Detecting spatio-temporal forest changes in the eastern section of semi-arid region in China using MODIS NDVI time series and BFAST model

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ABSTRACT

Forest is essential to human's life and has great ecosystem services function. The eastern section of semi-arid region in China is a typical forest-steppe ecotone with total forest cover around 0.15 million km^2, which is sensitive to climate changes. The study area located in the administrative region of Inner Mongolia, covering 24 counties which experienced significant development of society and urbanization from the end of 20^{th} century. Forest here changes frequently and its disturbances are complicated which lacking of forest change detection using time series to reveal the deeper change mechanism.

This study adopted the Breaks For Additive Season and Trend (BFAST) model using MODIS-Normalized Difference Vegetation Index (NDVI) time series from 2000-2013 in eastern section of semi-arid region in China. BFAST is an ideal model to detect changes within time series trajectories and has been proved its ability to detect not only forest gradual changes but also forest abrupt changes. We utilized the 'trend' to character forest gradual change, 'frequency' and 'magnitude' of breakpoints to character forest abrupt change.

The results shows that, 71.6% forest pixels were detected with positive change trend direction and 28.4% with negative change trend direction. Forest areas with decreasing NDVI mainly distributed among the boundaries of counties located in the middle part of the study area, forest areas with increasing NDVI mainly among counties located in top northern part and southern part of the study area. Forest abrupt changes characterized by the higher frequency and more violent magnitude clustering among northern part of the study area according to hot spot analysis.

The correlation and regression analysis revealed a certain positive correlation between long-term gradual forest change and urbanization, negative forest abrupt change with significant correlation with extreme precipitation and temperature events. Comparing the correlation of Pearson's r and regression results of R^2 and p-value with disturbance factors, precipitation has overwhelming control on forest NDVI change in eastern section of semi-arid China during 2000-2013.

This study is the first time that applying BFAST model in such a large area over a long period. The study suggests that the gradual forest change and abrupt change distribution have different spatio-temporal patterns, which not only appeals to people to pay attention to long-term forest decreasing areas, but also indicates the forest abrupt change areas need close attention as well. The correlation analysis revealed the dominant control of precipitation on forest abrupt change, and human disturbances play the main role in long-term gradual forest change. In conclusion, the study facilitates a better understanding of forest change distribution and change mechanism in semi-arid areas in China, which has important policy implications for long-term and sustainable development of forest conservation.

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1. INTRODUCTION

1.1. Background

Forest covers about thirty percent of the earth's land surface in the year of 2006, according to the report of Food and Agriculture Organization of the United Nations (FAO, 2006). Olsson *et al.* (2012) indicated that, forest not only provides products such as woods, fuel and others for human's life and production, but also has high ecosystem services function which is significant to the stabilization and improvement of ecological environmental components including carbon circulation, water, soil, the atmosphere and so on. Forest is the main terrestrial ecosystem on the earth, and forest change process happens spatially and temporary under the pressure of human or/and natural impacts. Substantial forest changes have been detected globally from 2000-2012 by Hansen (2013), with a total loss of 2.3 million km^2 compared to the low amount of forest gain of 0.8 million km^2.

Forest changes can be divided into three different types according to Verbesselt *et al.* (2010): seasonal change, gradual change and abrupt change. Seasonal change, always being driven by phenology related climatic variables like temperature and precipitation varying within a year. Gradual change refers to the changes related to gradual trend of the factors such as long-term climate variables or other long-term stress. Abrupt change, negative forest changes of forest cover loss or severe forest health decline being driven by disturbing forces like extreme climatic events (e.g., droughts and flood), fire, urbanization, pest. Analyzing forest dynamics will contribute to better understanding the natural and human influences on the forest ecosystem (Kumar *et al.*, 2014). It is necessary to study the spatial and temporal characters of forest changes for better identifying the change mechanism and the driving factors.

Efforts have been made to monitor forest changes. Forest inventory survey programs are performed at a range of scales, from the national to the continental. Although the forest inventory data will provide sufficient forest information, it is not the best source for forest change detection as these survey information are not always available, plus various definitions of the forest across countries and over time (Potapov *et al.*, 2015). Field investigation data also have the ability to present changes between a long time gap within certain forest stand. However, it is not possible to perform a large-scale survey also with high temporal frequency which would be both time- and money-consuming. Remote sensing images from space-borne sensors provide the most efficient and cost-low tool for detecting forest change and monitoring forest variation at a large scale (Hansen, 2013). With the advantages of open access and increasingly advanced remote sensing technologies, some novel applications have been promoted such as near real-time nationwide forest monitoring (Setiawan *et al.*, 2016). Here, previous studies related to forest change detection using remote sensing data were reviewed.

1.2. Research review

1.2.1. Change detection methods

Change detection is widely performed in detecting land cover changes especially vegetation changes based on remote sensing images. Change detection methods can be divided into two groups according to Gong *et al.* (2008): (1) bi-temporal change detection, and (2) temporal trajectory analysis. Most of the bi-temporal change detection methods focus on developing classification algorithms to find out differences between two images which always missed the messages within temporal trajectories. By comparing the difference between a pair of satellite images of two-time nodes focusing on the same area, bi-temporal change detections are performed. These change detection methods identify where changes happen between the given images of two-time nodes, normally use different methods for classification of 'change and non-change areas', and these images for comparison are always from same remote sensing products according to Tewkesbury *et al.* (2015). Then, methods of integrating different types of remote sensing images of different resolution were developed. For example, Zhang *et al.* (2016) carried out a change detection method based on multi-spatial-resolution remote sensing images and was tested in four real datasets to confirm its ability to improve the change detection effectiveness.

With the releasing of dense available satellite image time series, vegetation cover change trajectory over a long period can be expressed, which make it possible to detect phenological changes and abrupt changes within a long period, consequently make the temporal trajectory analysis popular. Although some researchers have developed methods to detect changes within time series (Kaufmann & Seto, 2001; Kennedy *et al.*, 2010), with the limitation of unable to be applied to high temporal resolution images, some seasonal and phenological changes within a year still cannot be detected as some changes might be hidden among the infrequently acquired images (Verbesselt *et al.*, 2010a). Some pixel-based change detection methods are getting popular. For example, Broich *et al.* (2011) developed an automatic method to map gross forest cover loss areas accurately by applying robust classifier using time series data. That study detected forest cover loss with high accuracy by integrating Moderate Resolution Imaging Spectro-radiometer (MODIS) and Landsat time series. But the outcome still focused on showing the difference between two-time nodes.

