellow), model predicted change and it persisted

0=nothing, 1=water class, 2=built-up class, 4 = forest class.

According to table 2.7, class 4 in 2014 will be predicted as class 2 in 2016. If in year 2016 the prediction of class 2 becomes real than this is a Hit (it will be colored in green in the prediction map). If not, then it is a Miss (red colored). If no change happened in the year 2016 then the model is predicted a false alarm (yellow colored).

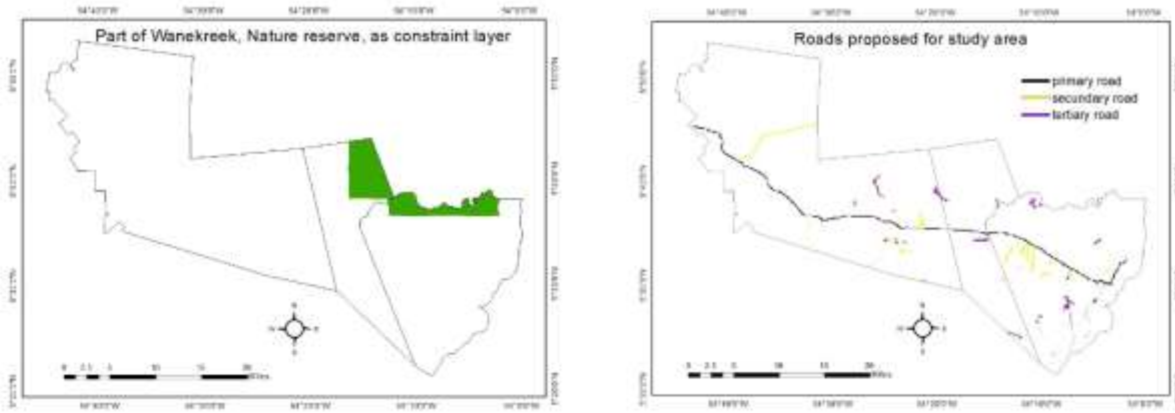
The second method of validation was through a validation tool in TerrSet. The tool analyzes the agreements for the predicted and real map of 2016 by using the K-standard and other variation of Kappa such as K-no and K-location (Eastman, 2016a).

2.2.5 Change prediction for the future

For future change prediction of the study area it is important to know what plans the future holds, what will drive LULC change (SPS, 2014). Drivers such as deforestation, urbanization, constraints, and infrastructure can have great impact on the predicted LULC of the area.

Part of the Nature reserve of Wanekreek, figure 2.5a, a protected area, was added as constraint to the planning tab of the LCM. A constraint is an area where no change is allowed. Also a road layer of 2014, figure 2.5b, was added in the planning tab. The roads were on secondary and tertiary level and build for deforestation and urbanization.

The business as usual scenario was modeled for the years 2016, 2025, 2045 and 2060. The future plans of the model prediction were based on the past development of the study area.



a. Constraints in study area **b. Roads of 2014**

Figure 2.5: (a) Constraints and (b) Roads 2014 in the prediction of Marowijne
Source from "Argis online" [Maps and Data] Natuurreservaten in Suriname. *GISsat_content 08/20/2018* .Using: *ArcGIS* [GIS-software]. Version 10.2.2. Paramaribo.

2.2.5.1 Process of change prediction

The process of change prediction was done with the change prediction tab in LCM with different explanatory variables that affect the future prediction in 2016, 2025, 2045 and 2060, based on the LULC change between 2008 and 2014. The change of the future was done by a Change Demand Modeling, through a default Markov Chain procedure. It predicts the future change by projecting the output of the MLP process (transition potentials) into the future by creating a transition probabilities file, a matrix (Eastman, 2016a). The future LULC prediction was done in recalculation stages where dynamic variables were recalculated. The amount of recalculation indicate the changes in the allocation. See table 2.8 for recalculation stages for the different years. Take 2025-2045 as an example, a time period of 20 years in 4 stages, meaning a split in 4 stages of 5 years (Eastman, 2016a).

Table 2. 8: LCM Modeling parameters for the prediction from 2014-2060

Prediction	Time period	Recalculation stage	Skip factor
2014-2016	3 years	4stages of 9 month	1
2016-2025	10 years	4stages of 2.5 years	1
2025-2045	20 years	4stages of 5 years	1
2045-2060	15years	4stages of 3.75 years	1

The dynamic road modeling was done for both scenarios with a basic road layer from 2014. The categories should be a primary, secondary and tertiary road. The primary road will develop by expanding in the endpoints, the secondary road can be formed from the primary road as new road and then extend. The tertiary road can be formed from the secondary road as a new road and then extend randomly. The road growth parameters were for secondary and tertiary roads. The road length dictates how much length the road grows in each dynamic stage. The road spacing was the minimum required distance between roads when being generated. The road growth parameter (table 2.9) were average values for modeling (Jiang, 2007). The mode for end point generation was set to stochastic highest transition potential to model new end-point of roads. The mode of route generation was set to highest transition potential route to connect areas of high transition potential. The 3 transition potential were added for end-point and road generation. The skip factor of 1 was chosen to specify at which stage the model builds new roads (Jiang, 2007)**.**

Table 2. 9: Road growth parameters for the road prediction in parts of Marowijne

	Average road length (km)	Average road spacing (km)
Secondary road	8-14 (1)	10-20 (02)
Tertiary road	3-10	4-15

Source: (Jiang, 2007). The Road Extension Model in the Land Change Modeler for Ecological Sustainability of IDRISI. *Proceedings of the 15th Annual ACM International Symposium on Advances in Geographic Information Systems*, 13:1–13:8. https://doi.org/10.1145/1341012.1341030

After all the inputs and maps for the prediction process were entered the output became a hard prediction map of the definite LULC-map, a soft prediction map of vulnerability of change, and a road prediction map of possible roads for the future.

3 Results

In chapter 2, different methods and steps for analyzing the study area were discussed. The results after implementation of the steps and methods for image classification, accuracy assessment, change analysis, transition potential, and change prediction are further shown as output in this chapter.

3.1 Image classification

Landsat images were classified with the ArcMap software. A supervised classification with Maximum Likelihood has produced the following LULC-maps for the years 1987, 1997, 2008 and 2014 (figure 3.1). Table 3.1 showed the classified area's in km^2 .

