QUANTIFY THE IMPACT OF LAND USE/LAND COVER CHANGE AND TEMPORAL AGGREGATION ON TIME SERIES ANALYSIS

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FEBRUARY, 2017

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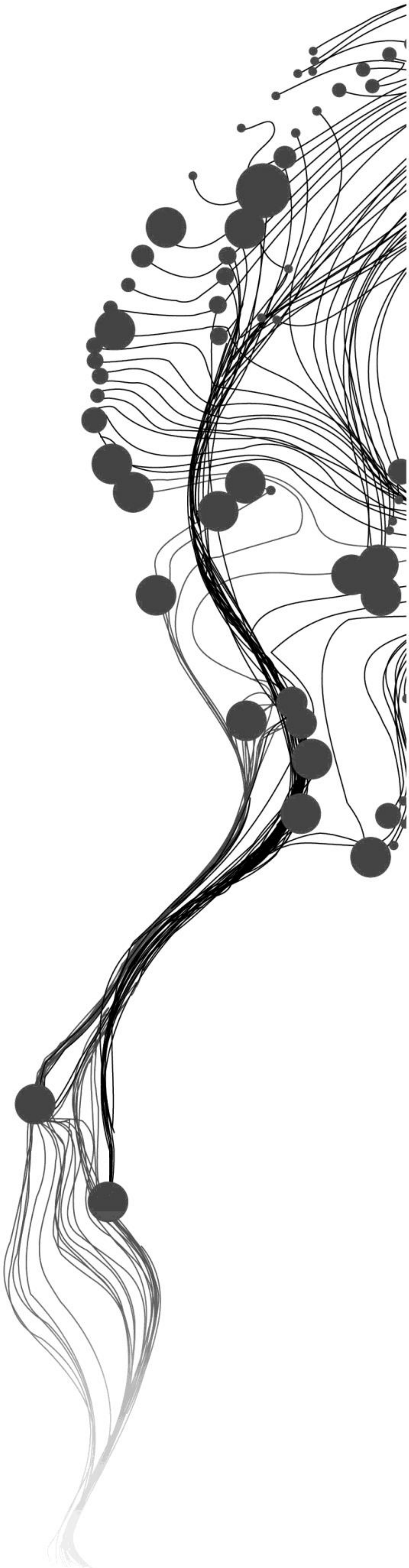

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Thesis submitted to the Faculty of Geo-Information Science and Earth Observation of the University of Twente in partial fulfilment of the requirements for the degree of Master of Science in Geo-information Science and Earth Observation.
Specialization: Geoinformatics

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ABSTRACT

Remotely sensed time series analysis is an effective geographical method to extract dynamic geographical information from remote sensing time series. It enables detection and quantification of gradual changes within the time frame covered, which is significant in global change studies. However, temporal size is the basic modifiable unit of remotely sensed data. Different temporal aggregations may lead to different inferences of same project over time series analysis. Meanwhile, Land Use/Land Cover (LU/LC) change is another crucial influence factor of time series analysis, which needs to be analysed under proper temporal unit sizes. The aim of this study is to explore the impact of LU/LC change and temporal aggregation on time series analysis. Particularly, this study focused on the effects of deforestation over Land Surface Temperature (LST) and Normalized Difference Vegetation Index (NDVI) time series. The study area is located in the Gran Chaco region. MODerate Resolution Imaging Spectroradiometer (MODIS) LST and NDVI data of the forest area in Gran Chaco region were used to study the LU/LC change and temporal aggregation components. Harmonic ANalysis of Time Series (HANTS) was performed in this study to obtain a gapless time series and to assess the impact of LU/LC on harmonics. The complete time series were classified to before and after deforestation periods based on the deforestation time. MODIS 8-day LST and NDVI was aggregated to 4 temporal aggregation levels: 16-day, monthly, seasonally and yearly. The study demonstrated the dependence of remotely sensed time series on temporal unit size and LU/LC change. It was observed that at lower temporal aggregation levels, the effects of temporal aggregation can be ignored.

Key words: temporal aggregation, time series analysis, Land Use/Land (LU/LC) Cover change

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1. INTRODUCTION

1.1. Motivation and problem statement

Time series analysis is a group of statistical methods for analysing and modelling an ordered sequence of observations. The methods most commonly used for time series to identify trends, periodicities, and auto-correlative relations of time series data (Gossel & Laehne, 2013). In geography, time series analysis is an invaluable and widely applied approach for studying earth surface changing and other ecological applications. With the rapid development of remote sensing technologies, after the latter part of the 20th century, more and more remote sensing time series datasets were provided by different sensors (Eerens et al., 2014). Since then, remote sensing-based time series analysis has been applied in many fields of geographical, such as environmental monitoring, species distribution modelling (Scharlemann et al., 2008), environmental epidemiology (Hamm et al., 2015).

Due to changes in the landscape and impacts of those changes, there is a rise in demand for updated geographic data are raising (Al-Fares, 2013). With the invention of remote sensing techniques, the study of Land Use/Land Cover (LU/LC) change based on remote sensing has given a useful and detailed way to monitor dynamics changes in the earth surface (Sarıyılmaz & Musaoğlu, 1997). Although there are several approaches for remote sensing-based time series analysis, such as simple summaries including the mean, median, maximum, minimum and more complicated methods including temporal Fourier analysis (TFA) and self-organizing maps (SOMs). However, those methods might not work properly in areas that have undergone abundant LU/LC changes. Moreover, most research regarding LU/LC change studies used time series analysis to detect changes, while neglecting the impact of LU/LC change on time series.

Remotely sensed data is collected at predefined spatial and temporal scale irrespective of the natural processes occurring on ground. The data under different resolutions can be acquired by data aggregation. Data aggregation is a statistical analysis method that gathers and expresses information in form of a summary. The aggregated data usually equals to the average of a variable across time series (Vlahogianni & Karlaftis, 2011), and a lower-frequency time series is obtained from averaging a variable of a higher-frequency time series (Tabar & Babai, 2013). Time series analyses are sensitive to data aggregation. According to previous studies, spatial aggregation may affect the result obtained from time series analysis (Jacobs-Crisioni et al., 2014). Similarly, the temporal aggregation problem has also been proven that it may lead to effects on time series analysis, such as the forecasting accuracy in the tourism industry (Athanasopoulos et al., 2011), misjudgements of statistics and traffic model choice (Vlahogianni & Karlaftis, 2011), and inaccurate vegetation seasonal trends (De Jong & De Bruin, 2012). However, temporal aggregation is an issue that has been widely ignored in remote sensing-based time series analysis.

Remote sensing time series analysis has already been widely applied to map and monitor the ecosystem state and dynamics (Pasquarella et al., 2016) and LU/LC change had received more and more attention from governments and institutes (Smith, 2014). However, limited attention has been paid to the impact of LU/LC change on remote sensing time series analysis. In addition, so far there have been very few studies exploring the impact of temporal aggregation on remote sensing-based time series analysis, which is a guideline for remote sensing data selection. Since LU/LC changes and temporal aggregation may influence the result of time series analysis, it is necessary to figure out the impacts caused by those two factors on time series analysis. It is therefore important to know how LU/LC and temporal aggregation affect time series summaries, such as summary statistics, trends, and harmonics. The aim of this study is to investigate the impact of LU/LC changes and temporal aggregation on remote sensing time series analysis.

1.2. Research objectives

1.2.1. General objective

The main objective is to quantify the effects of LU/LC change and temporal aggregation on time series analysis. Particularly, this study was focused on the effects of deforestation over Land Surface Temperature (LST) and Normalized Difference Vegetation Index (NDVI) time series.

1.2.2. Specific objectives and questions

Table 1-1 shows the specific research objectives and research questions of this study.

Table 1-1: Specific Objectives & Research Questions

Specific Objectives	Research Questions
1. Identify the effects of LU/LC changes on time series analysis.	1.1 Are there any differences between before and after a LU/LC change in the summary statistics of a time series?
	1.2 Can LU/LC change affect the trends and harmonics of time series variables?
2. Evaluate the effects of different temporal aggregation levels on time series analysis.	2.1 If the temporal aggregation levels are different, will it influence the result of time series analysis?
	2.2 Is there any relationship between temporal aggregation level and the slope of trend?
3. Study the effects of LU/LC change and temporal aggregation levels over time series analysis.	3.1 If the temporal aggregation level changes are there any differences in summary statistics, trends, and harmonics between before and after the LU/LC change event?
	3.2 Which statistic summary has the highest sensitivity to a change in temporal unit size?

1.3. Organization of thesis

This thesis is structured into 7 main chapters. Chapter 1 provides an introduction to the motivation, research problem and objectives of the study. Chapter 2 is the literature review, which presents current findings. In chapter 3, the study area and data are presented. Chapter 4 provides the methodology adopted to address the research objectives. The results obtained are given in chapter 5. The discussion is shown in chapter 6. Chapter 7 is the final conclusion and recommendations. Finally, after the last chapter are references and appendices.

2. LITERATURE REVIEW

2.1. Remote sensing-based time series analysis

Time series analysis is a group of statistical methods for analysing and modelling an ordered sequence of observations. Remote sensing is the technique of obtaining information about objects or areas from a distance, typically from aircraft or satellites (Lillesand et al., 1987). Remote sensing-based time series analysis is a geographical method to extract dynamic geographical information from remote sensing time series. Due to the development of remote sensing-based time series analysis approaches over the past 60 years, more and more time series datasets are provided by remote sensing sensors. Earth observation satellites, such as Système Probatoire d'Observation de la Terre (SPOT), MODerate Resolution Imaging Spectroradiometer (MODIS), Landsat TM, and Advanced Very High Resolution Radiometer (AVHRR) are often used to map land cover. Those sensors provide several kinds of time series variables, such as vegetation indices, biophysical variables, and temperature, which have been widely used in remote sensing time series analysis.

For a better understanding of the dynamic relationships and interactions between humans and natural environment, remote sensing-based time series analysis was used in several applications. Commonly, time series analysis has two objectives, which are to find out a regular behaviour for the identification and quantification of processes and to use the results of time series analysis to predict variable values. Several scientists used the results of time series analysis to conduct environmental monitoring, such as land surface changes detection, crop growth prediction, etc. In the past, several approaches to analyse remote sensing time series were employed to analyse time series. Simple summary statistics include the mean, median, minimum, and maximum. More complex methods such as Self-Organizing Maps (SOMs, Zurita-Milla et al., 2013), Temporal Fourier Analysis (TFA, Hay et al., 2006), Harmonic Analysis of Time Series (HANTS, Roerink et al., 2000) and Principal Component Analysis (PCA, Chen, 2016) were adopted by many scientists on remote sensing time series analysis.

Because of low cost, easy access and continuity, remote sensing-based time series analyses is receiving increased attention (Singh & Jeganathan, 2016). In earlier studies (around 1980s), scientists mainly studied attainment of time series from remote sensing data and some analysing, such as prediction, mapping, etc. The study of Becker and Choudhury (1988) figured out the relative sensitivity of NDVI and Microwave Polarization Difference Index (MPDI) using 2-year NOAA/AVHRR data. However, since the lacking of long-term community record at that time, the time series lengths are limited. With the development of remote sensing techniques, more and more long-term remote sensing time series analysis were developed. Some long-term ecological phenomenon can be analysed by remote sensing time series analysis. The LU/LC change is one of the study objects. Fu and Weng (2016) studied the LU/LC change and its impact on LST with 27 years Landsat images. They found that high-intensity urban land had the largest mean LST value and the difference between urban and non-urban covers is 1.8K per decade. Jeganathan and Nishant (2014) analysed the time series of MODIS and Global Inventory Modelling and Mapping Studies (GIMMS) vegetation indices to extract the growth rhythm of natural vegetation in India. The lengths of their time series were 10 years and 6 years. NDVI and EVI were taken as the time series variables in their research. They found different indices have different behaviours when extracting the crop growth rhythm by remote sensing-based time series analysis. In this study the phenology result from MODIS EVI was reliable and it was recommended for time-series vegetation related applications. However, none of these studies have taken into account LU/LC change when analysing time series.

2.2. Land use and land cover change

LU/LC change analysis are significant for monitoring, understanding and predicting the effects of complete human-nature interactions that span local, regional and global scales (Clark et al., 2010). Remote sensing and digital image processing make observation, identification, mapping, and monitoring of LU/LC change possible. Remote sensing data provides better characterization of land cover types, with intra-annual series informing on pheonological differences and inter-annual series informing on LU/LC dynamics (Gómez, White, & Wulder, 2016). Moreover, satellite remote sensing can provide consistent, repeatable measurements to capture the process of LU/LC changes, such as deforestation, reforestation, fire, crop cycles, etc. (Waylen et al., 2014). Because of the development of remote sensing technique, LU/LC change became easy to monitor and analyse, which is a huge improvement of land change science. Applications of remote sensing data made it possible to study LU/LC changes in less time, at low costs and with better accuracy (Rawat & Kumar, 2015). The impacts of LU/LC can be extensive and diverse, such as summary statistics, trends, and harmonics. For example, Sun et al. (2016) analysed the relationship between the LU/LC change and urban air quality. The result shows LU/LC can influence the variation trend of time series variable (particulate pollution). Meanwhile, LU/LC changes exerted an influence on current urban particulate pollution and a time-lag effect on subsequent years. Fu and Weng (2016) studied the impact of urbanization on LST time series analysis. In their research, they found that after urbanization, the difference between urban area and non-urban area was 1.8K per decades. Deforestation is one typical kind of LU/LC change event. Deforestation in the Gran Chaco region (South America) has attracted some attention from. Gasparri and Grau (2009) described the evolution of deforestation from 1972 to 2007 in Chaco area based on Landsat images. According to the result, deforestation started in the 1970s. Grau et al. (2005) connected the deforestation with the soybean market. With the increasing requirement of soybean, more and more forest areas were deforested and became farmland. This large-scale and short-term LU/LC change may lead to time series changes.

2.3. Temporal aggregation

Assessment of sharply LU/LC change, such as deforestation in South America, needs frequent measurements if it is to be incorporated into management and policy decision (Clark et al., 2012). Since that, the LU/LC change problem need to be studied with temporally consistent information and accuracy. To meet this requirement, temporal aggregation problem should be considered in LU/LC change problem. Temporal aggregation has been heatedly discussed in time series analysis. In temporal aggregation, the aggregated time series is obtained through the averaging of every *m* periods of the high frequency data, where *m* is the aggregation level. Figure 2-1 shows the sketch diagram of temporal aggregation.