1.2.2. Popular change detection algorithms for remote sensing data

Recently, attention are drawn by some methods (Verbesselt *et al.*, 2010; Cai & Liu, 2015; Jamali *et al.*, 2015) focusing on detecting changes using dense satellite time series which are capable of revealing phenological and seasonal variation of vegetation cover change. Here list three ideal change detection methods with the capacity of detecting trend and phenological change:

(1) Breaks For Additive Season and Trend (BFAST) model. Verbesselt *et al.* (2010) developed a time series change detection tool to detect land cover change called BFAST and later improved it (Verbesselt *et al.*, 2012). It has similar function with Haywood & Randal (2008)'s work by using monthly tourism data, however it is improved by using Seasonal-Trend decomposition procedure (STL) adapted from LOcally wEighted regreSsion Smoother (LOESS) of Cleveland *et al.* (1990). Verbesselt *et al.* (2012) improved BFAST and validated its' capacity of detecting abrupt changes in the seasonal and trend components of the time series and characterizing the detected changes with date, magnitude and direction. The limitation of this method was indicated by Jamali *et al.* (2015) that, despite the function provided for users to define the numbers they want to detect, it still has limitation space for users to define magnitude.

(2) Detecting Breakpoints and Estimating Segments in Trend (DBEST) model. Jamali *et al.* (2015) recently proposed a novel approach called DBEST for detecting changes in time series of vegetation indices. It has been applied to detect regional change trend and magnitude of Global Inventory Modelling and Mapping Studies (GIMMS)- Normalized Difference Vegetation Index (NDVI) over a long time series within a large area (Jamali *et al.*, 2015). By adopting Bayesian Information Criterion, this algorithm overcomes the problem of overestimating the number of the 'breakpoints'. Its advantages compared to BFAST is that, it is more flexible and manageable for users to define the scale of certain changes according to users' need. However, the shortcoming compared to BFAST is obvious, this method lacks the function of detecting changes in the seasonal components which make it infeasible to analyze the changes relating to vegetation phenology.

(3) Sub-annual Change Detection (SCD) model. Cai & Liu (2015) proposed a sub-annual change detection approach called SCD to detect change dates using 13 years MODIS 16-day NDVI and validated its

capacity by comparing with ground investigating data. The results showed that SCD has comparable capacity of detecting change dates with BFAST, however it cannot quantify magnitude and other characteristics of the changes.

1.2.3. RS time-series for forest change detection

Comparing to bi-temporal change detection, remote sensing time series applied with change detection methods usually use low spatial resolution images such as Advanced Very High Resolution Radiometer (AVHRR), MEdium Resolution Imaging Spectrometer (MERIS) and Visible Infrared Imaging Radiometer Suite (VIIRS) with the capacity of performing temporal trajectory analysis, however, leaving the tasks of classification challenging according to Gong et al. (2008). Change detection dealing with high temporal resolution time series are mainly applied in two types of studies: (1) Vegetation dynamics in large areas. For example, Jong et al. (2011) detected global vegetation greening and browning trends from 1981 to 2006 using time series of GIMMS-NDVI; (2) Specific land cover trajectory analysis. For example, Gao et al. (2016) using annual GIMMS-NDVI time series from 1982 to 2011 to analyze the productivity dynamic of the grassland by extracting information within grassland cover boundary. Landsat-derived time series have high spatial resolution and are also popular for forest change detection (Hermosilla et al., 2015; Huang et al., 2010). However, these Landsat-based time series are limited in regional scale because of cloud effects and other reasons (Lambert et al., 2015).

For different time spans of the time series applied, change detection can be divided into long-time serial analysis and near real-time serial analysis according to Gong *et al.* (2008). An example of long-time serial analysis is that Potapov *et al.* (2008) used annual MODIS time series combined with Landsat images to improve the accuracy of estimating annual forest cover loss and map the forest cover loss hotspot in boreal forests. Examples of near real-time serial analysis change detections include that Verbesselt *et al.* (2012) proposed a time series analysis approach using real-time MODIS satellite image time series to extract abnormal events within the time series. By generating 'vegetation greenness data' and performing change detection, Verbesselt *et al.* (2012) detected ecosystem disturbances in near real-time from 2000 to 2011 in Somalia. Sulla-menashe *et al.* (2014) characterized the size, severity and timing of forest disturbances among 11 years in the Pacific Northwest area using annual time series of MODIS-Normalized Burn Ratio (NBR).

1.2.4. Vegetation indices for forest change detection

Huete *and* Justice (1999) defined vegetation indices as the combinations of vegetation spectral characteristics related bands under proper arithmetic, are derived to present certain vegetation conditions detected from remote sensing images and are widely used in forest change detection. The Normalized Difference Vegetation Index called NDVI is one of the most popular vegetation indices in detecting forest changes (Lambert *et al.*, 2015; Lambert *et al.*, 2013; Wang *et al.*, 2005), which can distinguish high vitality vegetation from background features (Lawley *et al.*, 2016). Other indices applied for measuring forest cover include Enhanced Vegetation Index (EVI) (Matsushita *et al.*, 2007), Burned Area Index (BAI) (Quintano *et al.*, 2011) and Normalized Burn Ratio (NBR) (Sulla-menashe *et al.*, 2014). These indices can be directly applied to represent vegetation conditions, or indirectly applied by calculating and deriving phenological parameters related to vegetation growth like 'start of growing season(SOS)' and 'end of growing season(EOS) ' (Dong *et al.*, 2016; Wang *et al.*, 2016; Reed, 2006).