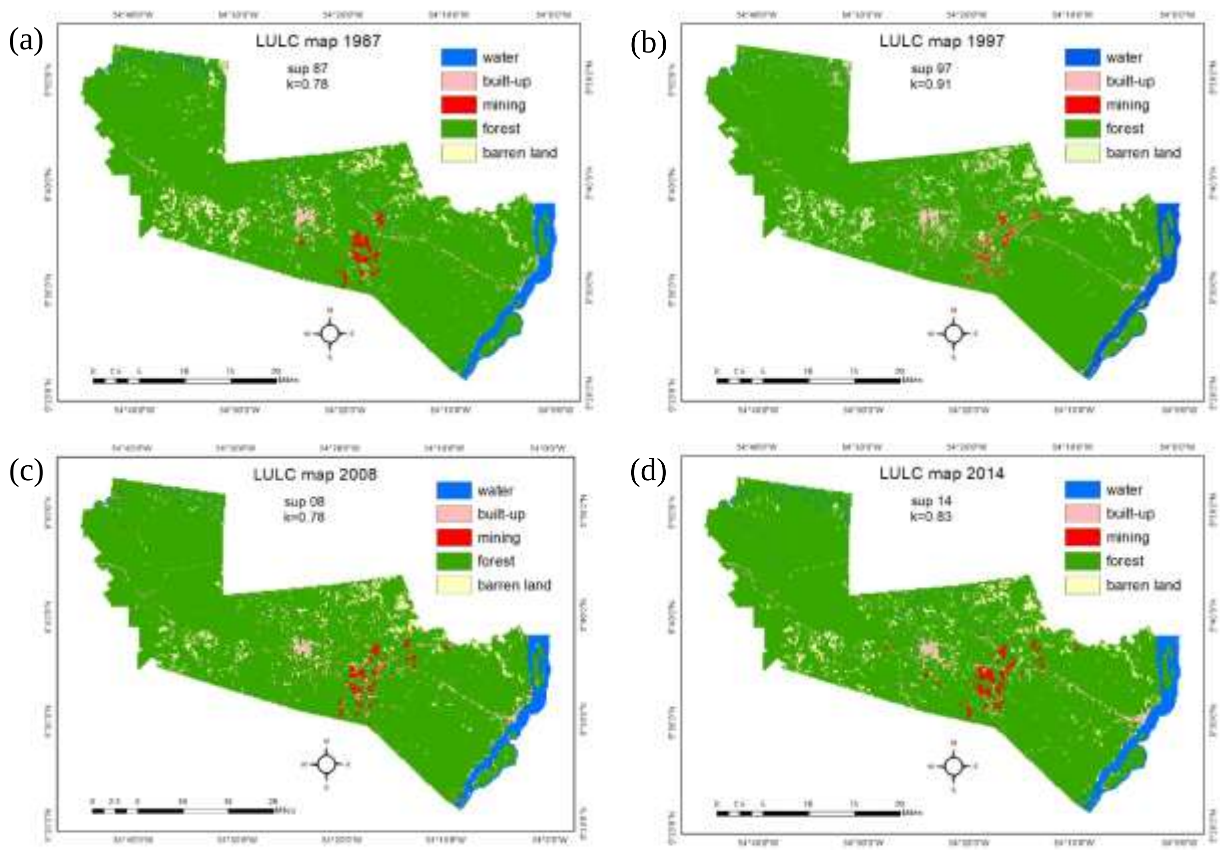


Figure 3.1: LULC maps after classification of classes for the years 1987, 1997, 2008 and 2014
Source from " (USGS, 2019)" [Maps] Landsat and land cover maps. Retrieved from https://earthexplorer.usgs.gov/
Using: *ArcGIS classification* [GIS-software]. Version 10.2.2. Paramaribo.

Table 3.1: Classified area's in km^2 for the years 1987, 1997, 2008, 2014 and 2016

Classes	Sup87,in km^2	Sup97,in km^2	Sup08,in km^2	Sup14,in km^2	Sup16,in km^2
1. Water	81.19	74.23	74.50	83.88	83.17
2. Built-up	25.38	46.84	44.83	37.77	64.77
3. Mining	17.77	15.84	23.17	24.68	19.64

4. Forest	1746.90	1715.48	1731.28	1730.47	1688.92
5. Barren land	97.77	116.62	95.03	92.40	112.50
Total Area	1969.00	1969.00	1969.00	1969.00	1969.00

Source from " (USGS, 2019)" [Maps] Landsat and land cover maps. Retrieved from https://earthexplorer.usgs.gov/

3.2 Accuracy assessment

The classified image were examined for accuracy, to find out how well it matched with the reference data. In table 3.2 the error matrix for the year 1997 is presented. For the error matrix of the year 1987, 2008 and 2014, see appendix 2.

User accuracy displays the probability of the classes in the map that represents the reality on the ground. According to the error matrix (table 3.2) water classification has the highest (100%) and barren land (85.96%) the lowest user accuracy. Producer accuracy displayed the probability the feature on the ground were presented in the map. According to the error matrix (table 3.2) the producer accuracy for forest is high (100%) and mining is low (84.61%). Table 3.3 shows an overview of the overall accuracy and Kappa of the classified images. Year 1997 has the highest (91%), and 1987 has the lowest Kappa value (78%).

Table 3.2: Error matrix from supervised classification 1997 (for LULC map of 1997)

Classification data		1	2	3	4	5	Row total
Water	1	51	0	0	0	0	51
Built-up	2	0	47	2	0	0	49
Mining	3	0	0	33	0	0	33
Forest	4	0	1	2	53	4	60
Barren land	5	3	3	2	0	49	57
Column total		54	51	39	53	53	250

Producer's Accuracy			User's Accuracy		
1= 51/54 =	94.44	%	1= 51/51 =	100.00	%
2 = 47/51 =	92.15	%	2 = 47/49 =	95.91	%
3 = 33/39 =	84.61	%	3 = 33/33 =	100.00	%
4 = 53/53 =	100	%	4 = 53/60 =	88.33	%
5 = 49/53 =	92.45	%	5 = 49/57 =	85.96	%

Overall accuracy = (51+47+33+53+49)/250 = 93%

Source from " (USGS, 2019)" [Maps] Landsat and land cover maps. Retrieved from https://earthexplorer.usgs.gov/

$$K = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r}(x_i + Xx_{+1})}{N^2 - \sum_{i=1}^{r}(x_{ii}Xx_{+1})} \quad = \frac{(250*(51+47+33+53+49))-((51*51)+(49*47)+(60*53)+(57*49))}{(250^2)-(((51*51)+(49*47)+(60*53)+(57*49))} = 0.91$$

Table 3.3: Accuracy assessment for the LULC map of 1987, 1997, 2008, 2014 and 2016

Year*	Sup87	Sup97	Sup08	Sup14	Sup16
Overall accuracy	0.82	0.93	0.82	0.86	0.84
Kappa	0.78	0.91	0.78	0.83	0.81

Source from " (USGS, 2019)" [Maps] Landsat and land cover maps. Retrieved from https://earthexplorer.usgs.gov/
Result Kappa for all maps after classification

3.3 LULC Change modeler 1987-2014

With the LULC Change modeler of TerrSet, the past LULC Change Analysis, the Transition Potentials, and the Change Prediction were done for the study area.

3.3.1 The past LULC change analyses

The past change analysis showed the amount of losses, gains and the net change for the classes of the classified image for an early and later time period. The change analysis was divided in four time period between: 1987-1997, 1997-2008, 2008-2014 and also for an overview over the time 1987-2014. Table 3.4 presented the change analysis over the time period between 1987 and 1997.

Table 3.4: Loss and gains of classes between 1987 and 1997 in parts of Marowijne

Classes	Area(km^2) 1987	Losses(km^2)	Gains (km^2)	Net change (km^2)
1. Water	82.81	-12.62	0.0	-12.62
2. Built-up	25.98	-15.34	36.76	21.42
3. Mining	18.16	-10.15	8.16	-1.99
4. Forest	1782.29	-87.95	62.35	-25.65
5. Barren land	99.94	-44.21	63.00	18.79

Source from “ (USGS, 2019)” [Maps] Landsat and land cover maps. Retrieved from https://earthexplorer.usgs.gov/ . Data achieved after placing maps 1987 and 1997 in *TerrSet* [GIS-software], LCM: change analysis

The greatest net change between 1987 and 1997 were found in the classes of forest, built-up and barren land. The ‘forest loss’ for forest class was 25.65km^2. The ‘forest gain’ for built-up and barren land class was 21.42 km^2 and 18.79 km^2. The concentration of the trend changes in classifications are shown in figure 3.2. The red area shows the highest and the green the lowest concentration.

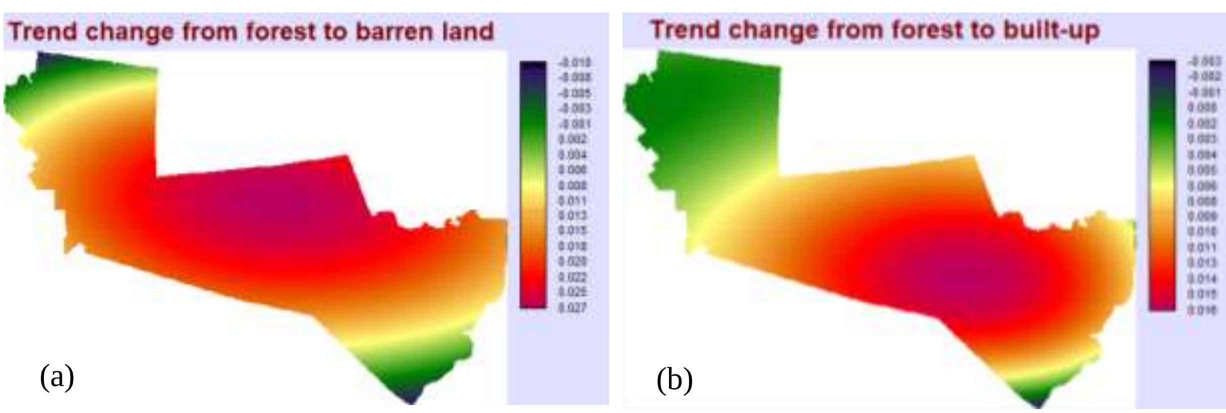


Figure 3.2: Concentration of trend change in the classes between 1987-1997
Using: *LCM, change analyse Tools for TerrSet* [GIS-software]. Version 18.31. Paramaribo. Copyright ©1987-2017 Clark Labs, Clark University.