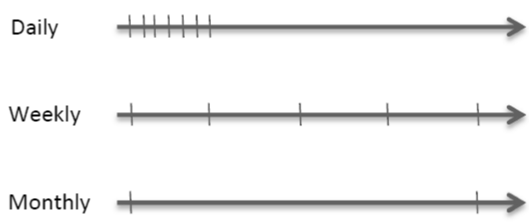

Figure 2-1: The sketch diagram of temporal aggregation

As the first stage of temporal aggregation studies, Zellner and Montmarquette (1971) proved that temporal aggregation can contribute to: (a) lower prediction precision, (b) lower power for test, (c) lacking power to short-term predictions and (d) less possibility of uncovering true short-run data behaviour. After that, in the study of Harrower et al. (2000), they proved that some geographic behaviour can only be seen in a certain temporal aggregation of time when visualizing temporal data. The temporal aggregation not only influences the geographic behaviour observation, but also affects the time series analysis. Vlahogianni and Karlaftis (2011) researched on the temporal aggregation problem of traffic data, with the aim to evaluate the impact on statistical characteristics and model choice. The traffic flow time series in this study was extracted from the central business district of Athens (Greece). Non-stationary, long memory and structural change in traffic data were detected in this study. In general, the results show that temporal aggregation distorts critical traffic flow information, leading to smoother temporal evolution and changing the core time series properties which exist at the disaggregated level.

3. STUDY AREA AND DATA

3.1. Study area

In this research, the study area is located in forest area of Gran Chaco region, South America, which spans Argentina, Bolivia and Paraguay (Eva et al., 2004). The Gran Chaco extends from about 17° to 33° S and between 65° and 60° W, and includes the largest continuous neotropical dry forest (Olson et al., 2001). Most of the region in Chaco is subtropical, and average temperatures are between 16 to 29 °C. This area covers approximately 647,500 km², and the main vegetation is xerophytic deciduous forests with multiple layers, including a canopy (trees), sub-canopy, shrub layer and herbaceous layer (Prado, 1993). The Gran Chaco harbours high biodiversity, including many endemic species. The Elevation range is 56 to 5377m and average of 326 ± 289m. Lowland areas, having elevation below 700m, cover 91% of the ecoregion (Clark et al., 2012). However, in the past decade, due to the recently accelerated expansion of cattle ranching and soybean cultivation there (Vallejos et al., 2015), more and more forest was damaged by large-scale farm and ranch operators (Gasparri & Grau, 2009). Several satellite images showed that the Gran Chaco area faces one of the fastest tropical deforestation rate in the world (Bestelmeyer, 2014). Figure 3-1 shows the location of the study area.

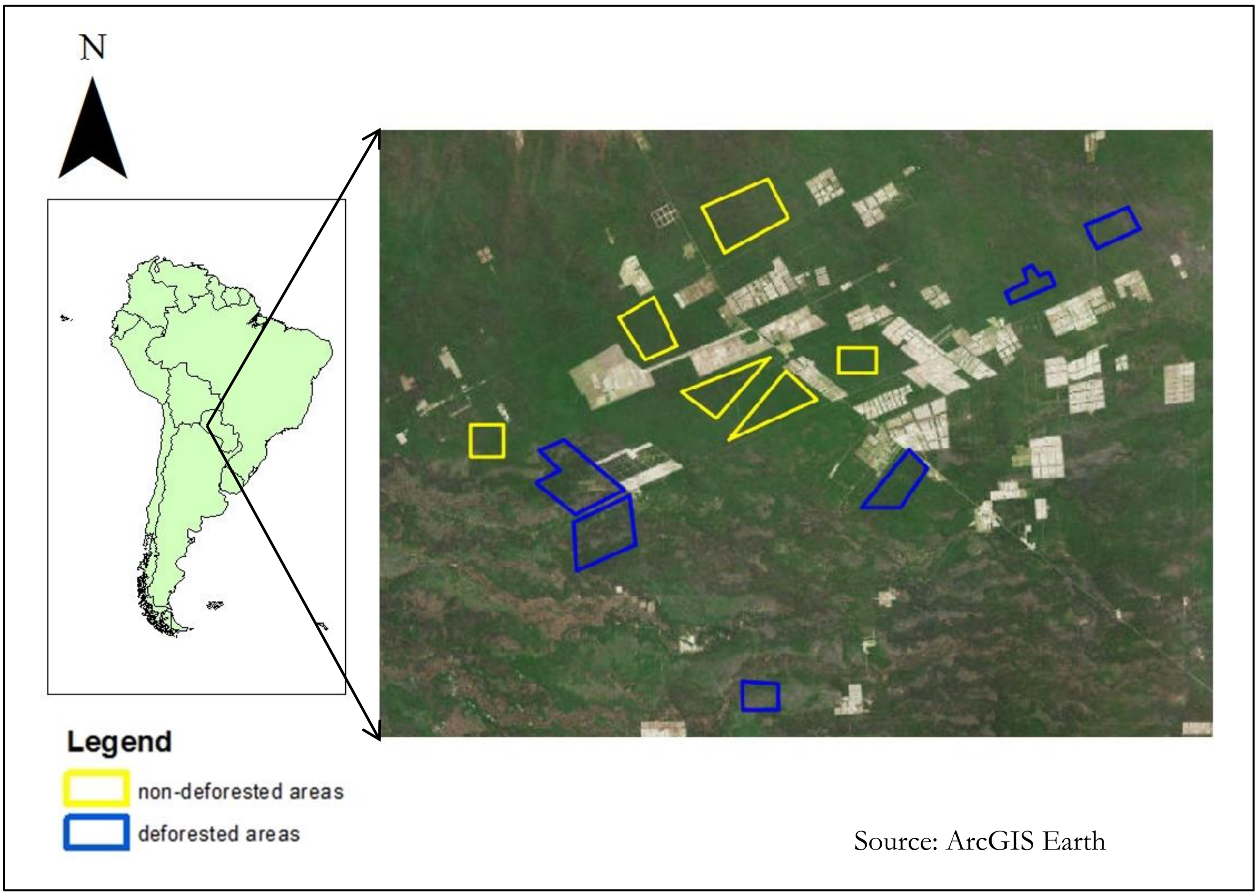

Figure 3-1: The study area is located in western Paraguay, which is a part of the Gran Chaco region.

3.2. Data used

In this research, MODIS data (http://modis.gsfc.nasa.gov) was used. MODIS is an important sensor in Earth Observation System (EOS), which is used to observe global biological and physical processes. Terra and Aqua satellites are the platforms on which MODIS is mounted. Terra was launched in 1999 by the National Aeronautics and Space Administration (NASA) of America. After 3 years, Aqua was launched on May 4, 2002. Terra passes from North to South across the equator at 10:30 am (local time), while Aqua passes South to North over the equator at 1:30 pm (local time). Terra and Aqua are observing the entire earth's surface every 1 to 2 days. Table 3-1 shows the basic information of MODIS.

Table 3-1: Basic information of MODIS (source: https://modis.gsfc.nasa.gov/)

Parameters	Value
Orbit	705km, descending node (Terra) or 1:30 p.m. ascending node (Aqua), sun-synchronous, near-polar, circular
Design life	6 years
Swath dimensions	2330km
Telescope	17.78 cm diam.
Size	1.0 x 1.6 x 1.0 m
Weight	228.7kg
Spatial resolution	250 m (bands 1-2), 500 m (bands 3-7), 1000 m (bands 8-36)
Number of brands	36

MODIS data is totally free and used by several countries around the world. There are 36 bands of MODIS. MODIS provides a diversity of products, which describe features of the land, oceans and the atmosphere that can be used for studies of processes and trends on regional or global scales. Compared with other remote sensing sensors, MODIS has longer time duration, which is suitable for long term time series analysis. Although AVHRR also has the longest duration time, the spatial resolution of AVHRR is low (1100 meters). Landsat TM has a fine spatial resolution (30 meters) and longer duration time (since 1982), but the revisit time is 16-day, which is too long for this study.

NDVI and LST are two time series variables in this study. So, MODIS Surface Reflectance (SR) product (MOD09) and MODIS Land Surface Temperature & Emissivity (MOD11) were used for this study. The NDVI time series was estimated by MODIS SR dataset. The spatial resolution of MODIS SR product is 250m, and the temporal resolution is 8-day. The spatial resolution of MODIS LST is 1km, and the temporal resolution is 8-day (Benali et al., 2012). The temperature accuracy of MODIS LST is 1K (Justice et al., 1998). Since the subtropical climate features, the data quality of daily data is quite low. Therefore, 8-day data were used as the smallest temporal unit. The 8-day NDVI images were estimated by 8-day MODIS SR product.

3.3. Data downloading

In this study, MODIS SR product and MODIS LST product were downloaded with the R software through MODIStsp (Busetto & Ranghetti, 2016). MODIStsp is a new R package that allows to automatize the creation of raster time series derived from MODIS Land products. The basic functions of MODIStsp are downloading, mosaicing, projection and resizing. All preprocessing parameters (such as processing

period, spatial extent, reprojection and resize options, output formats and rtc) can be set with a user-friendly GUI. The NDVI images can be estimated by this package automatically.
The format of the data is GeoTIFF. Table 3-2 shows the detailed data information. The MODIS land products downloaded are using sinusoidal projection. Sinusoidal projection is a Pseudocylindrical equal-area Projection (Snyder, 1987). However, to be convenient, all the remote sensing datasets in this case are transferred to WGS84/Latlong (EPSG: 4326). The projection transformation was done by MODIStsp (Busetto & Ranghetti, 2016). The horizontal tile number of data downloaded is 12, and the vertical tile number is 11. To efficiently store variables, both of downloaded NDVI and LST are scaled. The scale for NDVI is 10000, and the scale for LST is 50.

Table 3-2: basic information of downloaded data (source: https://modis.gsfc.nasa.gov/)

	MODIS SR	MODIS LST
Name	Surf_Ref_8Days_250m	Surf_Temp_8Days_1Km
Short name	MOD09Q1	MOD11A2
Platform	Terra	Terra
Starting date	2001-01-01	2001-01-01
Ending date	2012-12-30	2012-12-30
Output projection	Latlon WGS84	Latlon WGS84
Temporal frequency	8-day	8-day
Spatial resolution	250m	1km
Horizontal tile number	12	12
Vertical tile number	11	11

4. METHODS

4.1. Methodology flow chart

The methodologies adopted in this study are shown in the form of flowcharts (Figure 4-1). The first step was to locate the study area, and then to find out the non-deforested and deforested polygons that met the requirement. Based on the location of polygons, the related MODID LST and NDVI can be downloaded. Because the MODIS data downloaded have gaps and noises, HANTS method was used to obtain the cloud-free and gapless time series. Before applying HANTS, the acceptable parameter set should be chosen properly by experience. After that, the output of HANTS can be used to extract harmonic information and aggregate. After temporal aggregation, there are 5 different temporal aggregations of MODIS LST and NDVI totally. Through comparing the results of harmonic analysis, trend analysis and summary statistics under different time series and different temporal aggregation levels, the impact of LU/LC changes and temporal aggregation can be evaluated.

4.2. Time series analysis

Geographic Resources Analysis Support System (GRASS GIS) is a free and open source Geographic information system (GIS) software (Open Source Geospatial Fundation, 2015). GRASS GIS was used in this study to process time series data. In GRASS GIS, space time datasets are stored in a temporal database. After importing raster images, creating space time datasets and registering raster images to space time datasets, time series analysis can be performed. There were two basic space time datasets in this study: 8lst and 8ndvi, suggesting the original 8-day LST and NDVI time series respectively.

In order to figure out the impact of LU/LC change, there were 4 time series for each variable in this study (see in Table 4-1): complete series without deforestation, complete series with deforestation, before and after deforestation. Except the complete series without deforestation was based on non-deforestation polygons, the rest of the three time series were extracted from deforested polygons. In this case, the deforestation events in deforested polygons happened between 1st January 2006 and 31th December 2007, and the length of complete time series (with and without deforestation) are 12 years. So the lengths of time series before deforestation and after deforestation are 5 years.

Table 4-1: Sketch diagram of time series in this study

Location	Time series	Schematic diagram	Time period	Length
Non-deforested polygons	Complete series (without deforestation)		1/1/2001~ 12/31/2012	12 years
Deforested polygons	Complete series (with deforestation)		1/1/2001~ 12/31/2012	12 years
	Before deforestation		1/1/2001~ 12/31/2005	5 years
	After deforestation		1/1/2008~ 12/31/2012	5 years

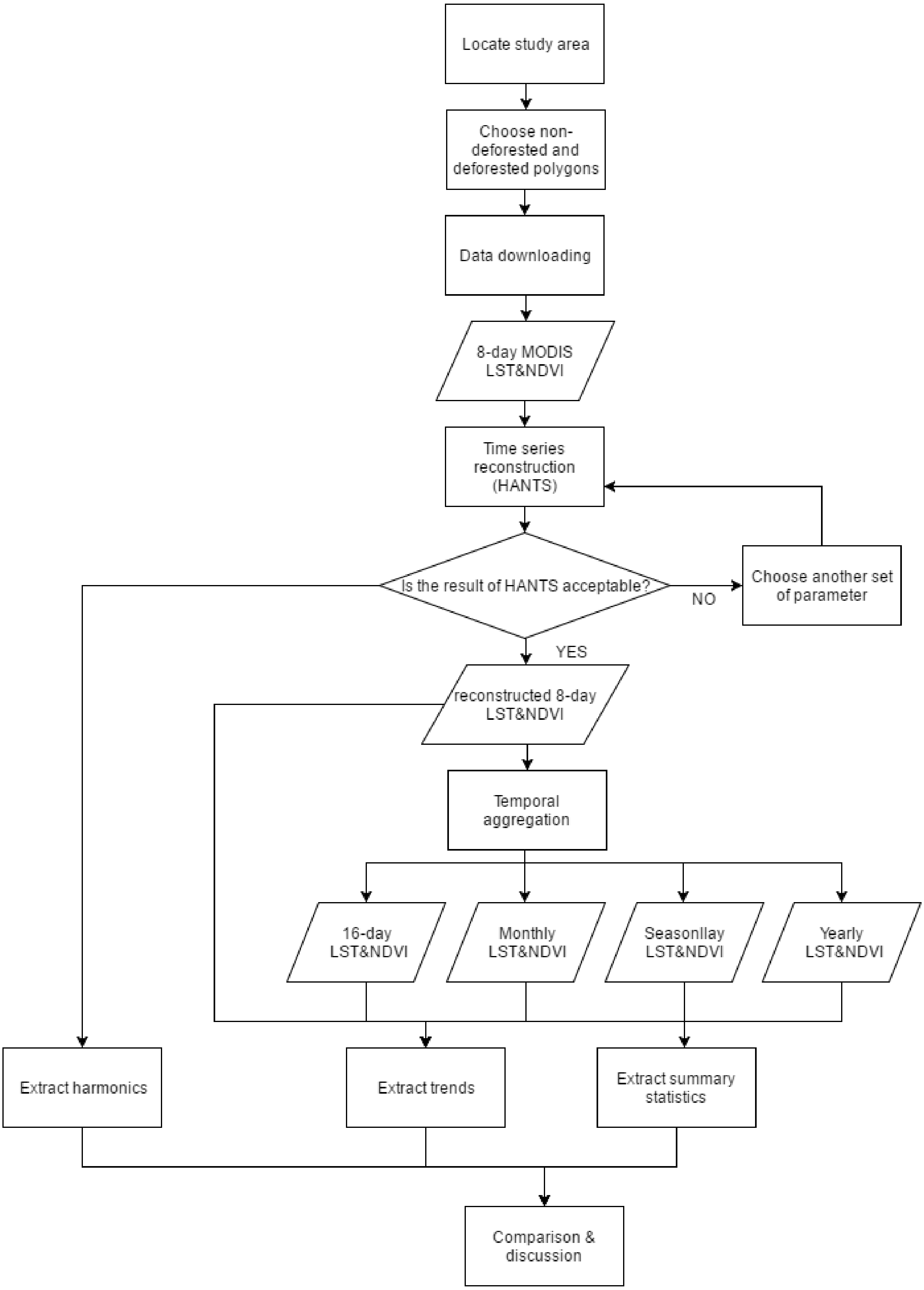

Figure 4-1: Flowchart of methodology in this study. There are four main sections in this flowchart: data pre-processing, time series reconstruction, data aggregation and time series analysis.