1.3. Problem statement

The eastern section of semi-arid region in China is the typical forest-steppe ecotone with significant climate change (Liu *et al.*, 2013). In recent 100 years, temperature has significantly risen during the winter of semi-arid and arid area in middle latitude of the Northern Hemisphere compare to other parts of the global land (Liu *et al.*, 2013). It consists significant parts of global change research. Recent years, with global warming, climate anomaly events frequently happen in semi-arid area were characterized as temperature rising and precipitation decreasing (Allen *et al.*, 2010; Liu *et al.*, 2013). Rotenberg & Yakir (2010) indicated that, forest in these areas, shows higher carbon storage capacity than global average forest (Liu *et al.*, 2013). If certain forest change happened, it might greatly influence the carbon sequestration. What's more, ecological ecotone with particular characteristics as the transition area between two ecosystems, is driven high attention for its sensitivity to climate change and is recognized as the global change early warning region (Song *et al.*, 2009).

Recently, some studies indicated special phenomenon related to forest change in this area. Liu *et al.* (2013) observed tree growth decline and also spatial forest distribution change related to climate variation. Other studies, Zhao *et al.* (2013) used GIMMS-3g to calculated vegetation phenology parameters and studied the vegetation phenology responding to climate changes from 1982 to 2013 in this area. The results showed that the vegetation phenology detected were greatly influenced by spring temperature and precipitation, and a lag effect of the temperature was observed. Our study area, consists of 24 county level regions, which experienced significant urbanization since 1978 (Liu & Leung, 2015) and the urbanization is still ongoing in these regions. Urbanization process will cause conversion from forest to urban land use, which will directly influence the forest ecosystem, and it will also increase human disturbances of logging and other human-related activities (Verbesselt *et al.*, 2010b) although with possible forest protection policy under implementing. However, there still lacks forest-focused change detection to reveal spatio-temporal distribution of forest change using long time series in the study area.

The detection of slight forest change using coarse resolution images is generally difficult according to Lambert *et al.* (2015). As this study area has the characteristic of forest fragmentation (Liu & Yin, 2013), using coarse resolution images might underestimate the presence of forest. MODIS data is a type of fine resolution images product with the resolution of 250m, which might not be the optimal choice regarding resolution for our study area. However, considering the size of our study area and the suggestion of image resolution of 250m-1000m for forest change detection according to other authors' work (Lambert *et al.*, 2015; Lambert *et al.*, 2013; Potapov *et al.*, 2009; Singh & Jeganathan, 2016; Sulla-menashe *et al.*, 2014), MODIS time series product with 250m resolution can meet our need. Considering data characteristics of regular data acquisition covering large areas, accessibility and the ready-qualified factors of our potential product, there is no doubt that 16-day moderate resolution MODIS-NDVI time series are the best choice to meet our study requirements for detecting forest changes with such frequency and resolution.

Forest change driving forces not only climate factors but also human forces need to be discussed for better understanding the forest change mechanism in the study area. However, this study area still lacks forest-focused change detection to reveal spatio-temporal distribution of forest change using long time series. By performing this research, gradual and abrupt forest changes in trend and seasonal components within MODIS-NDVI time series were extracted using BFAST model and were characterized with trend, frequency and magnitude, which will contribute to better monitoring forest change hot spots and for better understanding the forest change mechanism in semi-arid areas in China.

1.4. Research objectives

General objective:

The main objective of the study is to detect and characterize spatio-temporal forest changes in the eastern section of semi-arid region in China, and assess its association with climatic and human factors over 14 years (2000-2013) using satellite image time series and BFAST model.

Specific objectives:

- To detect the trend of gradual forest changes in the eastern section of semi-arid region in China between 2000 and 2013.
- To determine the frequency and magnitude of abrupt forest changes in the eastern section of semi-arid region in China between 2000 and 2013.
- To identify the hot spots of forest change in the eastern section of semi-arid region in China.
- To examine the correlation of forest change with selected climatic variables (precipitation and temperature) and human disturbance factor (urbanization).

1.5. Research questions

- What is the gradual forest change trend in the study area between 2000 and 2013?
- What are the frequency and magnitude of forest changes in the study area?
- Where are the hot spots of forest changes?
- Does the spatio-temporal patterns of forest change correlate with the selected climatic and human factors in the study area?

1.6. Research hypotheses

- Hypothesis 1
  H_0: There is no significant forest change trend detected over the 14 years between 2000 and 2013.
  H_1: The majority of forests in the study area has gradually increased over the 14 years between 2000 and 2013.
- Hypothesis 2
  H_0: There is no significant correlation between forest changes and human disturbance factors and climate factors.
  H_1: Abrupt forest changes (mainly loss) detected in this area has a significant and stronger correlation with human disturbance factors rather than climatic factors.

1.7. Thesis structure and research approach

In chapter 1, basic background is described with literature reviews of previous work, explanation of the research problem is provided, definitions of the research objectives, questions and hypotheses and the description of the outline of each chapter are explained. Chapter 2 introduces the study area from both natural and social aspect, with the explanations of data collection and data processing methods. Chapter 3 showing the result and explained the findings relevant to each research questions. Chapter 4 discusses the main findings of forest change and the approach in this research. Chapter 5 concludes the research and gives recommendations for potential further work.

Figure 1 describes the whole flowchart of main approaches consists in the research. The main body of the overall workflow can be divided into two parts. For the first part, pixel level MODIS-NDVI time series were extracted and pre-processed before input into BFAST model. The another part shows the running of BFAST model on the extracted time series and the spatial analysis, hot spot analysis with the forest change results, as well as the correlation analysis with urbanization and climate variables.