Looking at table 3.5, there is zero area of change from ‘forest to water’ transition, because there was a 0 km^2 value. The largest change occur in the ‘forest to barren land’ transition with 54.13 km^2. Looking at the data of transitions the human factor for economic and social welfare were most likely responsible for the change. The following change analyses between: 1997-2008, 2008-2014 and 1987-2014 are shown in appendix 3.

Table 3.5: Area change through transition in the classes between 1987-1997

Transition	Area of change (km^2)
Forest to water	0
Forest to built-up	28.27
Forest to mining	5.53
Forest to barren land	54.13

Data achieved after placing maps 1987 and 1997 in *TerrSet* [GIS-software], LCM: change analysis

3.3.2 The Transition Potential modeling

According to the data of table 3.4, the greatest net change of the study occurred in the forest class, with a forest loss of 87.95 km^2. The transition Potential model was then focused in the 'forest loss' group in the software TerrSet. The sub-models 'forest loss' ran with the following explanatory variables (drivers) of table 3.6.

Table 3.6: Explanatory variables with Cramer's value for the classes

	Classes					Overall	
Explanatory variables	Water	Built-up	Mining	Forest	Barren land	Cramer's V	type
DEM	0.630	0.1160	0.2746	0.5190	0.2880	0.3806	static
Slope	0.5426	0.0376	0.0385	0.3197	0.0511	0.2737	static
Distance deforestation 2014	0.134	0.2267	0.1588	0.1222	0.0499	0.0499	dynamic
Distance to mining 2014	0.1715	0.1396	0.2302	0.1715	0.1427	0.1745	static
Distance to roads 2014	0.1369	0.1859	0.0561	0.0965	0.0515	0.0515	dynamic
Distance to urban 2014	0.1255	0.2877	0.1376	0.2038	0.1479	0.1877	dynamic

Source from " (USGS, 2019)" [Maps] Landsat and land cover maps. Retrieved from https://earthexplorer.usgs.gov/ . Data achieved after placing maps 1987 and 1997 in *TerrSet* [GIS-software], LCM: Transition potential

Transition sub-model 'forest loss'

After running the transition sub-model 'forest loss' an accuracy of 85,04% and a skill measure of 0.78 was achieved. An accuracy >80%, meaning the transition model was good in modeling and a skill of 0.78 is a good prediction for the 'forest loss'. Table 3.7 shows the transition of forest to built-up with a skill measure of 0.7538, meaning a good prediction, and also a persistence of forest with a skill measure of 0.8935, meaning a good prediction for the sub-model. Figure 3.3 shows the prediction of areas for potential to transition of forest to built-up and barren land.

Table 3.7: Accuracy sub-model 'forest loss' for classes with skill measure

Class	Skill measure
Transition : forest to built-up	0.7538
Transition : forest to barren land	0.6475
Persistence : forest	0.8935

Source from " (USGS, 2019)" [Maps] Landsat and land cover maps. Retrieved from https://earthexplorer.usgs.gov/ . Data achieved after placing maps 1987 and 1997 in *TerrSet* [GIS-software], LCM: Transition potential

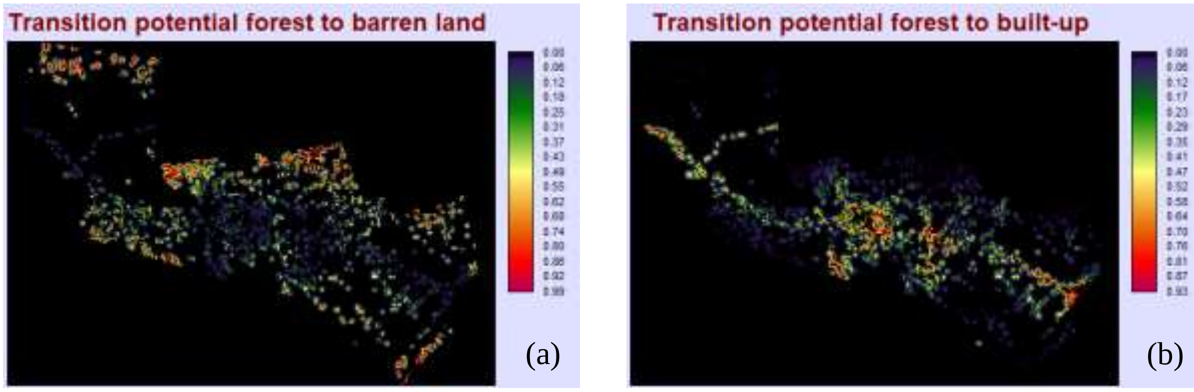


Figure 3.3: Areas of potential transition from forest to (a) barren land and to (b) built-up
Source data: from " (USGS, 2019)" [Maps] Landsat map,1987and 1997. Retrieved from https://earthexplorer.usgs.gov/
Using: *LCM, Transition potentials Tools for TerrSet* [GIS-software]. Version 18.31. Paramaribo. Copyright ©1987-2017 Clark Labs, Clark University

3.3.3 Change prediction and Model Validation 2016

LULC map prediction for 2016 was made, based on sub-model 'forest loss' in LCM of TerrSat. The predicted 2016 map was then compared with LULC reality map of 2016. Figure 3.4.

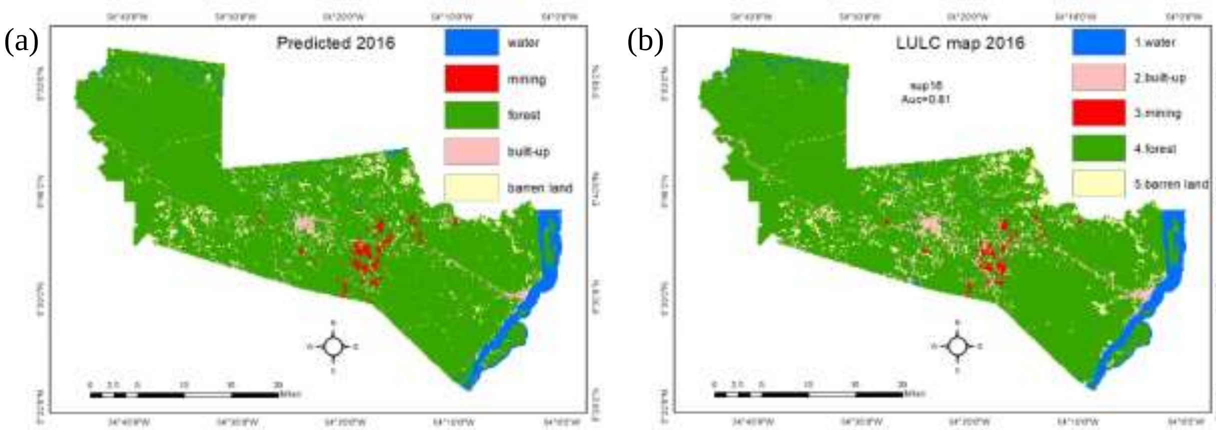


Figure 3.4: Predicted LULC map 2016 (a) and classified map of 2016 (b)
Source data: from " (USGS, 2019)" [Maps] Landsat map,1987and 1997. Retrieved from https://earthexplorer.usgs.gov/
Using: *LCM, Change Prediction Tools for TerrSet* [GIS-software]. Version 18.31. Paramaribo. Copyright ©1987-2017 Clark Labs, Clark University

The validation was done in two methods, the three ways cross-tab validation and through a VALIDATE toolbar. The validation of the predicted 2016 map was firstly done in the LCM-model by a three ways cross-tab validation for Hits, Misses and False alarm (see the result in figure 3.5). The percentage expressed in Hits are 7 %, for Misses 75% and False Alarm 17%. The percentages reports that the area has a small potential for changes. In 7 % times the prediction becomes reality, in 75% times it misses the reality and 17% times it is falsely predicted.