4.3. Data aggregation

The data was aggregated to 4 different aggregation levels based the 8-day data using average aggregation approach. This approach estimates the average value of space time raster datasets by a specific temporal granularity (Stasch et al., 2012). The whole time series was aggregated from 8-day temporal unit to 16-day, monthly, seasonally and yearly. Correspondingly, the number of image changed. This step was performed in GRASS GIS. Table 4-2 shows the temporal aggregation levels and corresponding number of images

Table 4-2: Aggregation levels of time series in this study, 8-day data is the original time series.

Temporal aggregation	8 days	16 days	1 month	1 season	1 year
Number of images	552	274	144	48	12

4.4. Harmonic analysis of time series (HANTS)

Over the past two decades, Harmonic ANalysis of Time Series (HANTS, Menenti et al., 1993; Verhoef et al., 1996; Roerink et al., 2000), a harmonic analysis based series reconstruction method, has been widely used to reduce the noise and fill the gaps in time series of remote sensing land surface products (Zhou et al., 2015), such as NDVI, LST, and Enhanced Vegetation Index (EVI, Julien et al., 2006; Westra & De Wulf, 2007; Zhang et al., 2008; Zhou et al., 2015). This algorithm considers only the most significant frequencies expected to be present in the time profiles, and then applies the least squares curve fitting procedure based on harmonic components (Roerink et al., 2000). HANTS employs both Fourier analysis and a repeated flagging of outliers within the time series (Garonna et al., 2016). To apply HANTS, 5 main parameters are required: the number of frequency, the high/low suppression flag, the valid data range, and the degree of overdetermindness. Compared with Fast Fourier Transform (FFT), another time series reconstruction method, HANTS can deal with time series of irregularly spaced observations and offer greater flexibility in the choice of frequencies and the length of the time series (Roerink et al., 2000). The amplitude maps were a part of HANTS outputs in GRASS GIS. The amplitude maps can be used to identify the dominant frequency (GRASS Development Team, 2017). The basic formula of HANTS is written as:

$$\tilde{y} = a_0 + \sum_{i=1}^{nf}[a_i \cos(2\pi f_i t_j) + b_i \sin(2\pi f_i t_j)] \quad (1)$$

$$y(t_j) = \tilde{y}(t_j) + \varepsilon(t_j) \quad (2)$$

Here,
$\tilde{y}$= reconstructed series
y= original series
ε= error series
t_j= time when y is observed
j= order of observation ($j = 1,2, \dots N$,N is the total number of images).
a_0= coefficient at zero frequency (the average of the series)
nf = number of periodic terms in the series
a_i, b_i= coeeficents of trigonometric components with frequency f_i

In this study, the performance of HANTS was evaluated by estimation of Root-Mean-Square Error (RMSE), which is a frequently used measure of the differences between values predicted by a model or an estimator and the values actually observed. However, there were some missing values in the original data, which did not have corresponding true value. Since that, these data cannot be employed to assess the fitted values of the HANTS algorithm. Those data were neglected when evaluating the performance of HANTS.

4.5. Trend analysis

Trend analysis is a fast, reliable and easy method of time series analysis. It is applicable to equidistant dataset (Gossel & Laehne, 2013). Linear regression is the most common method to detect changes in cyclic time seires (De Jong & De Bruin, 2012). The basic equation for the linear regression model is given by

$$y = \beta_0 + \beta_1 t + \varepsilon \qquad (3)$$

With:
y = estimated time series variable value at time *t*;
t = time;
β_1 = rate of variable changes;
β_0 = intercept of the model;
ε = residual.

In this equation, the independent variable is *t*, and the dependent variable is y. In this study, the trends of time series variables (NDVI & LST) under different temporal aggregation levels and different periods are figured out using this method. Through comparing of linear model parameters, the effects of temporal aggregation level and LU/LC change on trend analysis can be quantified.

In linear regression model, the p-value of slope shows whether there is any significant relationship between two variables by testing the null hypothesis (Yau, 2013). If the p-value is less than 0.05, then there is a significant relationship between the variables in the linear regression model.

5. RESULTS

This chapter describes the main findings of the research. Impact of aggregation and LU/LC were studied for both deforested polygons and non-deforested polygons. The results are presented below as five major sections:

- Deforested and non-deforested polygons selection
- Time series reconstruction
- Impact of LU/LC change
- Impact of temporal aggregation
- Impact of LU/LC change and temporal aggregation

5.1. Selection of non-deforested and deforested polygons

The study area is located at Asunción, Paraguay. To improve result reliability, the study area does not have big elevation changes, and it is away from water areas, mountain areas, and city areas. There were 6 non-deforested polygons and 6 deforested polygons selected in this study area, which guarantee the similar climatic characteristics. As for the deforested polygons, to get equal extent before and after deforestation period, the time of deforestation in those polygons should be reasonable. In this study, deforestation was mostly evident between 2006 and 2007. The whole time series began on 1st January 2001 and ended on 31th December. The main method of change detection was visual interpretation. There are several websites that provide dynamic forest status, one of which is Global Forest Watch (http://www.globalforestwatch.org), which provides detailed information regarding forest change under different layers. Comparing the satellite images from 2001 to 2015 in Global Forest Watch, the deforested polygons and non-deforested polygons were selected. Based on the location of the study area, related MODIS products were extracted. Figure 5-1 and Figure 5-2 show the locations of deforested polygons and non-deforested polygons.

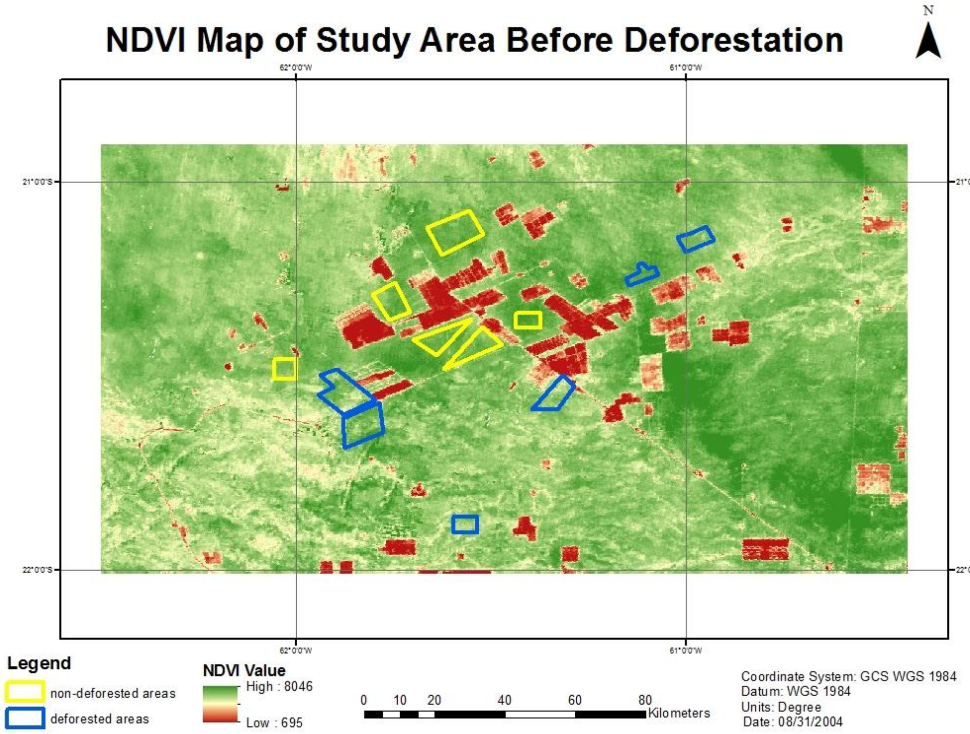

Figure 5-1: NDVI map of study area before deforestation

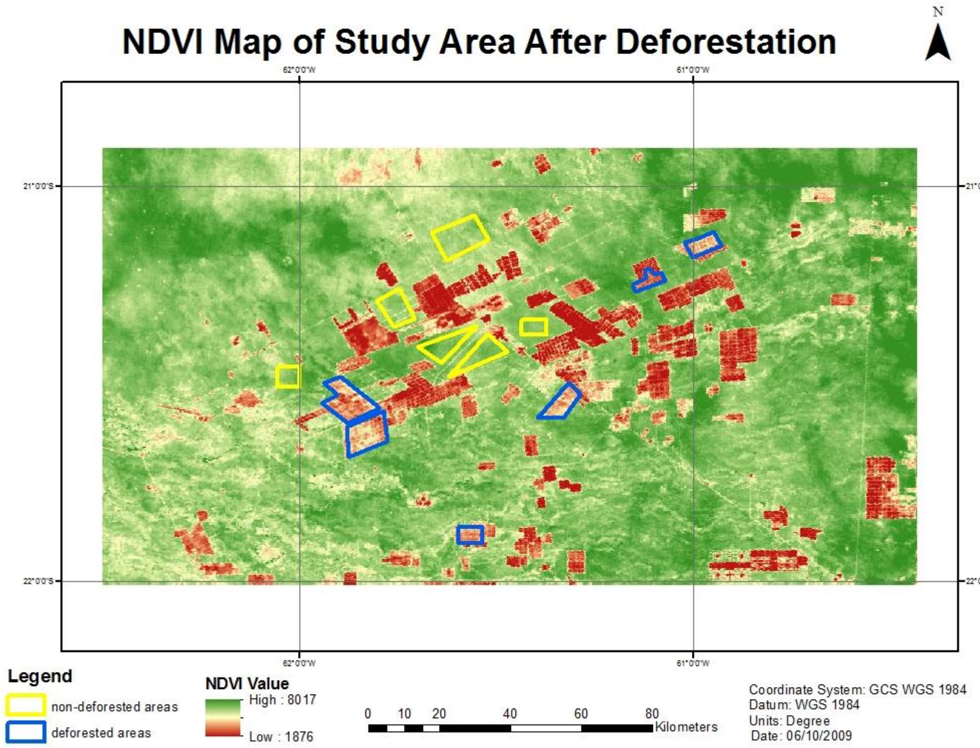

Figure 5-2: NDVI map of study area after deforestation

5.2. Time series reconstruction

The HANTS algorithm was applied for two purposes in this study: to obtain a gapless time series and to assess the impact of LU/LC on harmonics (for example, number of cycles per year). In this study, GRASS GIS implementation of HANTS was used (GRASS Development Team, 2017), this script can be found in Appendix I.

The parameters of the HANTS algorithm should be set carefully. However, there are no objective rules to determine the HANTS control parameters (Roerink et al., 2000). The common solution is to set the parameter in the basis of experience. So after reviewing several parameter settings in previous studies, the parameters setting was elaborated in Table 5-1. In this study, to evaluate the performance of HANTS with a common parameter setting scheme, the first four harmonics were selected to reconstruct LST and NDVI time series. The fit error tolerances were set as 0.1 K and 0.05 (NDVI unit). According to the user's guide of MODIS, the valid ranges of MODIS LST and NDVI ranged from 150K to 1310.7K and from -0.2 to1, respectively. The length of the base period is the number of images in one year, and in this study the base period is 46.

Table 5-1: HANTS parameters settings applied in this study

Parameters	Description	Values(LST)	Values (NDVI)
nf	Number of frequencies (above the zero frequency) is considered in curve fitting.	4	4
fet	Fit error tolerance, This parameter limits the difference between the model value and the real value.	0.1 K	0.05
dod	Degree of overdeterminedness, in order to get a reliable model, the number of valid observation should be bigger than (2 x nf -1).	7	7
range	Ignore values outside this range	(150,1310.7) K	(-0.2, 1)
base_period	Length of the base period, the number of observations in one year.	46	46

HANTS algorithm was applied to the 8-day LST and NDVI complete series and year by year separately. Figure 5-3 (a) demonstrates the original LST time series and HANTS reconstruction of the complete series for a pixel (61°54'15" W, 21°29'11" S), located in one of the deforested polygons. The reconstructed complete time series (the yellow line) is stable and regular. Figure 5-3 (b) illustrates the original LST time series and the series reconstructed year by year for that same pixel. In the later case, the complete time series was split into 12 sub-series, and the image number of each series was 48 (the last one was 46). There were 2 overlapping images at the beginning of each year (except 2001). In order to maintain the continuity of the time series, the 2 overlapping images of each year equalled to the average images between the last sub-series and the current sub-series. Compared with reconstructed complete series (see Figure 5-3 (a) and (b)), the RMSEs of the series reconstructed year by year stayed around 2.7, which was always smaller than the RMSEs of reconstructed complete series (between 3.2 and 3.8). Figure 5-4 and figure 5-6 exhibit the comparison of RMSE between the reconstruction of the complete series and the reconstruction year by year for LST and NDVI, respectively. As for the original NDVI series (see Figure 5-5), it had some lower outliers than LST original series. According to Figure 5-6, the RMSEs of year by year reconstructed NDVI series were lower than 0.11, and all of the reconstructed complete NDVI series RMSEs were lager than 0.12.