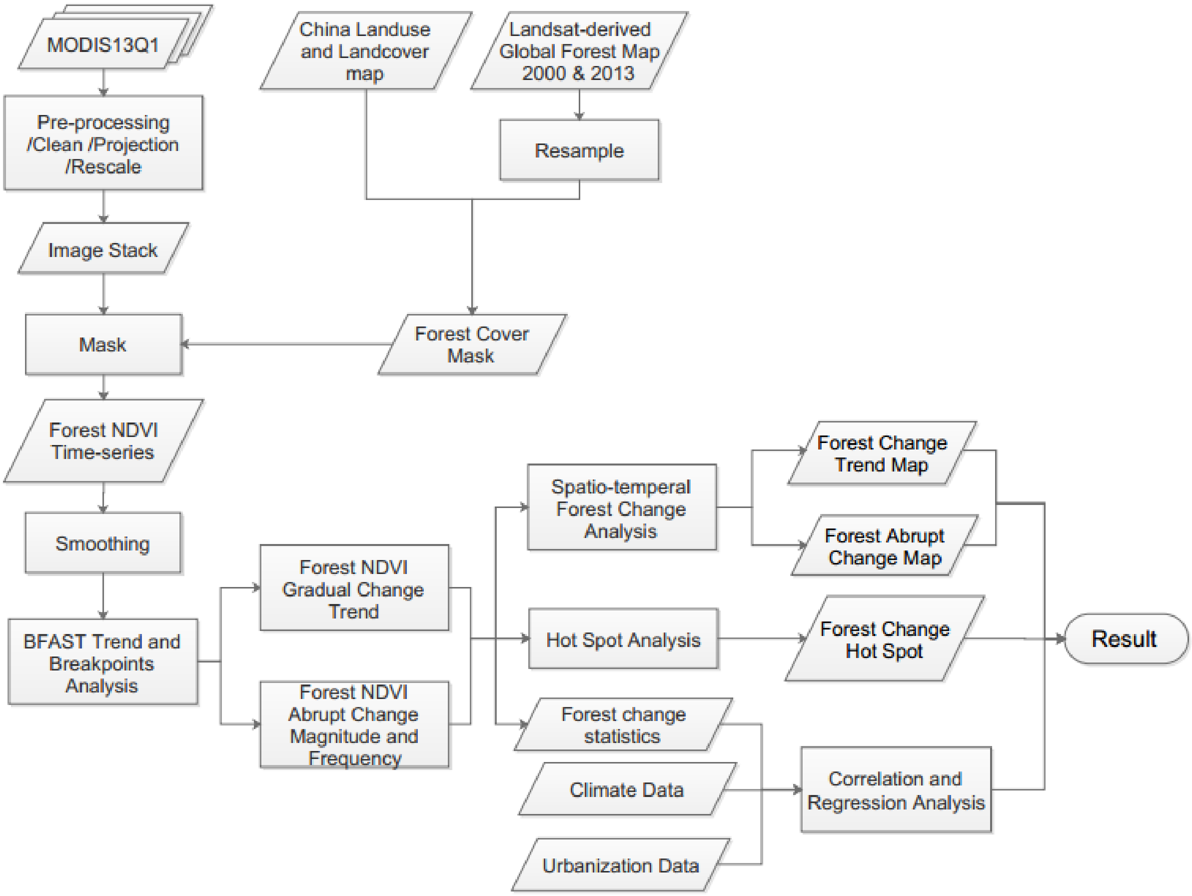

Figure 1. Research approach flowchart

2. MATERIALS AND METHODS

2.1. Study area

The study area consists of twenty-four counties, all of which are within Inner Mongolia Autonomous Region of China. The total area of land cover is 360,620 km², and the general social-economic data of each county are shown in Table 1 from census data of statistical yearbook of Inner Mongolia in the year 2000, which can be acquired from the website of National Bureau of Statistics of China (http://www.cnstats.org). The majority of the study area locate within northeast part of semi-arid climate from 42° - 53° N and 110° - 127° E as is shown in the arid and semi-arid distribution map (Figure 2). It is a typical forest-steppe ecotone with 146,071 km² of forest cover, which is sensitive to climate and human disturbances and the vegetation cover varies over spatial and temporal. According to Liu *et al.* (2015) the mean annual temperature is 2-12℃ and the mean annual precipitation is between 260-450 mm. The dominant tree species in the forest is *Pinus tabu- laeformis* Carr., another two common species are *Larix chinensis* Mill. and *Abies fargesii* Franch., with unusual forest mortality phenomenon observed here recent years (Kharuk *et al.*, 2013; Liu *et al.*, 2015). Map on the right side in Figure 2 shows the forest presence of each county in 2000 with county ID marked according to Table 1.

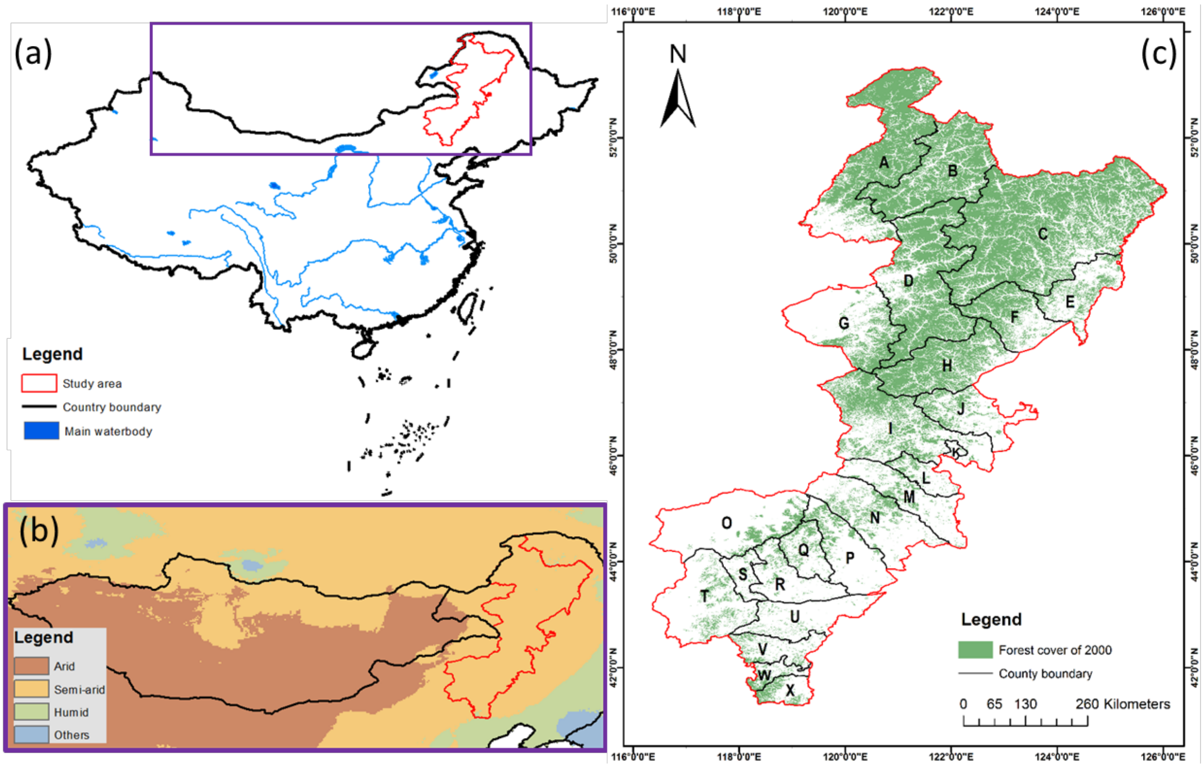

Figure 2. Location of the study area. (a) location of the study area in China; (b) location of the study area in arid and semi-arid distribution map of northern China; (c) forest cover map in 2000 with county ID.