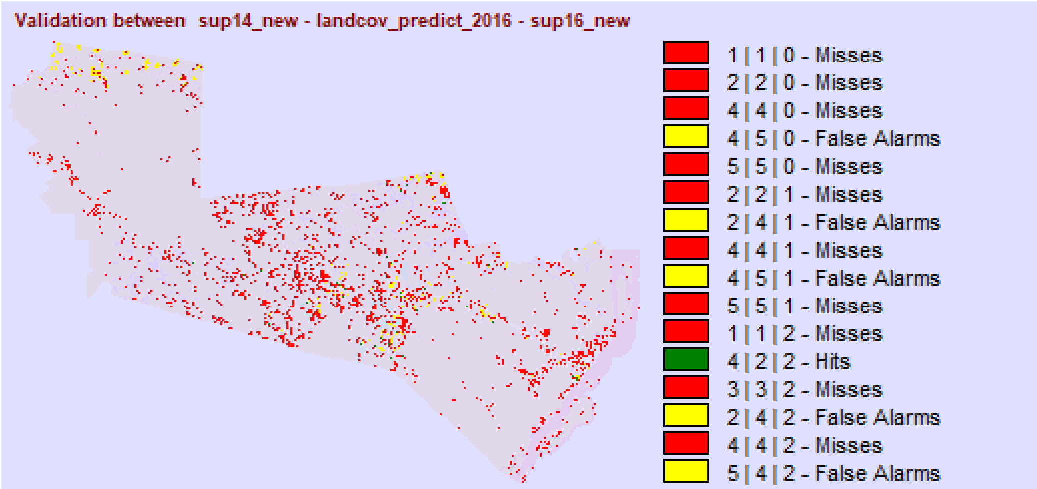


Figure 3.5: Three ways cross-tab for validation of LCM of predicted 2016 map
Source data: from " (USGS, 2019)" [Maps] Landsat map,1987and 1997. Retrieved from https://earthexplorer.usgs.gov/
Using: *LCM, Change Prediction ,validation Tools for TerrSet* [GIS-software]. Version 18.31. Paramaribo. Copyright ©1987-2017 Clark Labs, Clark University

The second method was through a VALIDATE toolbar, with component of agreements and disagreements in TerrSet. The second method of validation for the predicted and reality LULC map of 2016 resulted in a K-standard of 94%, a K-no of 96 % and a K-location of 95%. K-standard of 94 % means a very good agreement between the real and predicted LULC map of 2016. A K-no of 96 % means also a good agreement in terms of quantity of classification between the two maps. A K-location of 95 % means a very good agreement in terms of the location between the real and predicted LULC map of 2016.

3.4 Change prediction for the future

The change prediction for the future was done with the LCM prediction. The results in table 3.8 and figure 3.6 (a,b,c,d) display the different trends in the classes from 2016 to 2060. For built-up (figure 3.6 a) and barren land (figure 3.6 c) classes an increase in the area is predicted. For forest class (figure 3.6 b), a decrease in the area is predicted. Whereas in mining prediction (figure 3.6 d), the area has not changed.

Table 3.8: Changed area of prediction for the classes

	Changed Area (km^2)			
Classes	2016	2025	2045	2060
Built-up	46.34	58.93	66.55	67.61
Mining	25.35	25.35	25.35	25.35
Forest	1754.57	1705.28	1653.69	1639.69
Barren land	103.70	140.40	184.37	197.31

Source from " (USGS, 2019)" [Maps] Landsat and land cover maps. Retrieved from https://earthexplorer.usgs.gov/ . Data achieved in *TerrSet* [GIS-software], LCM: changed prediction

In table 3.9 the amount of area predicted that increases or decreases for the classes from 2025 to 2060 are shown.

Table 3.9: Changed area of prediction for classes

	Changed Area (km^2)			
Classes	2016	2025	2045	2060
Built-up	0	12.59	20.21	21.28
Mining	0	0.00	0.00	0.00
Forest	0	-49.29	-51.59	-14.00
Barren land	0	36.70	80.67	93.60

Source from " (USGS, 2019)" [Maps] Landsat and land cover maps. Retrieved from https://earthexplorer.usgs.gov/ . Result increases or decreases map area for the classes after changed prediction

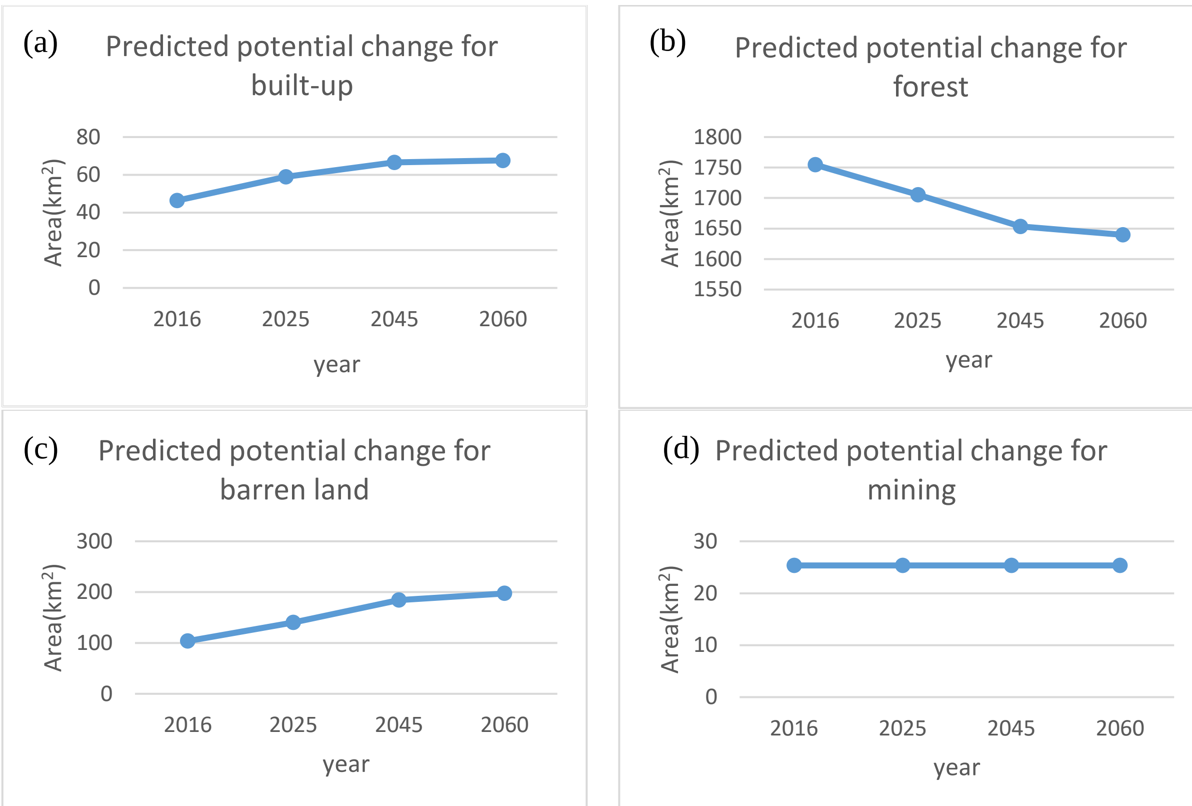


Figure 3.6: Predicted potential change of increase and decline in classes from 2016-2060.