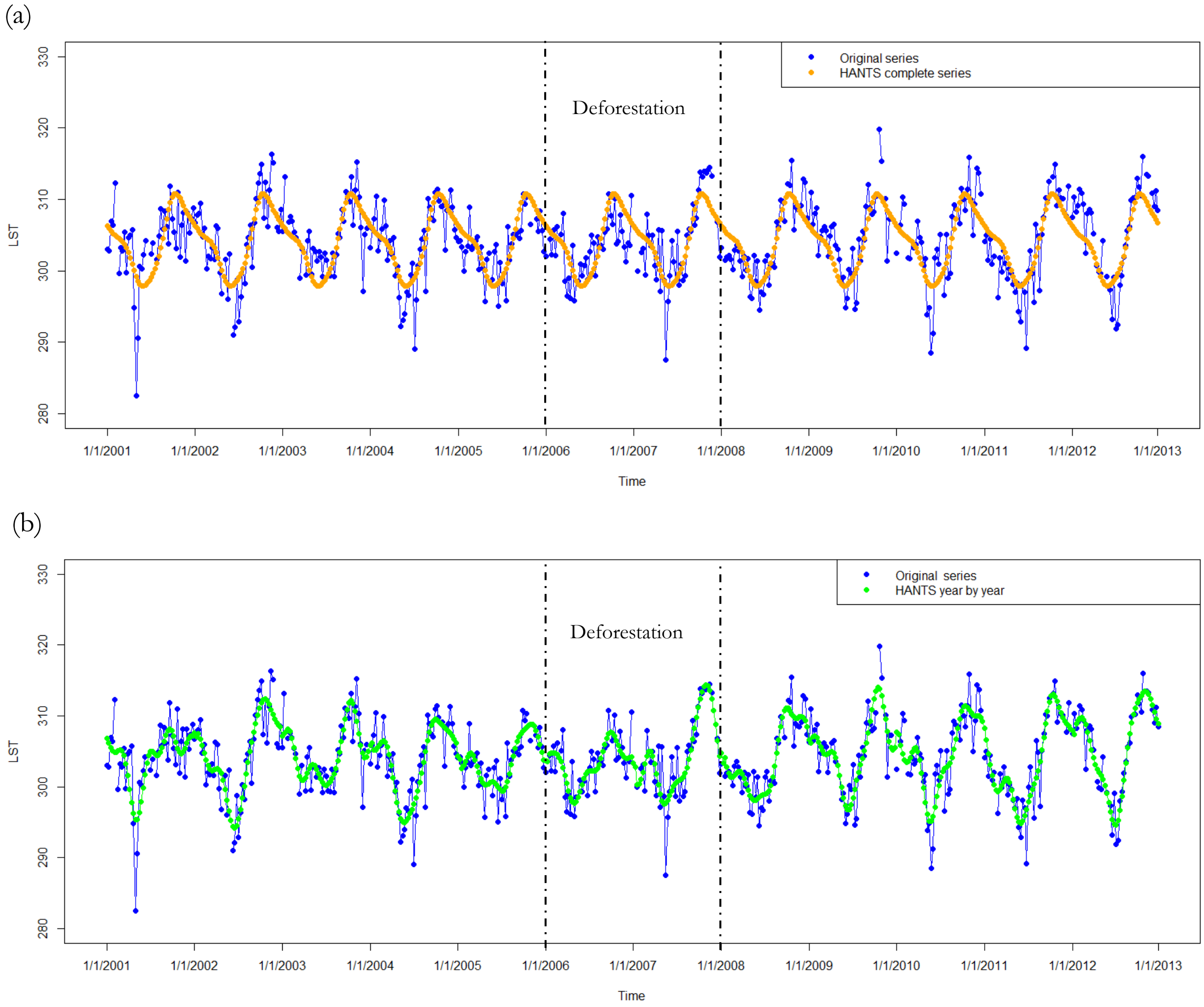

Figure 5-3: (a) Original LST time series (12 years) and reconstructed complete series (12 years) of a Pixel (61°54'15" W, 21°29'11" S) in deforested polygons and (b) Original LST time series (12 years) and reconstructed year by year series of the same pixel.

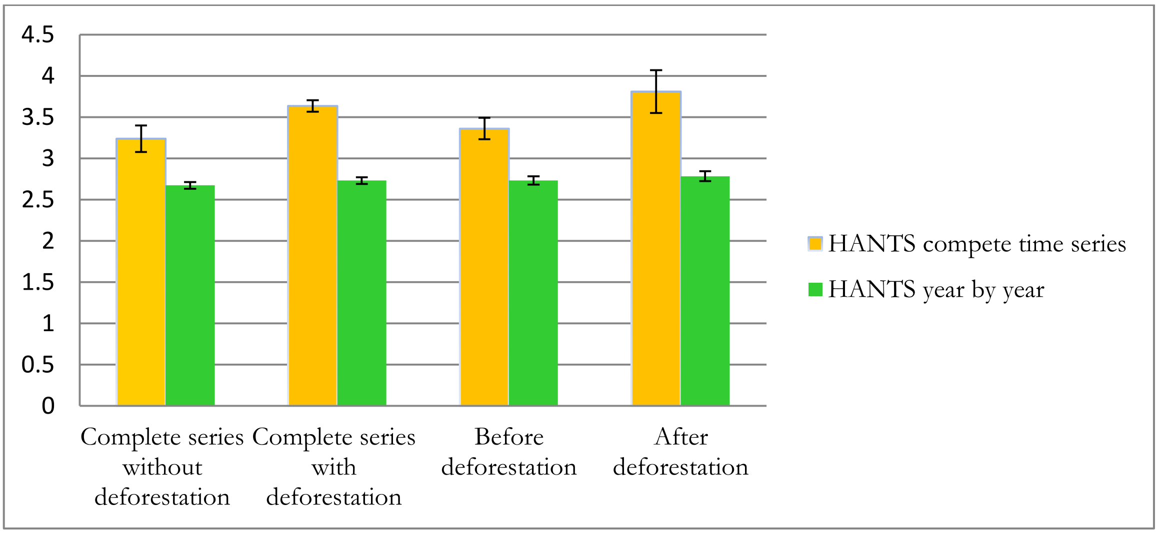

Figure 5-4: RMSE of reconstructed complete series and reconstructed year by year series (LST)

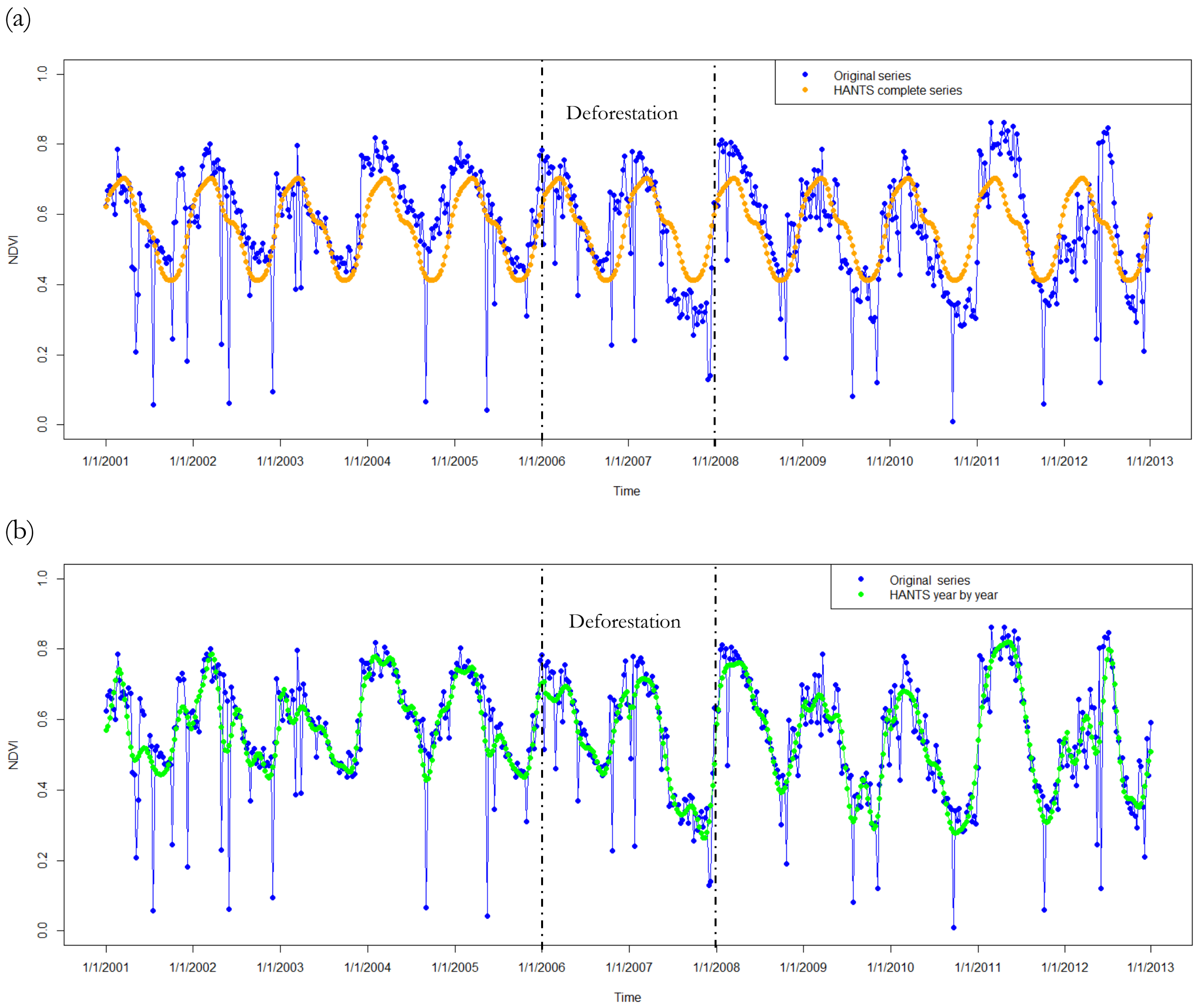

Figure 5-5: (a) Original NDVI time series (12 years) and reconstructed complete series (12 years) of a Pixel (61°53'54" W, 21°28'58" S) in deforested polygons and (b) Original NDVI time series (12 years) and reconstructed year by year series of the same pixel.

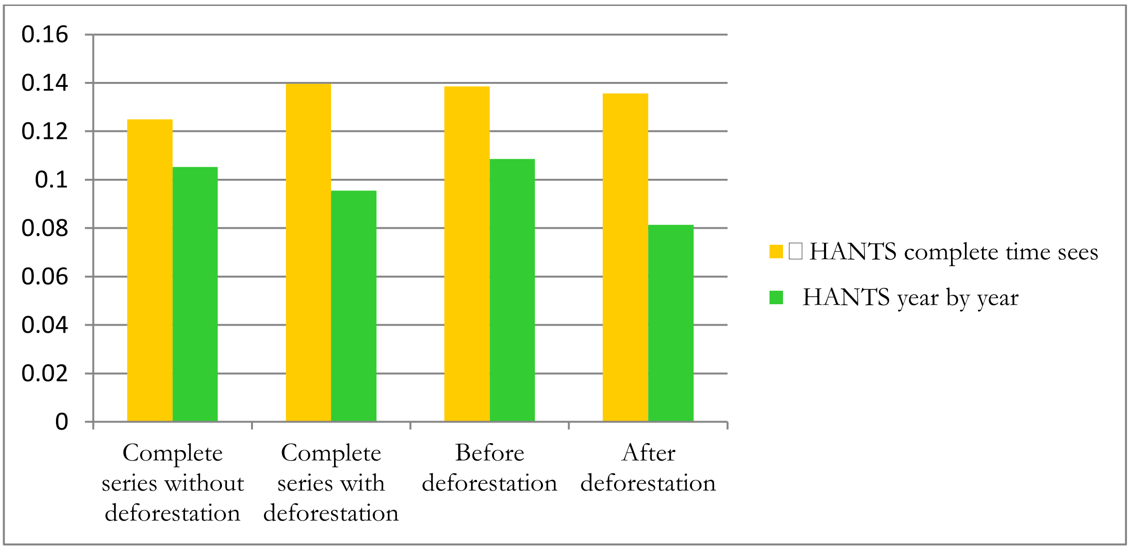

Figure 5-6: RMSE of reconstructed complete series and reconstructed year by year series (NDVI)

5.3. Impact of LU/LC change

In this study, the impact of LU/LC change on time series analysis was evaluated by comparing the summary statistics, trends and harmonics before deforestation and after deforestation. The reconstructed 8-day LST and NDVI was used to identify the impact. The period before deforestation started from January 1st, 2001 to December 31st, 2005, and the period after deforestation started from January 1st, 2008 to December 31st, 2012. The deforestation events happened during 2006 and 2007. The complete series without deforestation was a control group in this study. The pixels of control group were selected from non-deforested polygons. Table 5-2 and Table 5-3 show the summary statistics (mean median, maximum, minimum and standard deviation) and the average slope of 8-day LST and NDVI.

Table 5-2: The summary statistic and average slope of LST before deforestation and after deforestation (unit: K). Values of statistics in this table are average statistics of all pixels over the complete series

	Mean	Median	Maximum	Minimum	Standard deviation	Slope
Complete series without deforestation	303.639	303.770	313.567	293.501	4.777	-0.004
(sd)	0.155	0.193	1.240	0.420		0.006
Before deforestation	303.840	304.430	312.191	293.562	4.336	0.035
(sd)	0.225	0.369	0.846	0.858		0.017
After deforestation	305.614	305.654	318.845	293.799	6.218	0.040
(sd)	0.789	0.682	2.486	1.338		0.046

Table 5-3: The summary statistic and average slope of NDVI before deforestation and after deforestation (unit: NDVI unit). Values of statistics in this table are average statistics of all pixels over the complete series

	Mean	Median	Maximum	Minimum	Standard deviation	Slope
Complete series without deforestation	0.612	0.615	0.865	0.350	0.117	0.009
(sd)	0.012	0.016	0.017	0.031		0.058
Before deforestation	0.588	0.578	0.803	0.364	0.112	-0.206
(sd)	0.022	0.031	0.029	0.035		0.250
After deforestation	0.484	0.479	0.826	0.237	0.152	-0.497
(sd)	0.034	0.043	0.037	0.025		0.3421

Figure 5-7 and figure 5-8 illustrate the changes of summary statistics of LST and NDVI before deforestation and after deforestation. According to the graphs, the summary statistics of LST increased after deforestation. However, the maximum of NDVI had a small increase. The rest statistics of NDVI decreased after the deforestation. Meanwhile, the standard deviations of LST and NDVI grew. As for the results of trend analysis, according to Table 5-2 and table 5-3 the average slope of LST increased from 0.035 to 0.040, and the average slope of NDVI decreased from -0.206 to -0.497 (marked with grey in Table 5-2 and table 5-3). Both of them became steeper after deforestation. In addition, based on Table 5-4, more pixels had significant trends after deforestation.