As is shown in Table 1, the majority of the forest covers the northern part of the study area, and the counties located in south-eastern part are with higher density of population. What's more, counties with higher GDP mostly gathering in the southern part, and the county K is the county with least forest and land cover, but with a considerable economic level.

Table 1.Social economic data with forest and land cover information of each county

County ID	County NAME	GDP (10^8 RMB)	GDP Per Capita (RMB)	Population	Land Cover (km^2)	Forest Cover (km^2)
A	Ergun City	37	44,268	83,574	28,590	18,979
B	Genghe City	30	17,415	172,263	20,010	14,761
C	Oroqen Autonomous Banner	53	20,139	265,473	54,947	38,250
D	Yakeshi City	190	53,700	354,098	27,734	19,060
E	Morindawa Daur Autonomous Banner	90	27,418	328,482	10,177	2,700
F	Arun Banner	129	39,102	330,414	11,076	5,641
G	Evenk Autonomous Banner	93	64,561	143,473	18,756	4,582
H	Zhalantun City	104	24,323	366,300	16,800	11,125
I	Horqin Right Front Banner	75	22,163	338,427	25,581	9,799
J	Jalaid Banner	70	17,538	399,204	11,099	2,566
K	Ulanhot City	130	40,451	321,387	786	64
L	Tuquan County	56	17,858	313,680	4,719	933
M	Horqin Right Middle Banner	48	18,551	258,761	11,837	1,486
N	Jarud Banner	162	53,108	305,731	17,344	2,725
O	West Ujimqin Banner	102	129,012	79,149	22,716	2,198
P	Arhorqin Banner	92	30,633	299,559	12,926	1,851
Q	Bairin Left Banner	100	28,182	355,589	6,418	1,597
R	Bairin Right Banner	61	33,025	184,957	9,856	956
S	Linxi County	58	24,222	240,136	3,905	448
T	Hexigten Banner	124	49,204	252,134	19,053	2,112
U	Ongniud Banner	118	24,283	486,318	11,883	612
V	Songshan District	194	35,925	540,000	6,998	1,251
W	Harqin Banner	66	18,702	350,390	3,106	1,013
X	Ningcheng County	136	22,362	608,166	4,304	1,364

2.2. Data preparation

2.2.1. MODIS-NDVI time series data collection and processing

MODIS Terra vegetation index product images of MOD13Q1 of version 6 are available from NASA web facility (http://reverb.echo.nasa.gov/). This product produced at 16-day intervals and with multiple spatial resolutions, provides consistent spatial and temporal comparisons of vegetation canopy greenness, a composite property of leaf area, chlorophyll and canopy structure. The period span of the dataset downloaded is from 18th Feb 2000 to 18th Feb 2014 with totally 1292 images, per scene of the study area consists of 4 images, the time series contain 323 scenes of the study area with 23 scenes per year. Per study area scene cover of 4 images with the identifier tiles of h25v3, h25v4, h26v4 and h27v4. The projection of the images is sinusoidal under WGS84 spheroid.

MODIS-NDVI images with spatial resolution of 250m are imported using ERDAS from the original product. MOD13Q1 has already checked the data quality and done de-cloud according to the manual. As NDVI values code from -3000 to 10000, rescaling was performed to reduce file size by deriving DN values from 0-255 using the code provided by ITC (Ali *et al.*, 2014). After this, the re-scaled 323 images of 2000-2013 each scene were stacked through Erdas. TIMESAT program is an ideal method to reduce potential noise using adaptive Savitzky-Golay, which can be applied to derive smoothing NDVI time series (Jönsson & Eklundh, 2004). As the smoothing of the time series will affect the result of the BFAST analysis in a certain degree, smoothing should not be done too much which may hide some character of NDVI change leading to not being detected in BFAST. Here we performed Savitzky-Golay smoothing function in the second level using TIMESAT.

2.2.2. Forest cover mask

In this study, change detection methods were applied focus on the specific land cover of forest. We performed change detection within forest landscape with a forest cover mask derived from Chinese Land Use and Land Cover Map of 2000 with 250m spatial resolution. The map was acquired from Institute of Geographic Science and Natural Resources Research and was achieved from remote sensing interpretation and national land survey. As lacking the map source of comparable Chinese land cover map of 2013, we used Hansen's forest cover map as complementation. Based on this forest mask we managed analyzing every pixels' time series. The base map was complemented using a combination of Hansen *et al.* (2013)'s global forest cover map (http://earthenginepartners.appspot.com/science-2013-global-forest/download_v1.2.html), including forest cover areas both presence in the year 2000 and 2013. Hansen *et al.* (2013)'s work of forest cover change maps derived from Landsat images have a spatial resolution of 30m. Here, by resampling them into images with comparable spatial resolution with MODIS-NDVI of 250m, they were used as a component of forest reference mask. The final forest mask is shown in Figure 2, consist of 2,337,140 pixels with the resolution of 250m.