In figure 3.7 (a,b,c) the trends of increase and decline of the classes predictions can also be observed through the hard prediction of LULC maps. In figure 3.7, the greatest potential to change in forest and barren land classes lies on the north part of Marowijne. Also, a potential for built-up along the roads can be seen. There are no potential changes in mining class through the area, because the mining companies (Suralco and Billiton) have closed down.

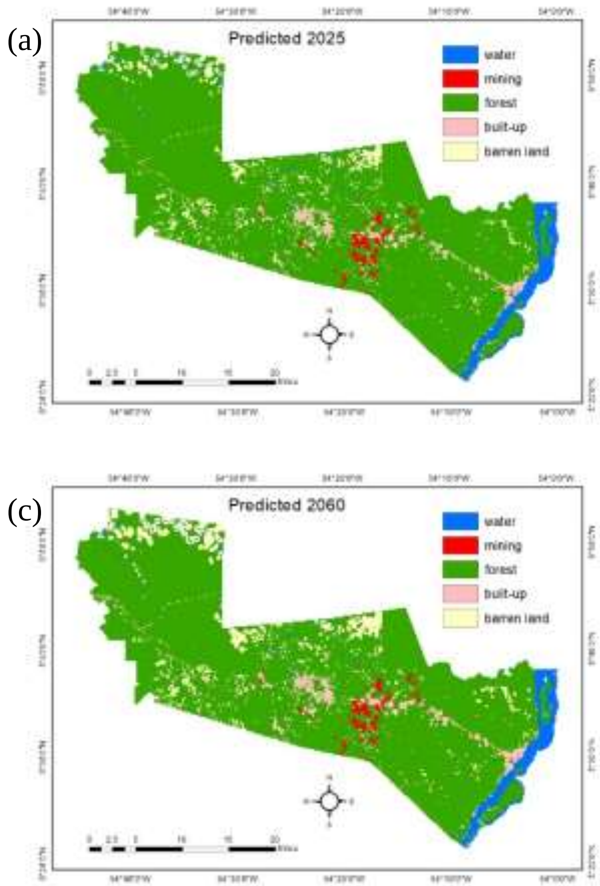
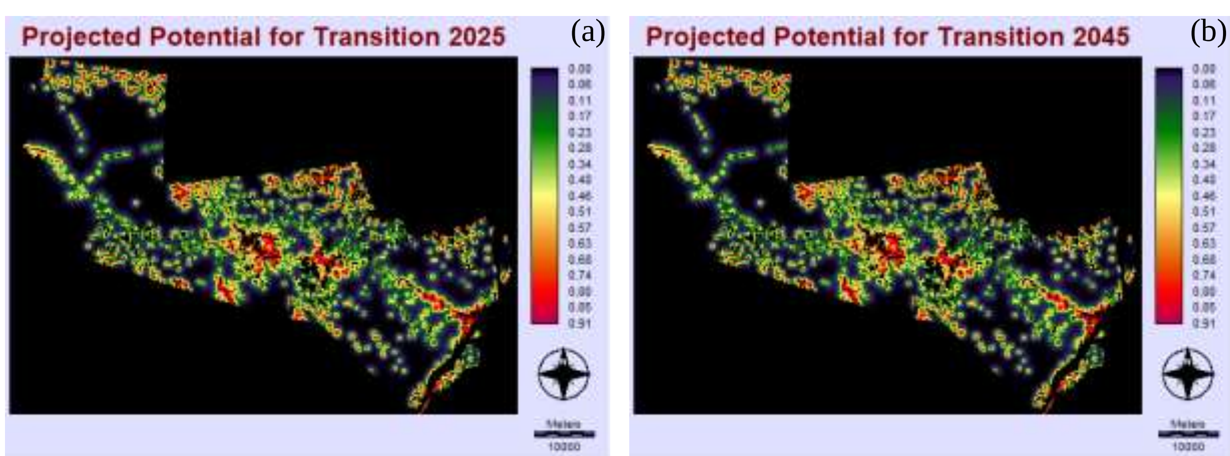


Figure 3.7: Hard prediction of LULC map from 2025-2060
Source data: from " (USGS, 2019)" [Maps] Landsat maps. Retrieved from https://earthexplorer.usgs.gov/ Using: *LCM, Change hard Prediction Tool for TerrSet* [GIS-software]. Version 18.31. Paramaribo. Copyright ©1987-2017 Clark Labs, Clark University

The soft prediction in figure 3.8 (a,b,c) displays the potential for transition of the classes. The red to green area represents a high to low potential for transition in the area. The transitions are mostly from deforestation and shifting cultivation in the red areas.



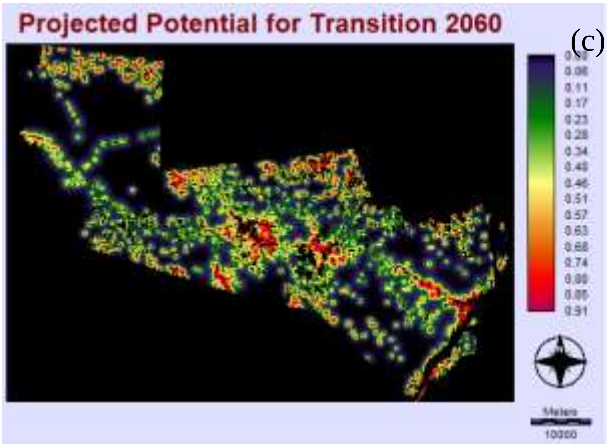


Figure 3.8: Soft prediction of LULC map from 2025-2060
Source data: from " (USGS, 2019)" [Maps] Landsat maps. Retrieved from https://earthexplorer.usgs.gov/ Using: *LCM, Change soft Prediction Tool for TerrSet* [GIS-software]. Version 18.31. Paramaribo. Copyright ©1987-2017 Clark Labs, Clark University

Road prediction maps were also a product of the LCM prediction. Figure 3.9 (a,b,c) shows the road prediction maps. Table 3.10 displays the length of the roads that were predicted. A dynamic road modeling procedure was used in both scenarios.