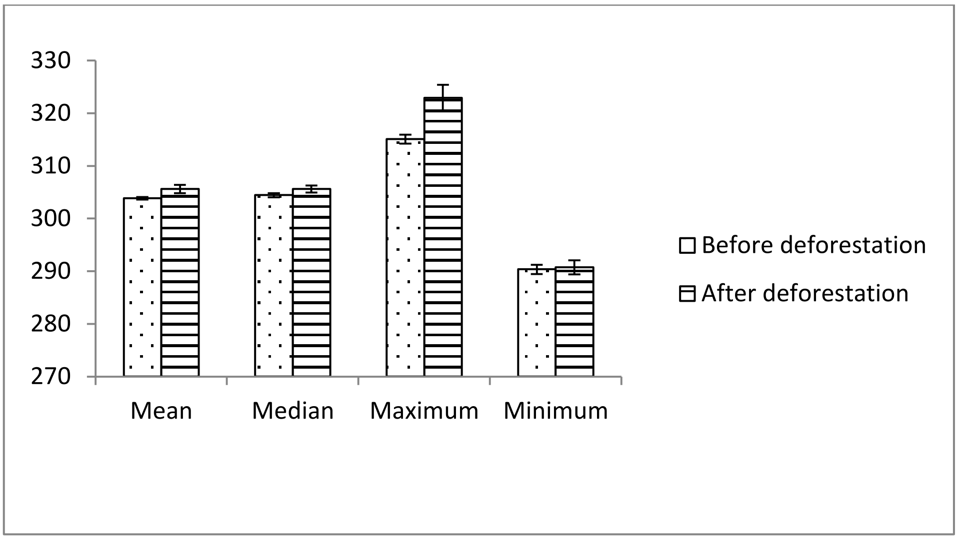

Figure 5-7: The changes of LST summary statistics between before deforestation and after deforestation (unit: K)

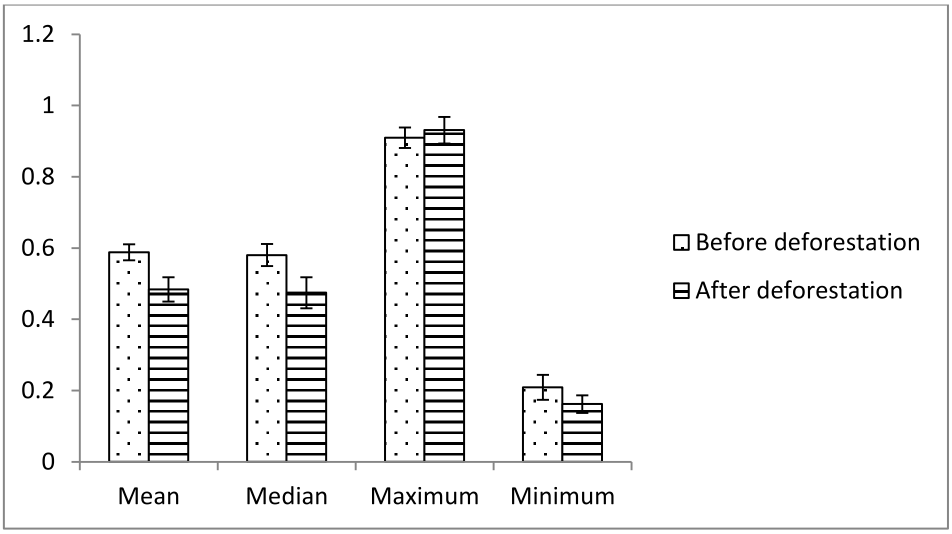

Figure 5-8: The changes of NDVI summary statistics between before deforestation and after deforestation (unit: NDVI unit)

Table 5-4: The percentage of pixel which had a significant trend (%)

	LST	NDVI
Complete series without deforestation	2.17	0
Before deforestation	15.55	35.34
After deforestation	21.45	63.08

In this study, HANTS was also used to evaluate the impact of LU/LC on harmonic analysis. Based on the output of HANTS, there was no change in the number of annual cycles before and after deforestation. It was always 1 cycle per year in both LST and NDVI series. Figure 5-9 (a) represents the original LST time series (12 years) and reconstructed series of a Pixel (deforested polygons,61°54'15" W, 21°29'11" S) if the deforestation was ignored. Figure 5-9 (b) displays the original LST series and the output of HANTS taking in to consideration the deforestation, which applied HANTS before and after deforestation separately.

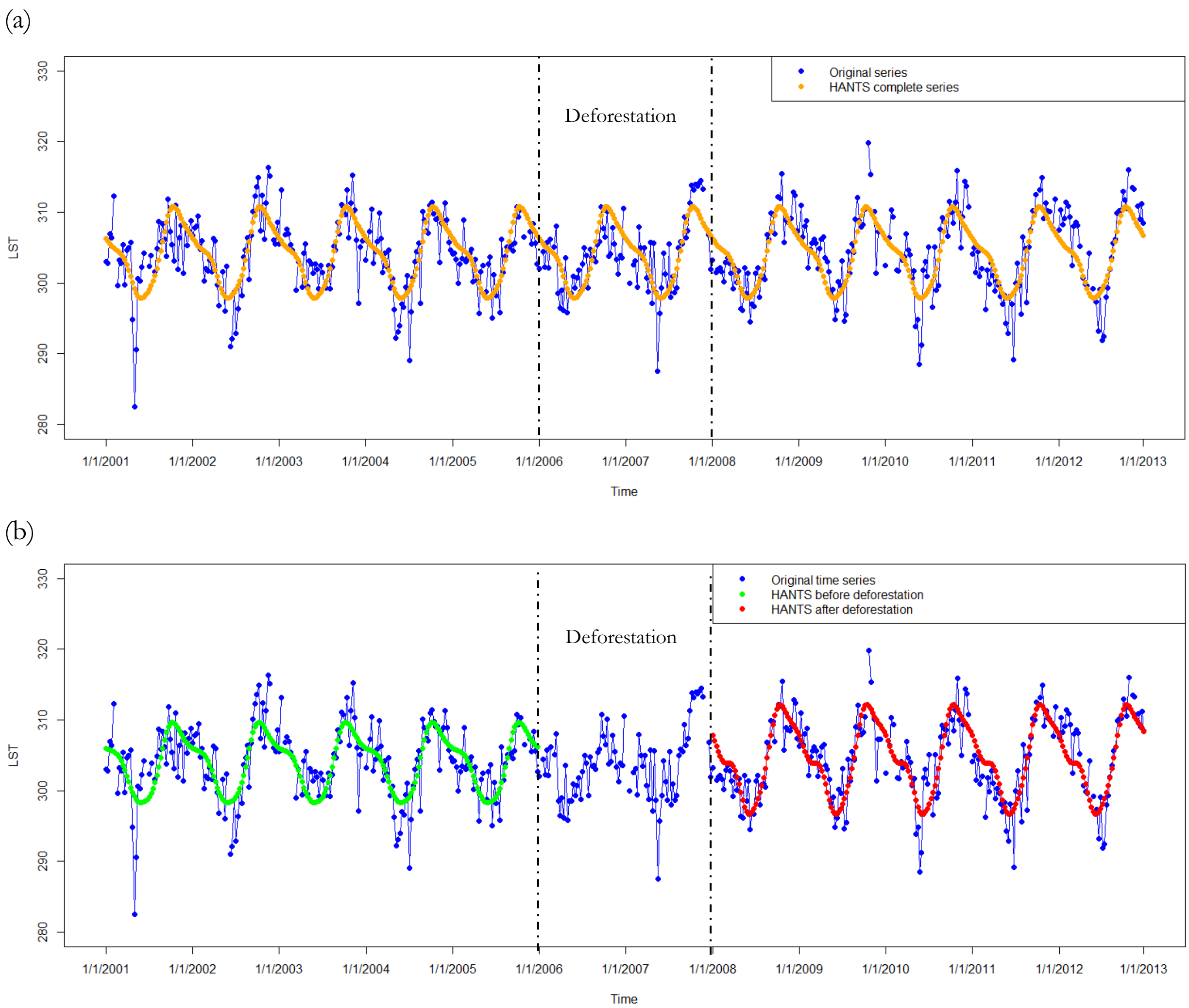

Figure 5-9: (a) Original LST time series (12 years) and HANTS complete series (12 years) of a Pixel (61°54'15" W, 21°29'11" S) in deforested polygons and (b) Original LST time series (12 years) and HANTS before deforestation (5years) and after deforestation (5 years) of the same pixel.

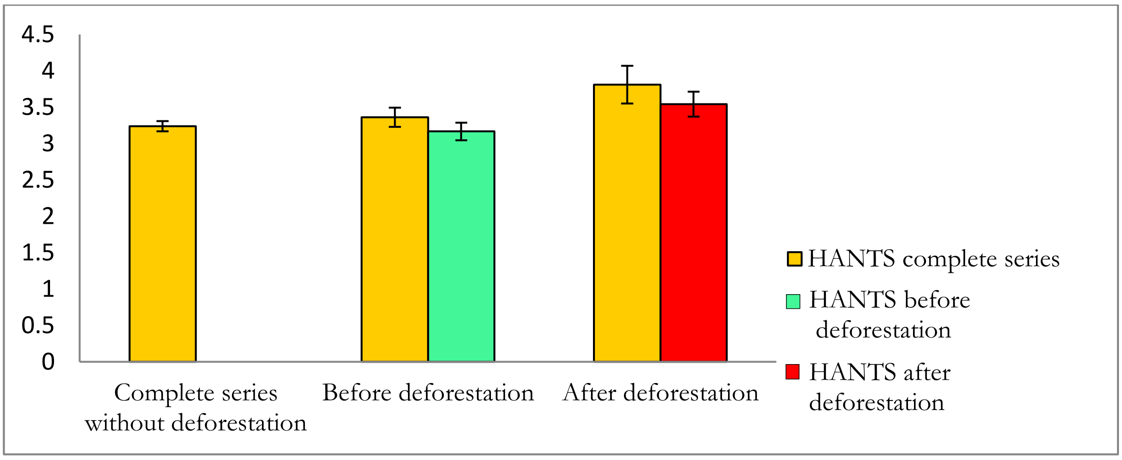

Figure 5-10: RMSE of HANTS complete time series (LST), HANTS before deforestation (LST), and HANTS after deforestation (LST)

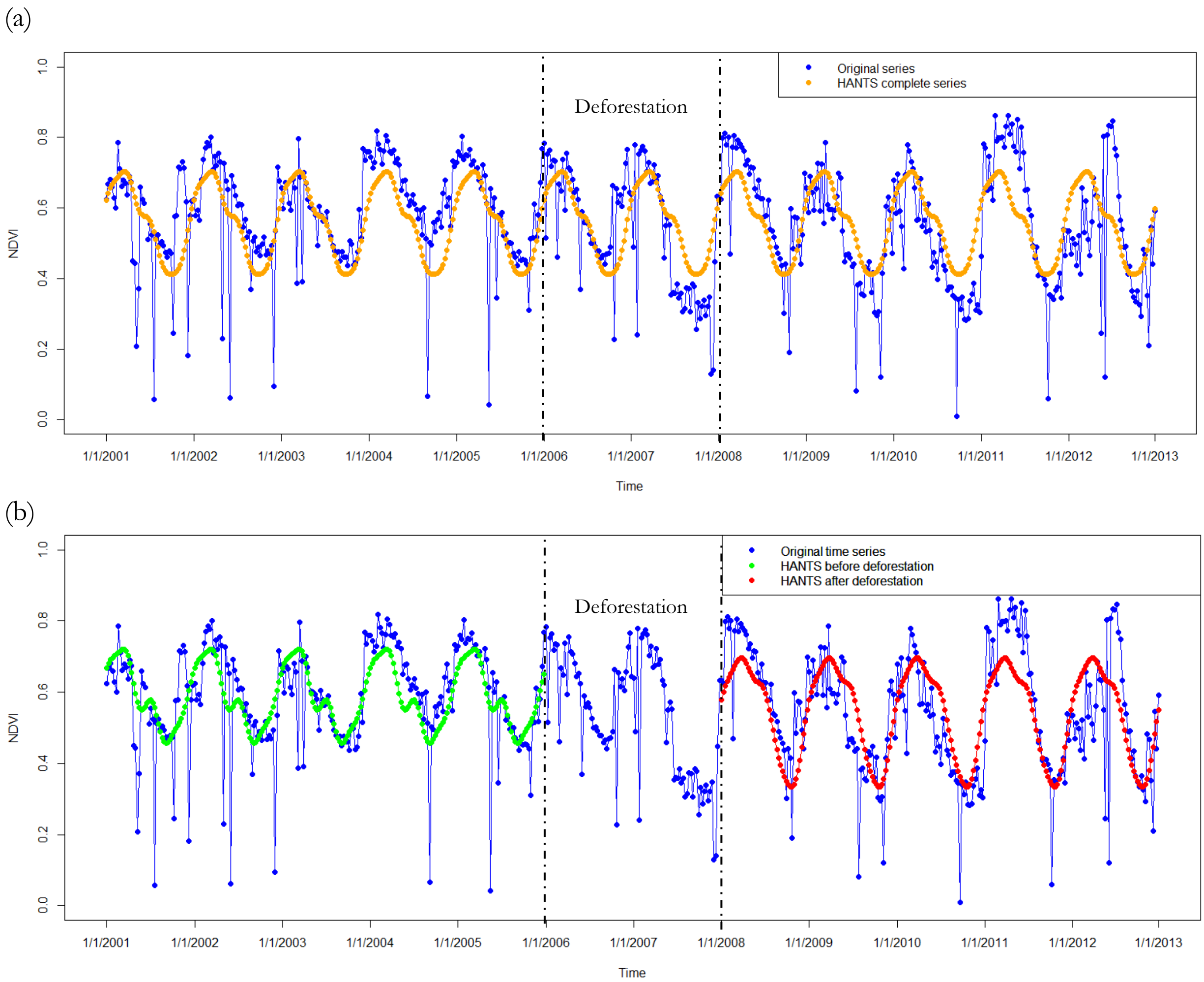

Figure 5-11: (a) Original NDVI time series (12 years) and HANTS complete series (12 years) of a Pixel (61°53'54" West, 21°28'58" South) in deforested polygons and (b) Original NDVI time series (12 years) and HANTS before deforestation (5 years) and after deforestation (5 years) of the same pixel.