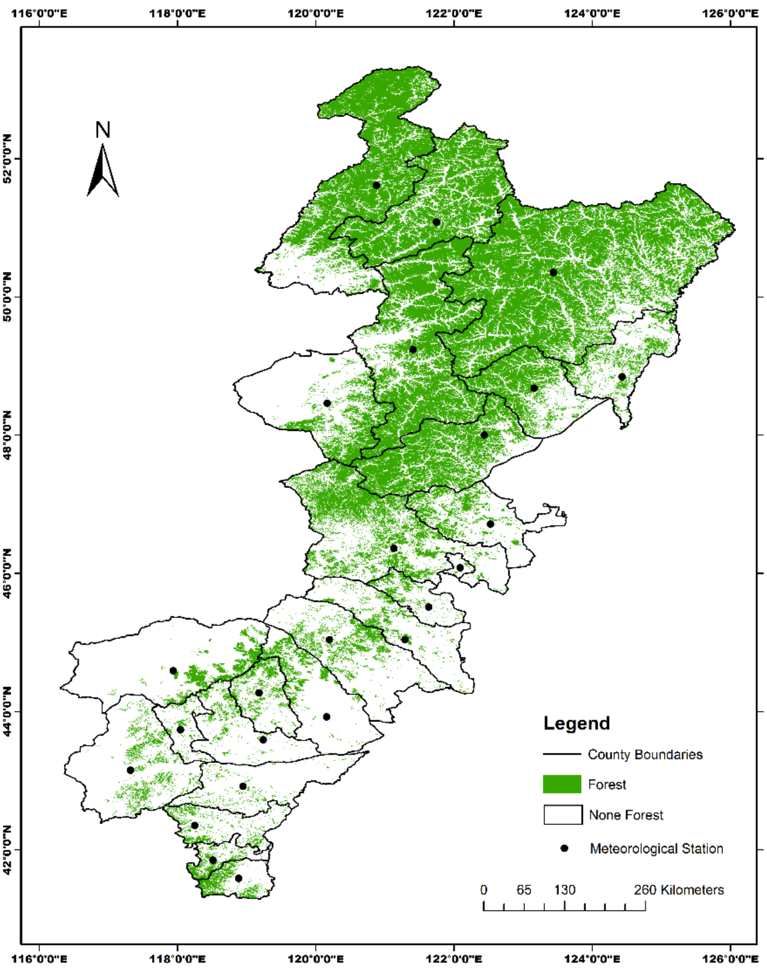

Figure 3. Forest mask in the study area

2.2.3. Climate data

Climate data was downloaded from the China Meteorological Data Sharing Service System of the China Meteorological Administration (http://cdc.nmic.cn/home.do). The location of 24 meteorological stations in each county of the study area is shown in Figure2. As vegetation change in semi-arid region is sensitive to climate variables especially extreme climate events (Tong *et al.*, 2016), special statistics represent for extreme precipitation and temperature events were selected and downloaded from the each meteorological station. Each meteorological station located in each county is represented by a comparable small letter of the county ID for later analysis of this thesis.

The index for precipitation selected is the Days of the Longest Period Continuously without Precipitation (DLP) during the study period 2000-2013. The index for temperature selected is the mean value of Days of the Longest Period Continuously with Maximum Temperature Above 35℃ (DLT35) in each year from 2000-2013. The values of the two indices for each meteorological station is shown in Table 2.

Table 2. Meteorological station records of two climate indices from 2000-2013

Meteorological Station ID	DLP	DLT35
a	151	1.3
b	138	3.8
c	116	4.5
d	98	2.5
e	60	1.3
f	63	1.4
g	113	0.9
h	96	1.7
i	105	2.2
j	98	1.5
k	35	0.2
k	39	0.4
m	42	0.6
n	37	0.3
o	49	1.1
p	94	5.7
q	39	0.1
r	116	2.9
s	77	2.8
t	46	1.2
u	74	1.6
v	98	0.4
w	120	3.8
x	34	0.1

Under the influence of elevation and other terrain factors, climate variables especially temperature vary within study area. Here we assume the records of the meteorological station were reliable within the 5km buffer, which means the pixels within the 5km circle of the corresponding meteorological station have the same precipitation and temperature condition. These pixels within each meteorological station buffer were extracted and the mean values of their forest change indices were calculated and recorded.

2.2.4. Night-time light image

Our study area is with a background of rapid urbanization since 1978 (Liu & Leung, 2015) and a booming start from the end of 20th century. Urbanization process will not only cause conversions of forest cover to other land uses, but also increase human disturbances of logging and other human-related activities (Verbesselt *et al.*, 2010b). Night-time light image products of remote sensing are getting popular in the research field of urban land detecting because its productive capacity of deriving proxy features stand for urbanization (Liu & Leung, 2015). DMSP-OLS Nighttime Lights Time Series Version 4 are popular because of it can provide the long time series of global urban land, and give beautiful panoramic views of humanity (Elvidge *et al.*, 2013).Here we used the images of this product for developing human disturbance of urbanization indices from 2000 to the end of 2013. DMSP-OLS Nighttime Lights Time Series Version 4 are free and available from the website of the National Geophysical Data Center of the National Oceanic and Atmospheric Administration of the USA (http://ngdc.noaa.gov/eog/dmsp/). It is a cloud-free annual data excluded with noises like sunlit, sun glare, moonlit and others. The data products provide gridded cell based on stable night- time lights with a digital number (DN) ranged from 0 to 63. Night-time light time series in our study area were extracted and the urbanization from 2000 to 2013 was presented by the DN values variation per pixel. Night-time average light over China in 2000 is shown in Figure 4.