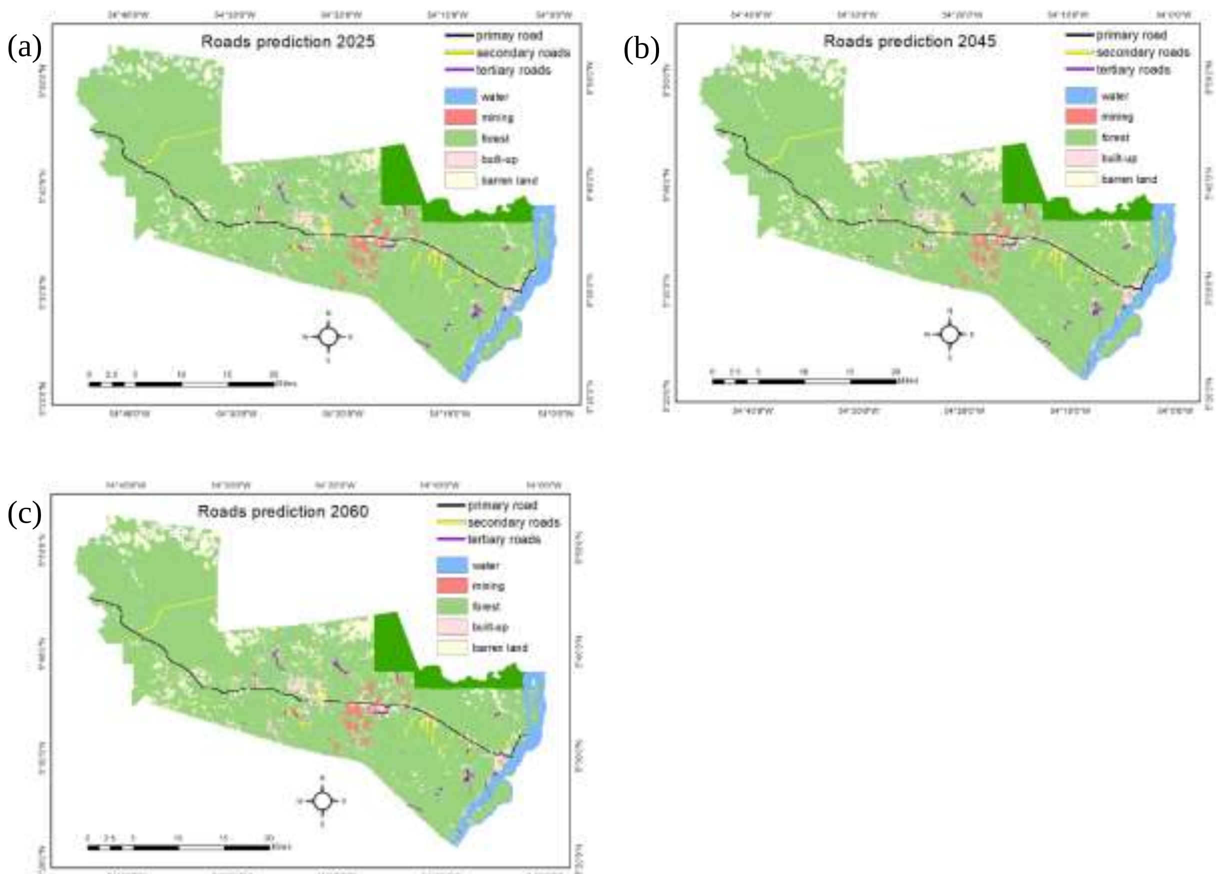


Figure 3.9: Road prediction maps from 2025-2060

Source data: from " (USGS, 2019)" [Maps] Landsat maps. Retrieved from https://earthexplorer.usgs.gov/
Using: *LCM, road Prediction Tool for TerrSet* [GIS-software]. Version 18.31. Paramaribo. Copyright ©1987-2017 Clark Labs, Clark University

The results of the road predictions were not significant for a great impact on the classes, because of small changes in road developments as predicted in table 3.10.

Table 3.10: Length of road prediction in 2016, 2025, 2045 and 2060

	2016	**2025**	**2045**	**2060**
Primary road (km)	149.48	149.48	149.48	149.52
Secondary road (km)	100.48	100.48	100.48	100.48
tertiary road (km)	92.93	93.7	94.19	94.32
Total (km)	**342.89**	**343.66**	**344.15**	**344.32**

4 Discussion

In the discussion the results and limitations that were found during the research were discussed. The results for discussion were about the subjects: the LULC change analysis, the explanatory variables, model validation and change prediction. The limitations were on the research subjects: classification, accuracy assessment and transition potential of the study area.

4.1 LULC Change analysis

The results of the study area show that the LULC change happened mainly through deforestation between 1987-2014. Between 1987 and 1997 changes were found in the classes of forest and by built-up. In the forest class, changes were mostly from deforestation and from reforestation, because of the closure of Suralco. In built-up, changes were from infrastructure and housing. Between 1997-2008 the major change was from forest and barren land. In barren land, changes were from shifting cultivation and small agriculture. In the forest class, changes were made by logging. Between 2008-2014 the major change was from forest and barren land. In the forest, changes were from deforestation. In barren land, changes were from shifting cultivation and small agriculture. There was also a FAO-report (FAO, 2010) and background study from (NIMOS, SBB, & UNIQUE, 2017) that says otherwise. The report and background study (NIMOS, SBB, & UNIQUE, 2017) were done for the entire country rather than the study area and the results were not similar. In the reports there is continued increase in deforestation between 2000-2014, whereas in the research there is also reforestation. The reason for reforestation in the study area lies, because of a small research area approach.

4.2 Explanatory variables

Explanatory variables ‘Distance to deforestation 08-14’ accomplish transition from ‘Forest’ to deforestation in the study area. This explained where the highest potential to change in ‘Forest’ area was located between 2008-2014. This was as predicted in the hard prediction (figure 3.7), the north part of Marowijne, because of the access to infrastructure and forest concession in the area. Explanatory variables that accomplish transition from ‘built-up and barren land’ is the variable ‘Distance to urban 08-14’, explaining where the highest potential to change (figure 3.2) in ‘Urban and barren land’ took place between 2008-2014. The surrounding area in the ‘urban’ was changing, because of population growth, needs for livelihood and development. Mostly because of human activity such as small scale farming and shifting culture for building crops (NIMOS, SBB, & UNIQUE, 2017).

4.3 Model validation

The accuracy assessment for the classification of the LULC maps according to Kappa statistics are about 80 % to 91 %, see the results in table 3.3. This proves of a good agreement between real and predicted LULC maps during classification.
When comparing the 2016 classification with 2016 prediction validation, the result is a K-location of 95% with hits of 7% and misses of 75%. K-location shows the agreements for location and hits the amount of correctly predicted changed pixel. The misses show the missed predicted changed pixel. When K-location were calculated all pixels were compared, even pixels in unchanged area. When hits or misses were calculated the pixels within areas of change prediction of the classes were compared. The area near the town Moengo showed a lot of misses. The people uses the area for small scale agriculture, timber logging and shifting cultivation for crops planting for a short or long time period. Later when the area was abandoned, because of little yield, it becomes overgrown with secondary forest or vegetation (NIMOS, SBB, & UNIQUE, 2017). This explains the misses that the model could not predict.

4.4 Change prediction

After the hard prediction in TerrSet, LULC map for 2025, 2045 and 2060 was made. In the predictions an increase in built-up and barren land was seen. Further a decrease in forest area was predicted by the model. The mining areas were unchanged, because of no mining activity and plans in the future by Suralco (Snijders, 2018). The greatest change in the area was in forest, because between 2008 to 2014 there was already a decrease in the forest area. With the LCM, the historical change pattern was taken for the future prediction.
The explanatory variable 'Distance to roads 08-14' had made little transition in the road prediction of the study area in the model. The results of the road predictions were not significant for a great impact on the classes, because of small changes in road developments as predicted.

4.5 Limitations of the study

4.5.1 Classification

For the study area Landsat images were used with a resolution of 30 meter pixel which was good for nationwide research. For detailed research with more accuracy, maps with 30 meter pixel will not be enough for high resolution image classification. The results with high resolution images data could distinguish the difference very easily between LULC classes by making an accurate classification. These classifications would then make accurate change analyses and predictions.

4.5.2 Accuracy assessment

Looking at the accuracy, the year 1997 got an accuracy (Kappa) of 91%. This is because of a cloud free image in the study area. The image of 1997 was only cut and clipped for the area of interest and then classified. The other images were not cloud free and had to be made cloud free before classification. For images to be cloud free the cloud area were taken into classification. The cloud in the image were then manipulated to the correct classification (of course by comparing it with Google earth images). The more manipulation is needed for a cloud free image, the more error or the lower the accuracy of the image.

4.5.3 Transition potential sub-model 'forest gain' and 'forest loss'

For the study area, two transition potential sub-model were created, the 'forest gain' and the 'forest loss'. The drivers for 'forest gain' and 'forest loss' were images of 'DEM', 'slope', 'Distance to deforestation 2014', 'Distance to mining 2014', 'Distance to roads 2014' and 'Distance to urban 2014'. These drivers has more or less the potential to cause LULC change in the study area. The DEM, slope and mining were static which had little change on the LULC of the area. The greatest change happens with the dynamic drivers like deforestation, roads and urban.

When modeling 'forest gain', a low accuracy of 20,15% and average skill measure of 0.0019 was achieved. Because of a low accuracy and skill measure in 'forest gain', this sub-model was not acceptable for the transition. For 'forest loss' an accuracy of 85,04% and a skill measure of 0.78 was achieved that was acceptable for further modeling.

The LCM used logic patterns to build the model. The patterns were given by the explanatory variables for the transition. Why the accuracy and skill were low for 'forest gain' modeling can be that extra explanatory variable were missing. Or the transition pattern from the explanatory variables could not be recognized because of average Cramer's value.