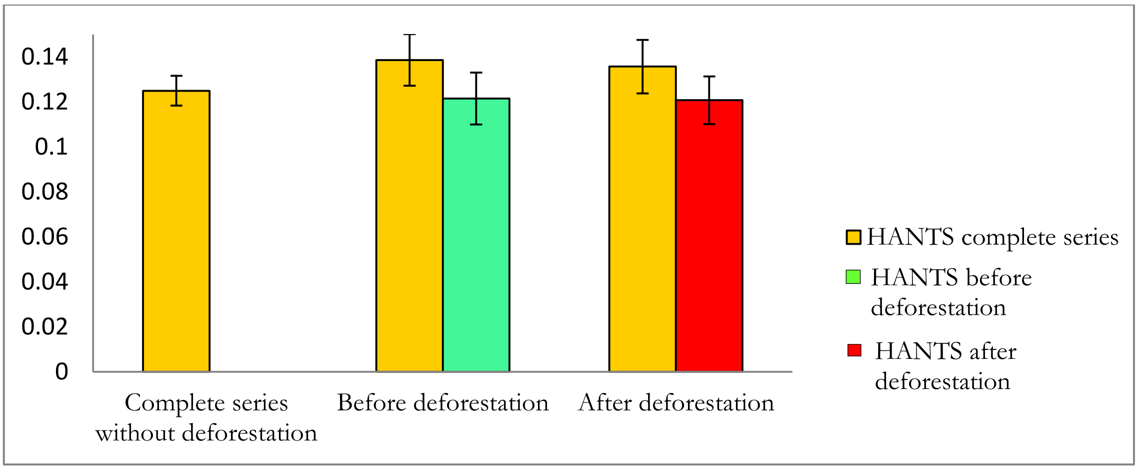

Figure 5-12: RMSE of HANTS complete time series (NDVI), HANTS before deforestation (NDVI), and HANTS after deforestation (NDVI)

Figure 5-11 (a) and (b) illustrates the similar result with figure 5-9 (a) and (b), but the time series variable is NDVI. Figure 5-10 and figure 5-12 shows the RMSEs of reconstructed series ignoring deforestation and RMSEs of reconstructed series considering deforestation. According to those two graphs, reconstructed LST and NDVI time series had a better fitting if the deforestation was considered.

5.4. Impact of temporal aggregation

MODIS LST and NDVI 8-day data were aggregated to explore the impact of aggregation. LST and NDVI data were aggregated to 4 levels of aggregation. In total, 5 different temporal aggregation levels were considered: 8-day, 16-day, monthly, seasonally and yearly. In this research, summary statistics (mean, median, maximum, minimum and standard deviation) and slopes of trend analysis were indicators of changes.

Figure 5-13 depicts the variation tendency of summary statistics and standard deviation with increasing temporal aggregation. For both NDVI and LST series, the mean and median remained about the same. Meanwhile, the maximum went down but the minimum went up, and the gap between maximum and minimum became smaller.

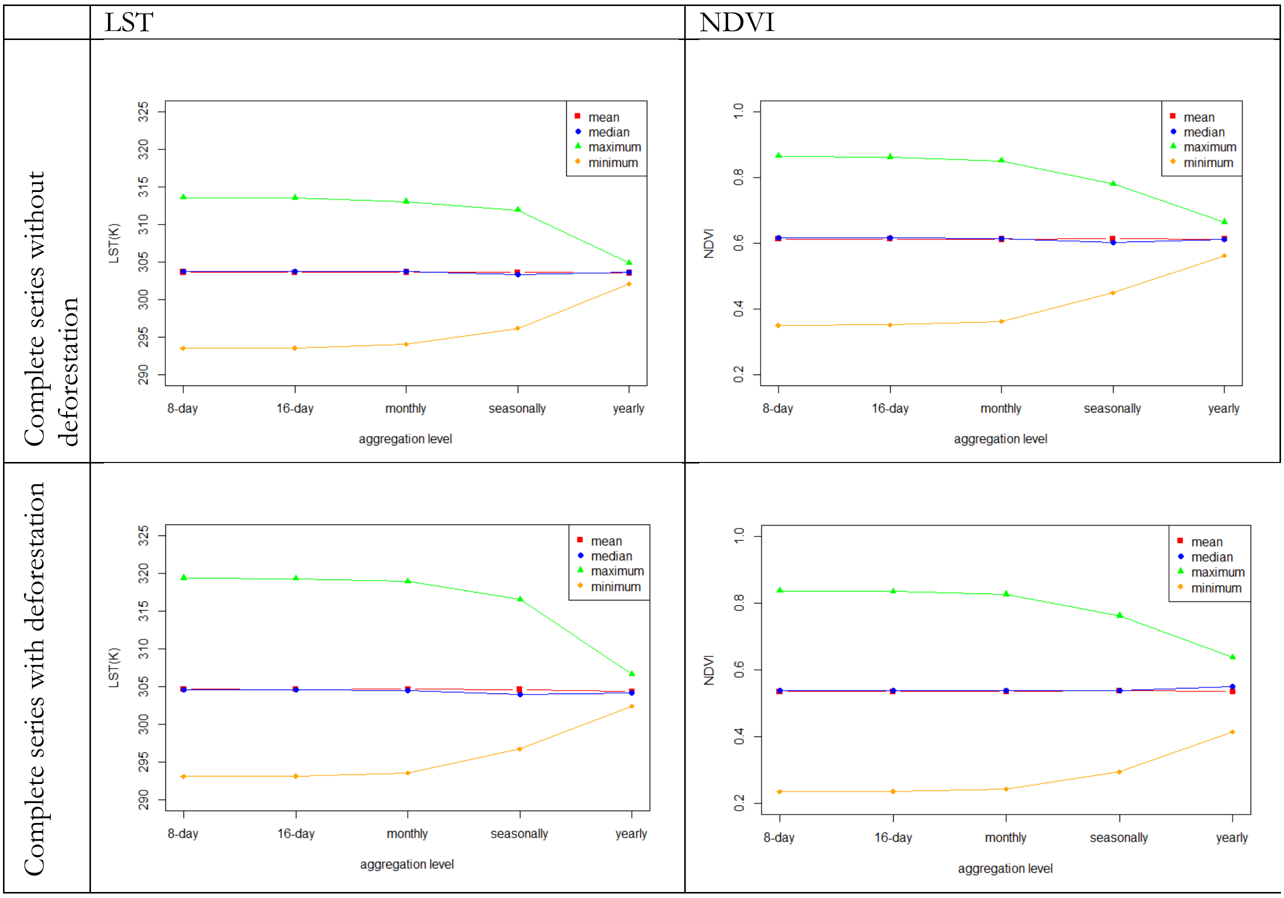

Figure 5-13: The summary statistics of LST and NDVI under different temporal aggregations

As for the standard deviations of LST and NDVI under different temporal aggregations, before seasonally, the standard deviations did not have a very big change with the increasing temporal aggregation level. However, the seasonally temporal aggregation was the inflection point, after that point, the standard deviations had a sharp decreasing. Table 5-5 shows the detailed standard deviation information of the original 8-day temporal aggregation and different temporal aggregation levels.

In this study, linear regression method was used to quantify the trend of LST and NDVI. Table 5-6 shows the percentage of LST and NDVI pixel which had a significant trend under different temporal aggregations. The patterns of percentage changes were different between different time series. In general, the percentages of pixel which had a significant trend of complete series with deforestation decreased before seasonally but increased after. Meanwhile, the percentages of complete series without deforestation had different changing pattern between LST and NDVI. Table 5-7 illustrates the average slope and standard deviation of slope under different temporal aggregations. With the increasing temporal aggregation, the slope remained stable before and became smoothly after seasonally aggregation level.

Table 5-5: The standard deviation of LST and NDVI under different temporal aggregations (LST unit: K)

		8-day	16-day	Monthly	Seasonally	Yearly
LST	Complete series without deforestation	4.777	4.781	4.783	4.188	0.922
	Complete series with deforestation	5.444	5.445	5.448	4.813	1.220
NDVI	Complete series without deforestation	0.117	0.117	0.115	0.092	0.032
	Complete series with deforestation	0.147	0.147	0.143	0.127	0.075

Table 5-6: The percentage of the LST and NDVI pixel which had a significant trend under different temporal aggregations (%)

		8-day	16-day	Monthly	Seasonally	Yearly
LST	Complete series without deforestation	2.17	0	0	0	15.44
	Complete series with deforestation	92.71	86.22	62.00	6.88	28.54
NDVI	Complete series without deforestation	0	5.91	0.62	0	0.03
	Complete series with deforestation	99.42	99.11	98.64	95.38	78.06

Table 5-7: The average slope of all pixels and standard deviation (sd) of slope under different temporal aggregations

		8-day	16-day	Monthly	Seasonally	Yearly
LST	Complete series without deforestation	-0.0038	-0.0037	-0.0039	-0.0035	-0.0139
	(sd)	0.0059	0.0058	0.0059	0.0061	0.0056
	Complete series with deforestation	0.0376	0.0373	0.0374	0.0366	0.0222
	(sd)	0.0120	0.0119	0.0120	0.0120	0.0100
NDVI	Complete series without deforestation	0.0093	0.0101	0.0063	0.0146	0.0535
	(sd)	0.0576	0.0570	0.0580	0.0598	0.0588
	Complete series with deforestation	-0.4202	-0.4191	-0.4215	-0.4188	-0.3721
	(sd)	0.1141	0.1139	0.1140	0.1154	0.1161

5.5. Impact of LU/LC change and temporal aggregation

The differences of time series statistics between before deforestation and after deforestation under different temporal aggregation levels illustrated the impact of LU/LC change and temporal aggregation. Table 5-8 and table 5-9 show LST and NDVI statistics of before and after deforestation under different temporal aggregation levels. In those two tables, the summary statistics are mean, median, maximum, minimum and standard deviation. The standard deviation of each summary statistics was shown in the following row under the corresponding statistics. The first part of those two tables statistic of complete series without deforestation, which is the control group. The rest two parts are statistic of before and after deforestation. The impact of LU/LC change and temporal aggregation was evaluated by comparing statistics before and after deforestation under different temporal aggregation. For example, in Table 5-8, differences of mean between before and after deforestation was evaluated by comparing values marked with yellow and green in proper order of temporal aggregation levels.

Table 5-8: Summary statistics (unit: K) and average slope for LST before and after deforestation under different temporal aggregation levels. Values of statistics in this table are average statistics of all pixels over the complete series.

		Mean	Median	Maximum	Minimum	Standard deviation	Slope
Complete series without deforestation	8-day	303.639	303.77	318.567	293.5013	4.777	-0.0038
	(sd)	0.155	0.193	1.240	0.420		0.0059
	16-day	303.610	303.709	313.514	293.550	4.781	-0.0037
	(sd)	0.155	0.206	1.222	0.415		0.0058
	Monthly	303.638	303.741	313.008	294.056	4.783	-0.0039
	(sd)	0.156	0.209	1.180	0.419		0.0059
	Seasonally	303.598	303.293	311.900	296.176	4.188	-0.0035
	(sd)	0.155	0.250	0.790	0.436		0.0061
	Yearly	303.544	303.684	304.862	302.072	0.922	-0.014
	(sd)	0.146	0.238	0.283	0.317		0.0056
Before deforestation	8-day	303.840	304.430	312.191	293.562	4.336	0.0346
	(sd)	0.225	0.369	0.846	0.858		0.0167
	16-day	303.818	304.385	312.151	293.626	4.327	0.0350
	(sd)	0.225	0.382	0.859	0.871		0.0170
	Monthly	303.845	304.389	311.909	294.106	4.349	0.0348
	(sd)	0.223	0.345	0.782	0.775		0.0170
	Seasonally	303.771	303.740	310.720	297.268	3.609	0.0331
	(sd)	0.205	0.365	0.666	0.286		0.0174
	Yearly	303.868	303.816	304.425	303.404	0.440	-0.0048
	(sd)	0.208	0.223	0.351	0.256		0.017
After deforestation	8-day	305.614	305.654	318.845	293.799	6.218	0.04
	(sd)	0.789	0.681	2.486	1.338		0.0458
	16-day	305.567	305.558	318.777	293.807	6.199	0.0417
	(sd)	0.782	0.692	2.492	1.341		0.0454
	Monthly	305.610	305.584	318.319	294.431	6.219	0.0395
	(sd)	0.785	0.759	2.497	1.650		0.0456
	Seasonally	305.476	305.008	315.968	297.227	5.475	0.0432
	(sd)	0.771	0.728	2.092	0.924		0.0445
	Yearly	305.096	305.029	306.600	303.725	1.260	0.0130
	(sd)	0.650	0.709	0.922	0.561		0.035

Table 5-9: Summary statistics for NDVI before and after deforestation under different temporal aggregation levels. Values of statistics in this table are average statistics of all pixels over the complete series

		Mean	Median	Maximum	Minimum	Standard deviation	Slope
Complete series without deforestation	8-day	0.612	0.615	0.865	0.350	0.117	0.00938
	(sd)	0.012	0.016	0.017	0.031		0.0576
	16-day	0.612	0.615	0.862	0.352	0.117	0.0101
	(sd)	0.012	0.016	0.017	0.031		0.0571
	Monthly	0.612	0.614	0.850	0.362	0.115	0.00636
	(sd)	0.012	0.016	0.017	0.031		0.0580
	Seasonally	0.614	0.603	0.779	0.449	0.092	0.0146
	(sd)	0.012	0.016	0.014	0.020		0.0598
	Yearly	0.612	0.611	0.664	0.563	0.033	0.0535
	(sd)	0.012	0.010	0.014	0.022		0.0588
Before deforestation	8-day	0.588	0.578	0.803	0.364	0.112	-0.206
	(sd)	0.022	0.031	0.029	0.035		0.250
	16-day	0.587	0.577	0.800	0.366	0.112	-0.182
	(sd)	0.022	0.031	0.028	0.035		0.260
	Monthly	0.587	0.578	0.791	0.378	0.110	-0.221
	(sd)	0.023	0.031	0.027	0.035		0.252
	Seasonally	0.589	0.574	0.750	0.461	0.090	-0.182
	(sd)	0.022	0.028	0.023	0.030		0.260
	Yearly	0.588	0.591	0.615	0.554	0.032	0.0195
	(sd)	0.022	0.024	0.024	0.024		0.261
After deforestation	8-day	0.484	0.479	0.826	0.237	0.152	-0.497
	(sd)	0.034	0.043	0.037	0.025		0.342
	16-day	0.484	0.479	0.824	0.239	0.152	-0.502
	(sd)	0.034	0.043	0.037	0.025		0.337
	Monthly	0.464	0.448	0.817	0.245	0.150	-0.513
	(sd)	0.036	0.042	0.038	0.026		0.338
	Seasonally	0.485	0.476	0.720	0.298	0.129	-0.506
	(sd)	0.034	0.038	0.038	0.030		0.350
	Yearly	0.484	0.475	0.557	0.422	0.066	-0.170
	(sd)	0.034	0.035	0.036	0.048		0.345

The data of Figure 5-14 and figure 5-15 was calculated by statistic after deforestation minus before deforestation. According to Figure 5-14, with the increasing temporal aggregation, the differences of LST mean and median between before and after deforestation did not have a very big change. The differences of mean were always around 1.7K, while the differences of median were around 1.2K between before and after deforestation. The differences of LST maximum decreased slowly at first and then sharply dropped down to 2.15K and the LST minimum always had the smallest differences, which were around 0.2K between before and after deforestation. Figure 5-15 illustrated how the differences of NDVI summary statistics changed with the increasing temporal aggregation level. In general, same with LST, the changing ranges for each statistics were not big at the first two aggregation levels (8-day and 16-day). The minimum of NDVI had the biggest absolute changing between before and after deforestation. After seasonally temporal aggregation, the changing of differences started to fray.