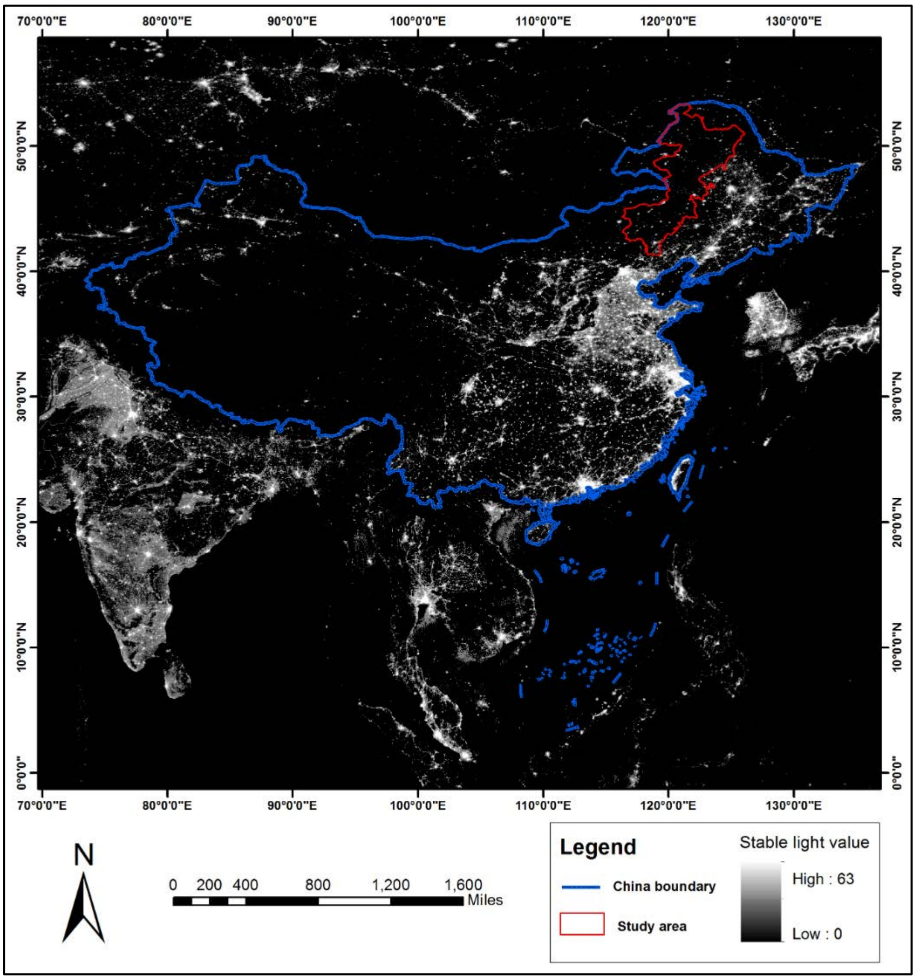

Figure 4. Night-time average stable light from space 2000_ DMSP-OLS

The row product of the night-time light images cannot be compared pixel to pixel among the time-series, as the satellite sensor was aging and was replaced by certain years (2004 and 2010) when it was out of commission. Several ways can reduce these problematic issues, one way is to apply the log light per area when doing regression with other indices according to Henderson *et al.* (2012). Here using parameters according to Elvidge *et al.* (2013) we performed inner-calibration of the final yearly time series. To represent the character of night-time light change within the study area during study period, the mean value of the night-time light from 2000-2013 each county was calculated, also the slope of the trend produced from simple linear regression of the mean values were calculated. As is shown in Figure 5, the procedure of deriving these two indices is as described as followed. Each of the yearly nighttime light images from 2000-2013 was extracted by study area mask from geometrically correlated images. Then the extracted night-time light images were stacked in order from the year 2000 to 2013, for each year, mean values of night-time light DN value in each county were recorded.

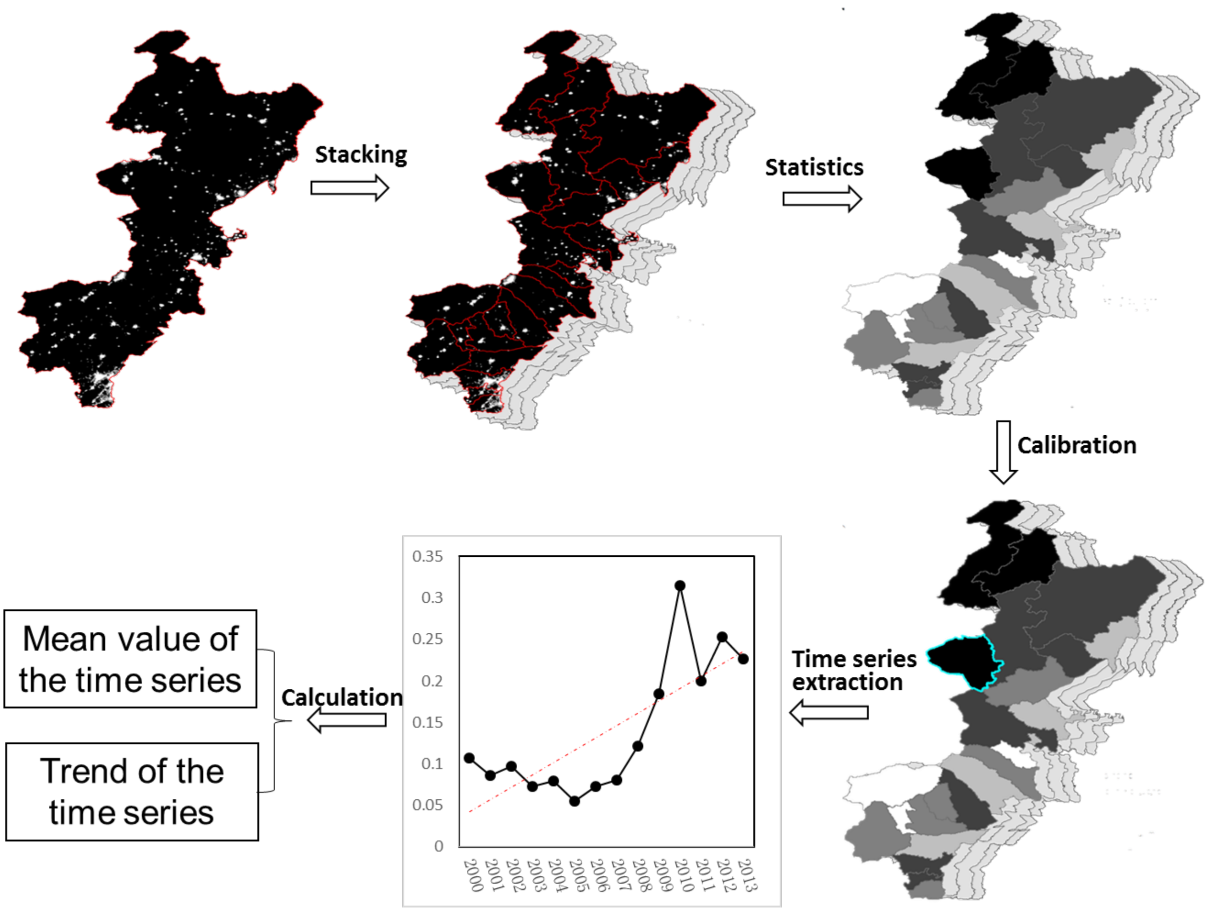

Figure 5. Steps for deriving night-time light indices per county of 2000-2013 for this research