5 Conclusions and recommendation

5.1 Conclusions

The greatest LULC changes in parts of Marowijne between 1987 and 2014 was in forest loss. Between 1987 and 1997 a deforestation of 31.42 km^2 occured through mining bauxite, building of houses and agriculture shifting cultivation. Between 1997 and 2008 a deforestation of 15.62 km^2 took place mainly, because of shifting income from mining bauxite to timber logging. Between 2008 and 2014 a deforestation of 16.43 km^2 took place, because of building of houses, timber logging, tertiary roads building and agriculture shifting cultivation.

To produce LULC map predictions of 2025, 2045, and 2060, the transition trends of 2008 to 2014 was projected in the future prediction taken into account 2014 to 2016 for validation. The prediction was for a business as usual scenario with deforestation and built-up as drivers of LULC change. Observing the predictions, the trend of deforestation continued. The explanatory variables responsible for the transition from forest to ‘built-up’ and ‘barren land’ was the ‘distance to deforestation 2014’ and ‘distance to urban 2014’ variable. The predictions show that the major forest change occurred in the north of part of Marowijne from forest to barren land. The reason can be, because of timber logging in the area. Most of the north of part of Marowijne forest was given as forest concessions.

The transition of ‘mining’ of bauxite in the area between 2008 and 2014 had stopped since 2010, because of closure of Billiton. Mining in the study area has no effect on the future transition and prediction. Between 2008 and 2014 no major change in primary and secondary road development took place in the area. The road developments did not change the predictions, but had influenced the built-up location in the roads area.

5.2 Recommendation

Suriname is going through an economic unstable period (2020) with domestic and foreign debts. Further because of closing down multinationals, reduction of oil prices, unstable gold prices and the threat of the corona-virus globally. It is therefore suggested that the model be further analyzed for research, because of a standstill or constant change in planning and development of the study area. With a new government elected for 2020-2025, plans for Marowijne were developed during their campaign before the elections. Plans like allotment projects, sport centers, public houses, new school facilities, agriculture production center, wood industry and tourism were promoted.

Based on the conclusions and research findings further research are needed when implementing the development plans in the predicted model for Marowijne. Explanatory variable like the government plans have importance in the development and transition of the LULC in the area. Marowijne is strategically close to Europe (French- Guyana), drivers like tourism and agriculture in that area can easily develop.

With the model prediction, deforested areas were identified. These areas can also be monitored as a baseline for deforestation for the future, by all means in conjunction with all stakeholders.

Study on LULC change can also be done on the effect the area has on climate change, on the ecosystem services, and its economic value. With the identification of economic, social, and environmental value of the area (so called ‘hot spots’), the government can promote conservation. In the future, improved and faster software programs with better options for LULC model prediction will be developed. It is recommended to do research with a better or improved software program for better prediction models for other research areas.

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Appendices

Appendix 1. LULC Classification system for remote sensing

Level I	Level II
1. Urban or built-up land	1.1 Residential
	1.2 Commercial and services
	1.3 Industrial
	1.4 Transportation, communications and utilities
	1.5 Industrial and commercial complexes
	1.6 Mixed urban or built-up land
	1.7 Other urban or built-up land
2. Agricultural land	2.1 Cropland and pasture
	2.2 Orchards, groves, vineyards, nurseries and ornamental horticultural areas
	2.3 Confined feeding operations
	2.4 Other agricultural land
3. Rangeland	3.1 Herbaceous rangeland
	3.2 Shrub and brush rangeland
	3.3 Mixed rangeland
4. Forest land	4.1 Deciduous forest land
	4.2 Evergreen forest land
	4.3 Mixed forest land
5. Water	5.1 Streams and canals
	5.2 Reservoirs
	5.3 Reservoirs
	5.4 Bays and estuaries
6. Wetland	6.1 Forested wetland
	6.2 Nonforested wetland
7. Barren land	7.1 Dry salt flats
	7.2 Beaches
	7.3 Sandy areas other than beaches
	7.4 Bare exposed rock
	7.5 Strip mines, quarries and gravel pits
	7.6 Transitional areas
	7.7 Mixed barren land
8. Tundra	8.1 Shrub and herbaceous tundra
	8.2 Herbaceous tundra
	8.3 Bare ground tundra
	8.4 Wet tundra
	8.5 Mixed tundra
9. Perennial snow or ice	9.1 Perennial snowfields
	9.2 Glaciers

Source: (Anderson, 1976). *A land use and land cover classification system for use with remote sensor data* (USGS Numbered Series No. 964). Retrieved from http://pubs.er.usgs.gov/publication/pp964

Appendix 2. Error matrix

Error matrix LULC map 1987

Classification data		1	2	3	4	5	Row total
Water	1	43	0	0	0	0	43
Built-up	2	1	36	2	0	0	39
Mining	3	0	0	30	0	0	30
Forest	4	6	12	5	53	13	89
Barren land	5	0	3	1	0	40	44
Column total		54	50	51	38	53	250

Producer's Accuracy			User's Accuracy		
1= 43/54 =	79.63	%	1= 43/43 =	100.00	%
2 = 36/50 =	72.00	%	2 = 36/39 =	92.31	%
3 = 30/51 =	58.82	%	3 = 30/30 =	100.00	%
4 = 53/38 =	139.47	%	4 = 53/89 =	59.55	%
5 = 40/53 =	75.47	%	5 = 40/44 =	90.91	%

Overall accuracy = (43+36+30+53+40)/250 = 82%

Source from " (USGS, 2019)" [Maps] Landsat and land cover maps. Retrieved from https://earthexplorer.usgs.gov/
Result after *pivot table Tools for ArcGIS* [GIS-software]. Version 10.2.2. Paramaribo. Copyright ©1999-2014 ESri Inc.

Error matrix LULC map 2008

Classification data		1	2	3	4	5	Row total
Water	1	40	2	0	0	0	42
Built-up	2	1	43	2	0	2	48
Mining	3	1	1	31	0	0	33
Forest	4	4	5	6	53	13	81
Barren land	5	8	0	0	0	38	46
Column total		54	54	51	39	53	250

Producer's Accuracy			User's Accuracy		
1= 40/54 =	74.07	%	1= 40/42 =	95.24	%
2 = 43/51 =	84.31	%	2 = 43/48 =	89.58	%
3 = 31/39 =	79.49	%	3 = 31/33 =	93.94	%
4 = 53/53 =	100.00	%	4 = 53/81 =	65.43	%
5 = 13/53 =	71.70	%	5 = 38/46 =	82.61	%

Overall accuracy = 0.82

Error matrix LULC map 2014

Classification data		1	2	3	4	5	Row total
Water	1	34	0	0	0	0	34
Built-up	2	0	47	1	0	1	49
Mining	3	4	3	36	0	2	45
Forest	4	0	0	0	53	5	58
Barren land	5	16	1	2	0	45	64
Column total		54	54	51	39	53	250

Producer's Accuracy			User's Accuracy		
1= 34/54 =	62.96	%	1= 34/34 =	100.00	%
2 = 47/51 =	92.16	%	2 = 47/49 =	95.92	%
3 = 36/39 =	92.31	%	3 = 36/45 =	80.00	%
4 = 53/53 =	100.00	%	4 = 53/58 =	91.38	%
5 = 45/53 =	84.91	%	5 = 45/64 =	70.31	%

Overall accuracy = 0.86

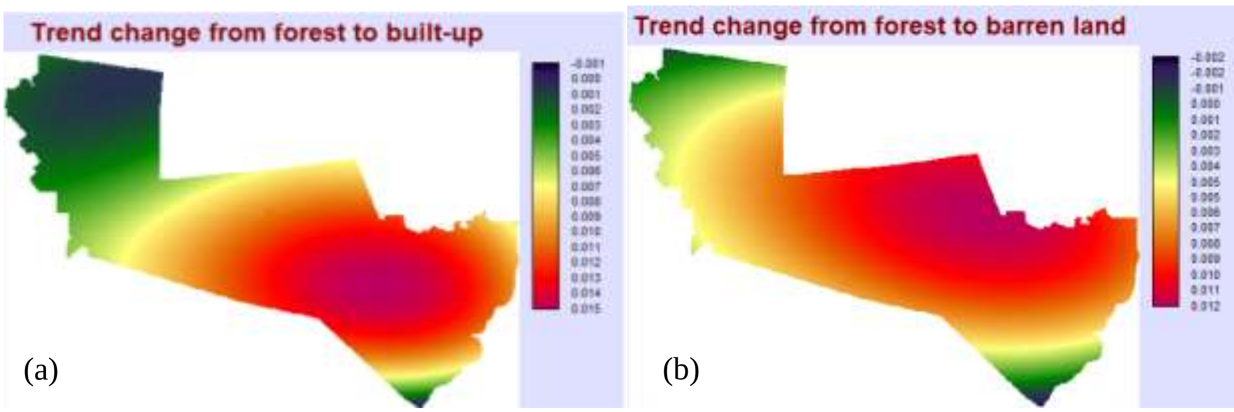
Source from " (USGS, 2019)" [Maps] Landsat and land cover maps. Retrieved from https://earthexplorer.usgs.gov/
Result after *pivot table Tools for ArcGIS* [GIS-software]. Version 10.2.2. Paramaribo. Copyright ©1999-2014 ESri Inc.