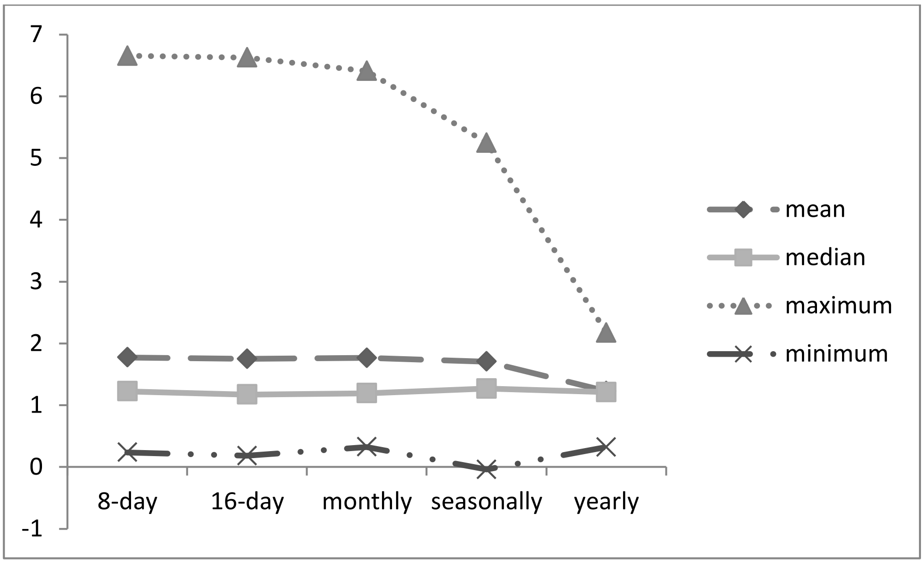

Figure 5-14: The differences of LST summary statistics between before and after deforestation under different temporal aggregation levels. The absolute value shows the difference quantity, and the plus-minus sign represents positive or negative changes (after deforestation minus before deforestation, unit: K).

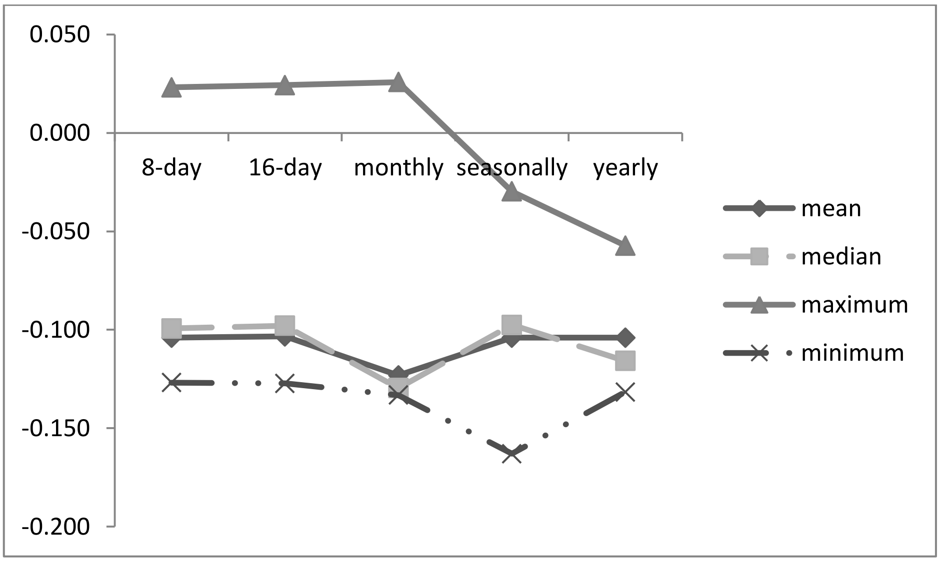

Figure 5-15: The differences of NDVI summary statistics between before and after deforestation under different temporal aggregation levels. The absolute value shows the difference quantity, and the plus-minus sign represents positive or negative changes (after deforestation minus before deforestation, unit: NDVI unit).

Figure 5-16 described the differences of LST standard deviation between before and after deforestation, and all the temporal aggregations had a positive change. It means that the standard deviation of LST increased after deforestation under any temporal aggregation level in this study. With increasing temporal aggregation levels, the gaps of standard deviation between before and after deforestation slightly reduced at first, and then the gap rapidly decreased, and the turning point is seasonally aggregation level. The standard deviation of NDVI had the same behaviours with the increasing temporal aggregation (see in Figure 5-17). Figure 5-18 and 5-19 show the differences of LST and NDVI average slop between before and after deforestation. The differences of slope had more complex tendency with the raising temporal aggregation level. The LST average slope had positive changes under all temporal aggregation level, while the NDVI had negative changes. However, the differences of LST average slope fluctuated with a narrow at first, and then decreased sharply after monthly aggregation level (see in figure 5-19). As for NDVI, according to figure 5-19, this fluctuation of absolute differences continued until seasonally aggregation level, and then rapidly dropped down.

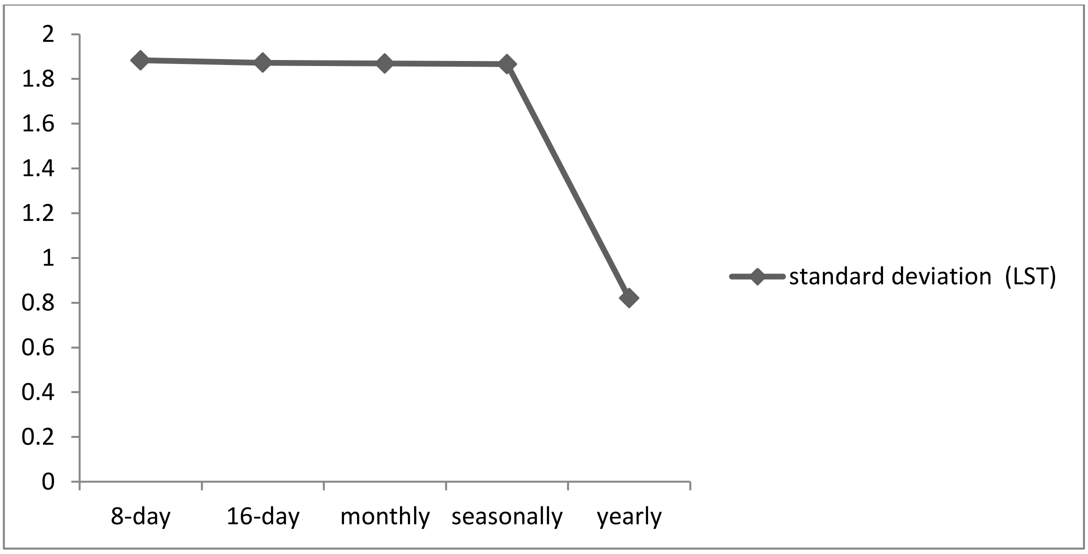

Figure 5-16: The differences of LST standard deviation between before and after deforestation. The absolute value shows the difference quantity, and the plus-minus sign represents positive or negative changes (after deforestation minus before deforestation, unit: K).

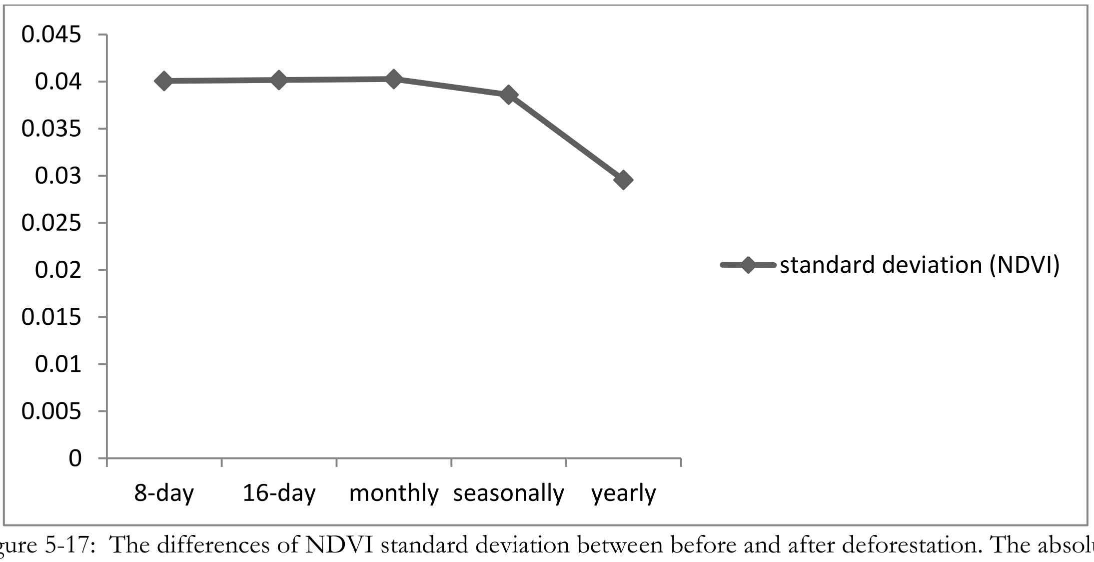

Figure 5-17: The differences of NDVI standard deviation between before and after deforestation. The absolute value shows the difference quantity, and the plus-minus sign represents positive or negative changes (after deforestation minus before deforestation, unit: NDVI unit).

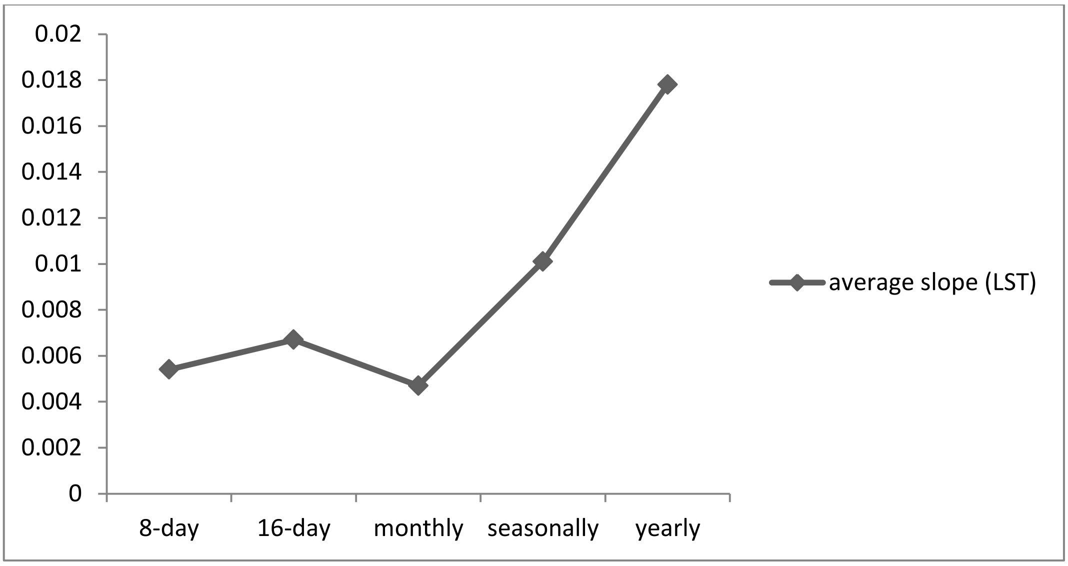

Figure 5-18: The differences of LST average slope between before and after deforestation. The absolute value shows the difference quantity, and the plus-minus sign represents positive changes or negative changes (after deforestation minus before deforestation).

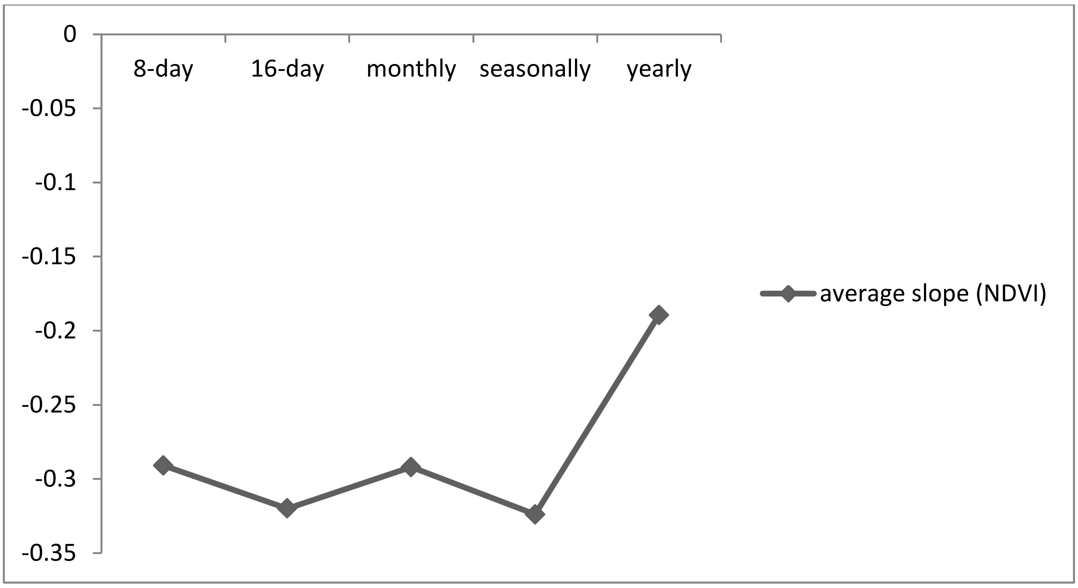

Figure 5-19: The differences of NDVI average slope between before and after deforestation. The absolute value shows the difference quantity, and the plus-minus sign represents positive changes or negative changes (after deforestation minus before deforestation).