Appendix 3. Change Analysis LULC maps

Los and gains between 1997 and 2008 in the parts of Marowijne

Classes	Area(km^2) 1997	Losses(km^2)	Gains (km^2)	Net change (km^2)
1. Water	76.06	-6.29	6.42	0.13
2. Built-up	47.99	-33.68	31.78	-1.9
3. Mining	16.23	-7.11	14.51	7.4
4. Forest	1757.89	-58.46	93.86	35.4
5. Barren land	119.5	-69.55	28.53	-41.02

Source from " (USGS, 2019)" [Maps] Landsat and land cover maps. Retrieved from https://earthexplorer.usgs.gov/ . Data achieved after placing maps 1997 and 2008 in *TerrSet* [GIS-software], LCM: change analysis



Concentration trend change between 1997-2008

Using: *LCM, change analyse Tools for TerrSet* [GIS-software]. Version 18.31. Paramaribo. Copyright ©1987-2017 Clark Labs, Clark University.

Area change through transition in the classes between 1997-2008

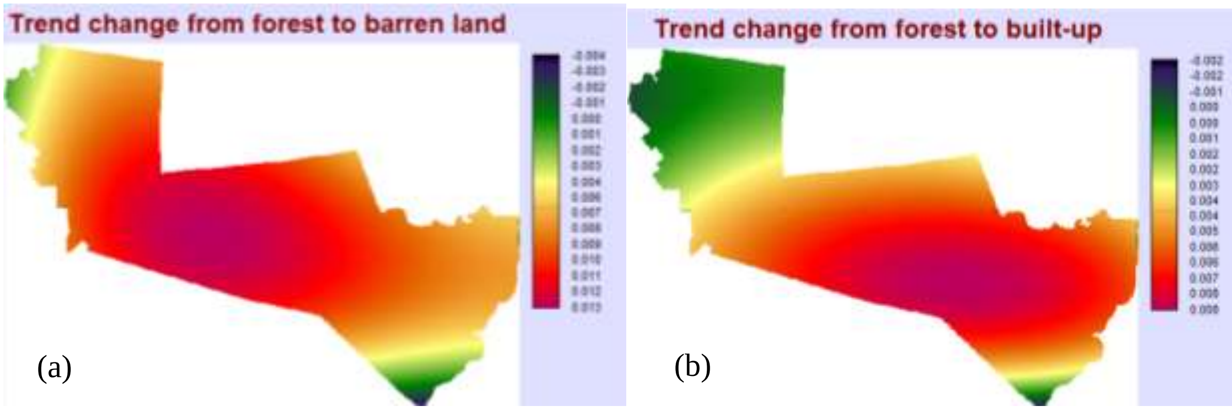
Transition	Area of change (km^2)
Forest to water	3.37
Forest to built-up	24.97
Forest to mining	6.81
Forest to barren land	23.29

Data achieved after placing maps 1997 and 2008 in *TerrSet* [GIS-software], LCM: change analysis

Los and gains between 2008 and 2014 in the parts of Marowijne

Classes	Area(km^2) 2008	Losses(km^2)	Gains (km^2)	Net change (km^2)
1. Water	76.24	-0.49	10.48	9.99
2. Built-up	45.93	-25.10	17.72	-7.38
3. Mining	23.66	-6.66	8.47	1.82
4. Forest	1792.86	-49.86	30.32	-19.54
5. Barren land	78.27	-19.52	34.64	15.12

Source from " (USGS, 2019)" [Maps] Landsat and land cover maps. Retrieved from https://earthexplorer.usgs.gov/ . Data achieved after placing maps 2008 and 2014 in *TerrSet* [GIS-software], LCM: change analysis



Concentration trend change between 2008-2014

Using: *LCM, change analyse Tools for TerrSet* [GIS-software]. Version 18.31. Paramaribo. Copyright ©1987-2017 Clark Labs, Clark University.

Area change through transition in the classes between 2008-2014

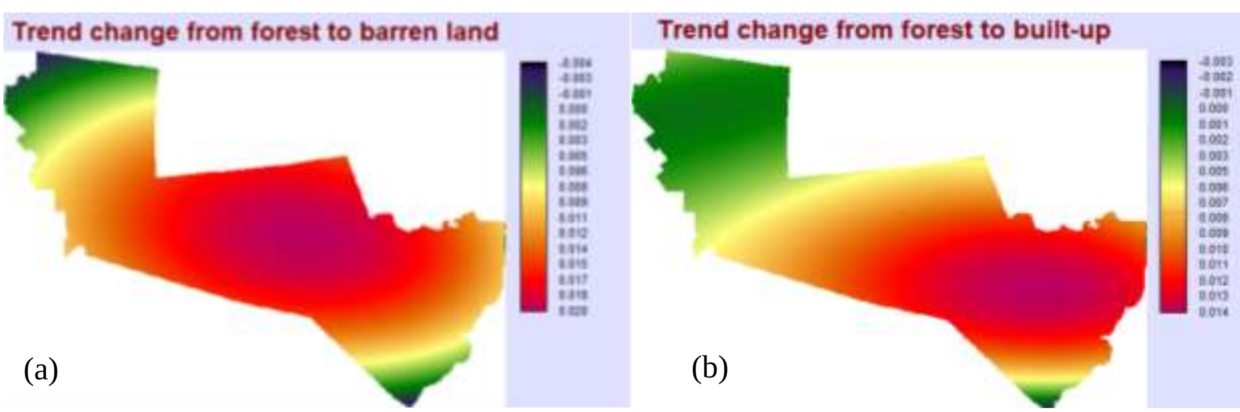
Transition	Area of change (km^2)
Forest to water	2.51
Forest to built-up	14.4
Forest to mining	4.5
Forest to barren land	28.44

Data achieved after placing maps 2008 and 2014 in *TerrSet* [GIS-software], LCM: change analysis

Los and gains between 1987 and 2014 in the parts of Marowijne

Classes	Area(km^2) 2008	Losses(km^2)	Gains (km^2)	Net change (km^2)
1. Water	76.24	-5.97	6.23	0.26
2. Built-up	45.93	-13.09	25.33	12.24
3. Mining	23.66	-3.69	10.89	7.2
4. Forest	1792.86	-79.46	66.18	-13.28
5. Barren land	78.27	-49.05	42.63	-6.42

Source from " (USGS, 2019)" [Maps] Landsat and land cover maps. Retrieved from https://earthexplorer.usgs.gov/ . Data achieved after placing maps 1987 and 2014 in *TerrSet* [GIS-software], LCM: change analysis



Concentration trend change between 1987-2014

Using: *LCM, change analyse Tools for TerrSet* [GIS-software]. Version 18.31. Paramaribo. Copyright ©1987-2017 Clark Labs, Clark University.

Area change through transition in the classes between 1987-2014

Transition	Area of change (km^2)
Forest to water	5.6
Forest to built-up	23.23
Forest to mining	9.9
Forest to barren land	40.7

Data achieved after placing maps 1987 and 2014 in *TerrSet* [GIS-software], LCM: change analysis