6. DISCUSSION

The study has applied HANTS in order to reconstruct a gapless time series. Also, it demonstrated that the information on geographical objects captured by remotely sensed data are not independent of temporal aggregation and LU/LC change. Temporal aggregation and LU/LC change issues are two major uncertainties in time series analysis. Those two factors are discussed below in the light of the findings of the study.

6.1. Time series reconstruction

The HANTS was applied to deal with time series of irregularly spaced observations. It was observed in section 5.1. Since there is no objective rules to determine the HANTS control parameters (Roerink et al., 2000), the common solution is to set a parameter as per experiences. For example, the number of frequency (nf) used for curve fitting is very crucial for the fitting result and varies with specific applications or study areas. Zhou et al., (2015) used 4 frequencies for reconstruction of global NDVI while Julien et al. (2006) applied 2 frequencies to reconstruct LST time series over Europe. However, Moody and Johnson (2001) argued that higher-order frequencies could be retained and used to evaluate high temporal variability, and Geerken et al. (2005) demonstrated that phenology-related information on rangeland was generally contained in the first five harmonics. In this study, to evaluate the performance of HANTS with a common parameter setting scheme, the first four harmonics were selected to reconstruct LST and NDVI time series. Fit error tolerances were set as 0.1 K and 0.05 (NDVI unit). The valid ranges of LST and NDVI ranged from 220K to 339.9K and from 0 to1. The length of the base period is the number of images in one year, and in this study the base period is 46.

Results showed that HANTS had better performance when it is applied year by year than applied to the complete series. It would be expected that the time series of each year had variability. If HANTS was applied on a long-term time series, there was only one fixed model during the complete series, while the annual variability of that time series was lost. The reconstructed year-by-year time series guaranteed the uniqueness of each year, which made the reconstructed time series closer to reality. The majority of HANTS reconstruction studies have been conducted on a yearly basis. For instance, Xu and Shen (2013) applied HANTS on MODIS LST data taken in the year 2005. This method is consistent with that of Julien et al. (2006) who reconstructed LST and NDVI time series over Europe between 1982 and 1999 on a yearly basis as well. Moreover, for long-term time series with LU/LC change, applying HANTS year by year can retain the annual modifiability of time series variables especially in LU/LC changing periods, which is significant for LU/LC change analysis.

6.2. Impact of LU/LC change

The impact of LU/LC changes on time series analysis was illustrated in section 5.3. Deforestation is one of the typical LU/LC changes in geography. According to the result of control group (complete series without deforestation), only a few pixels had significant trends, and the average slope were closed to zero. That means the impact of LU/LC change was independent in this study.

The result suggests that the deforestation increased LST, while decreased NDVI in that study area. Owing to deforestation, land cover type was changed from forest to bare soil or crops, which have the smaller specific heat capacity and NDVI values than forest. Moreover, after deforestation, the decreased vegetation density exposed more land surface. The increasing standard deviation attributable to deforestation suggested that the time series became more extreme and uncertain than it was before. Accordingly, more pixels had significant trends and the trends became steeper. In the same vein, Polcher and Laval (1994) studied the impact of deforestation on the tropical climate, finding that a reduction in vegetation cover made evaporation more difficult, and that soil temperature rose in order to reach a new equilibrium of the energy system. This finding was corroborated by Arroyo-Rodríguez et al. (2017), who investigated the impact of forest fragmentation on climate change, which suggested that forest loss increased temperature.

The result also illustrated that the HANTS did not have a good performance if the LU/LC change was not considered. The reason for this may be that, the LU/LC change influenced the behaviors of time series variables. If the LU/LC change is ignored when applying HANT, the variability of time series variables before and after deforestation was lost, which made the reconstructed time series cannot fully represent the real time series. Furthermore, according to the results of HANTS, there was no change in the number of cycles of LST and NDVI between deforestation and after deforestation. There was only 1 cycle per year. In agricultural studies, the cycle number of vegetation index (such as NDVI and EVI) depends on the number crop phenological cycle (Li et al., 2014). Resultantly, the deforested polygons in this study might have single cropping season after deforestation, which means the deforested polygons only had one-time crop growing per year or remained as pastures after deforestation.

6.3. Impact of temporal aggregation

MODIS LST and NDVI data of the deforested and non-deforested polygons were combined into 5 aggregation levels, i.e. 8-day, 16-day, monthly, seasonally and yearly. Correspondingly, the image numbers of time series were 552, 274, 144, 48 and 12. It was observed in section 5.4, that with the raising of temporal aggregation level, the mean and median of LST and NDVI kept stable, and the differences between maximum and minimum became smaller. In addition, the standard deviation decreased due to the raising temporal aggregation level. It would be expected that, with an increasing of aggregation levels, the variability of time series variables decreased. Because the aggregation method applied was average, the patterns of variables became smooth. However, the mean and median would not be affected as much as maximum and minimum. Furthermore, the higher temporal aggregation levels led to a smaller slope of linear regression. Similar results were drawn by Vlahogianni and Karlaftis (2011) who investigated the effects of temporal aggregation on time series of traffic volume and occupancy in in urban signalized arterials. As a result, an increase in temporal aggregation levels gave rise to a smoother evolution of statistics.

According to the results, with the increasing temporal aggregation, the average slopes of LST and NDVI were stable before seasonally aggregation level and then changed greatly. This finding was corroborated with the study done by De Jong and De Bruin (2012), who analysed the temporal aggregation effect for a harmonic model of 26 years NDVI time series with 44 temporal aggregation levels. They suggested that spatial patterns are hardly perceivable at fine temporal aggregation levels, but they became apparent at coarser levels. It can be expected that, in this study, before seasonally temporal aggregation level, the spatial patterns are too difficult to be perceived. The storage of this study is that the number of aggregated time series was small (1 original 8-day time series and 4 aggregated time series). The sample size was quite small to conclude the existence of any pattern. So, the tendency after yearly aggregation level cannot be observed.

6.4. Impact of LU/LC change and temporal aggregation

The differences of summary statistics and trend analysis between before and after deforestation were compared under different temporal aggregation levels in section 5.5. According to the results, the differences of mean and median of LST and NDVI kept stable with the increasing temporal aggregation levels. It is because during the aggregation process, based on the results from the impact of temporal aggregation on summary statistics, the mean and median did not have obvious changes with the increasing temporal aggregation. Since that, the differences of mean and median between before and after deforestation retained stable. However, with the increasing temporal aggregation, the differences of LST maximum between before and after deforestation had a sharply decline after seasonally aggregation level, while the differences of minimum was more stationary. The reason may be that the extreme high LST values became higher since the deforestation, and with the increasing temporal aggregation, those extreme high LST were averaged gradually after seasonally temporal aggregation. However, the ranges of the lowest LST did not change a lot before deforestation an after deforestation. Same with LST, the differences of NDVI statistics before and after deforestation did not change a lot at fine temporal aggregation levels (8-day and 16-day). The differences of maximum were positive before seasonally aggregation level, while the differences of minimum were negative. It would be expect that, after deforestation, the range of NDVI became bigger than before. However, with increasing temporal aggregation levels, the variability of time series was lost. Since that, the higher temporal aggregation cannot represent the changing of NDVI range between before and after deforestation accurately.

In this study, because the average aggregation method reduced the variability of the time series, the maximum and minimum of NDVI and LST had highest sensitivities to the changes of temporal unit size. The maximum of LST and the minimum of NDVI had highest sensitivities of deforestation.

6.5. Limitation of study

There are certain limitations to this study. First, there are three factors of modifiable temporal unit problem: temporal aggregation, temporal segmentation and temporal boundary (Cheng & Adepeju, 2014). In this study, only temporal aggregation was studied. Other two factors were controlled but without further research. Second, due to the time constraint of MODIS data, there are only 5 temporal aggregation levels, which is limited. To conclude the existence of any pattern, sample size of 5 is small. So that the result would have been much emphatic if more aggregations were done. Third, only two time series variable were studied. To expand the extent of this study, maybe more time series variable (such as leaf area index, polarization difference brightness temperature, etc.) can be also studied. Forth, in this study, only one kind of temporal aggregation method was used (average). There are several kinds of temporal aggregation methods can be applied, such as maximum, minimum, etc. It may have different result compared with average aggregation method.

Despite these limitations, the results from the study provide insight to the issue of LU/LC change and temporal aggregation on time series analysis.

7. CONCLUSION AND RECOMMENDATIONS

7.1. Conclusion

Remotely sensed data is collected at predefined temporal scale irrespective of the natural processes occurring on ground. There are numerous choices of remotely sensed sensor for users. Therefore, it is important to understand the impact of temporal scales on remote sensing-based time series analysis. Meanwhile, as a significant changing factor of remote sensing time series, LU/LC change issue should be considered as well. This study explored the possible impact of two factors (temporal aggregation and LU/LC change) on remote sensing time series analysis.

As a typical LU/LC change, the deforestation influences on time series analysis in the Gran Chaco region was evaluated, and the MODIS LST and NDVI time series was aggregated to different temporal aggregation level in order to identify the impact of temporal aggregation on time series analysis. It shows that the temporal aggregation can affect the maximum, minimum, standard deviation and the average slope of linear regression on high aggregation levels. However, at lower aggregation levels of a fine temporal aggregation time series, the effect of temporal aggregation is too small to be observed. In this study, the impact of temporal aggregation became significant after seasonally aggregation level. The threshold is decided by the season number in one year.

As for the impact of deforestation, the result shows that the deforestation can affect the summary statistics and trend analysis in the study area. The deforestation increased the total standard deviation and mean LST while decreased the mean NDVI. Meanwhile, more pixels had a significant trend after deforestation, and the slopes became steeper. According to the results of HANTS, the deforestation did not change the time series cycle number in this study area. In addition, the HANTS has a better performance if the deforestation is considered. The unique character of LU/LC change and different human behaviours may lead to different changes on time series analysis. For example, planting multi-seasonal crops after deforestation may raise the time series cycle number in base period. Other kinds of LU/LC change such as urbanization, reforestation, may give rise to different influences on time series analysis.

When temporal aggregation and LU/LC change are both considered in time series analysis, the quality (positive or negative) of LU/LC impact on summary statistics will not change whatever the temporal aggregation is low or high. In other words, if the differences of statistics caused by the LU/LC change are positive (or negative), those differences will keep positive (or negative) after temporal aggregation.

In this study, the HANTS algorithm was proven that it is a powerful tool not only to reconstruct time series, but also acquire the harmonic information of time series. Applying HANTS year by year can keep the time series variability and characters for each year, which has lower RMSE than applying HANTS to the complete time series. In this way, the reconstructed time series by HANTS is closer with reality.

7.2. Recommendation

It is recommended that if the time series is much longer than the temporal resolution, then at lower level of temporal aggregation effects can be ignored. However, at higher aggregation levels it becomes crucial to take the impact of temporal aggregation in to consideration; otherwise the results can be inconsistent. Secondly, the issue of LU/LC should not be ignored when analyse the time series to avoid the discrepancies in the results. Different LU/LC change may lead to different impacts on time series analysis. Finally, if there are LU/LC changes in long-term time series then the HANTS should be applied at least before and after LU/LC change separately. In order to have a better result of time series reconstruction, the HANTS should be applied on yearly basis. In this way, the annual variability can be reserved, which makes the reconstructed time series closer to reality.

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APPENDIX I: GRASS GIS SCRIPT

```
# set region right
g.region raster=MOD09Q1_NDVI_2001_001 save=study_area
g.region –p

# create the space-time dataset
t.create type=strds temporaltype=absolute output=8ndvi semantictype=mean title="MODIS NDVI in\
chaco" description="MODIS NDVI in chaco south america"

# register maps in time series
g.list type=raster > names_list
for mapname in `cat names_list` ; do
  # parse
  year_start=`echo ${mapname:13:4}`
  doy_start=`echo ${mapname:18:3}`
  # convert YYYY-DOY to YYYY-MM-DD
  doy_start=`echo "$doy_start" | sed 's/^0*//'`
  START_DATE=`date -d "${year_start}-01-01 +$(( ${doy_start} - 1 ))days" +%Y-%m-%d`
  # print mapname, start date
  echo "$mapname|$START_DATE" >> map_list_and_start_time_8ndvi.txt
done
t.register input=8ndvi file=map_list_and_start_time_8ndvi.txt

# create the intervals
t.snap type=strds input=8ndvi

#register again the last map with proper start and end date
t.register type=raster input=8ndvi map=MOD09Q1_NDVI_2012_361 start="2012-12-26"
\end="2013-01-01" --o

#HANTS
r.hants file=lst_maplist.csv nf=4 fet=1000.0 dod=7 base_period=46 sufffix="_hants_1"
amplitude="_am"

#aggregate
t.rast.aggregate input=8ndvi output=16day_ndvi basename=16day_ndvi method=average\
granularity="16 days"

# extract pixel-based time series
t.rast.out.xyz strds=8ndvi output=8day_ndvi.csv
```

APPENDIX II: R SCRIPT

```
# linear regression
yeye<-read.csv("C:/Users/ljx93_000/Desktop/total output/ndvi_nondeforestation_1year.csv",\
header=F, sep="|")
yeye<-yeye[,-1:-2]
yeye<-t(yeye)
yeye<-data.frame(yeye)
time<-read.csv("C:/Users/ljx93_000/Desktop/total output/timeyear.csv",header=F, sep=",")
for (i in 1:8210)
{output<-summary(lm(yeye[,i]~time[1:12,]))
x<-output$coefficients[2,"Estimate"]
write.table(x,file="ndvi_non_year_1.csv",append=T,sep="|", row.names = F,col.names = F)
y<-output$coefficients[2,  "Pr(>|t|)"]
write.table(y,file="ndvi_non_year_2.csv",append=T,sep="|", row.names = F,col.names = F) }
```