2.3. Change detection with BFAST

BFAST can analyze remote sensing time series by decomposing it into 'trend', 'seasonal' and 'remainder' components per pixel (Verbesselt *et al.*, 2010). These analyses were performed using the BFAST package (http://rpackages.ianhowson.com/rforge/bfast/) in the statistical environment R. According to Verbesselt *et al.* (2010), the BFAST model is described as the equation followed:

$$Yt = Tt + St + et, \ t = 1 \dots n,$$

where Yt is the time series data at time t; Tt is the trend component which refers to changes of long-term change trend; St is the seasonal component which refers to phenology vary in seasons which always depend on climate variation within a year; et is the remainder component which refers to changes beyond trend and seasonal components; and n is the number of observations within time series (Lambert *et al.*, 2015). BFAST has the ability to detect changes within trend and seasonal components, where trend component has already been fitted with piecewise linear model and seasonal model with 'dummy', 'harmonic' or 'none' three types to choose from. The high performance of computing support can be activated by setting parameter 'hpc' to 'foreach', which called another package in R to support the high performance of this analysis. Here, we defined two types of the output, one is for long term trend and the other is for breakpoints. An example of time series from the study area within forest landscape is given in Figure 6.

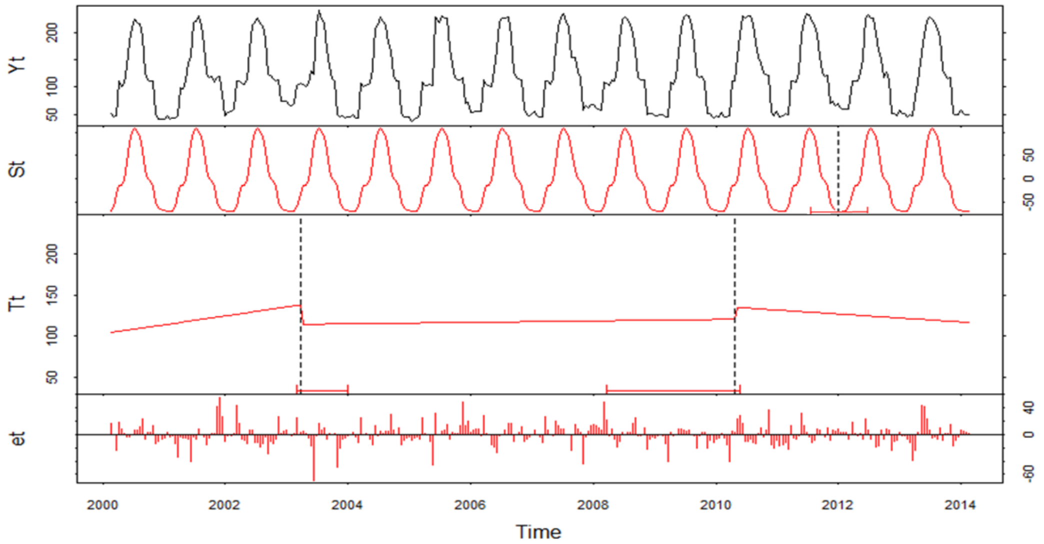

Figure 6. A time series of pixel processed with BFAST

2.3.1. Trend analysis

Trend of the time series were calculated per pixel using the whole time series to see the long-term forest change trend within trend component from 2000 to 2013. The calculated trends are the slope of the piecewise linear regression lines for each pixel. The trend direction can be either positive or negative. The trend values of pixels were grouped into three classes (significant positive, significant negative and no significant trend); the mean value of trends in each county were grouped into five classes. Then the significance of trends were assessed by testing the slope of the trend against the null slope using *t*-test according to the description of Lambert *et al.* (2013).

- Trend level 1 (slope>0, p<0.01): Significant positive trends of forest activity showing a potential forest strong growing trend.

- Trend level 2 (slope>0, 0.01<*p*<0.05): Mild positive trends of forest activity with a low degree of forest growth increasing trend.

- Trend level 3 (slope>0 or slope <0, *p*>0.05): No significant trend of forest activity change.

- Trend level 4 (slope<0, 0.01<*p*<0.05): Mild negative trends of forest change, with a low level of forest growth decrease.

- Trend level 5 (slope<0, *p*<0.01): Significant negative trends of forest change indicating the counties with forest growth seriously decreased or forest cut down.

2.3.2. Breakpoint analysis

BFAST can also identify abrupt changes in the time series by detecting breakpoints in the linear trend and seasonal components per pixel. Breakpoints detected in trend component can be recognized as events with the land cover change between forest and non-forest. Breakpoints detected within seasonal components usually indicate small quick forest changes related to phenological changes within forest. The 'h' parameter can be adjusted to define the minimum distance between detectable breaks (Lambert *et al.*, 2015). In this study, the parameter 'h' was set to meet the demand of detecting changes with a time span of at least one complete phenological cycle, which satisfied the outcome of the time gap between two breakpoints would not shorter than one year. The 'break' parameter was also set to determine the maximum of the breakpoints between 2000 and 2013. Here we chose maximum of 5 breakpoints to be detected as preparation test for randomly selected time series showing maximum 5 breakpoints was tested. Moreover, the seasonal component has several fitting selections to choose from, 'dummy', 'harmonic' or 'none', as is described in the manual of BFAST. The selection 'none' means no seasonal model be fitted, which will result in all seasonal changes detected. Here we selected 'harmonic' which fit natural vegetation seasonal growing trend most (Verbesselt *et al.*, 2010). For all the time series of each pixel, we recorded the count of breakpoints detected per pixel and extracted the magnitude of major breakpoints detected. As the number of breakpoints is a kind of proxy to represent the happening rate of the abrupt change, the recorded number of breakpoints range from 0-5 is the calculated frequency of the abrupt change but not mean exactly the real change happen in the field. The only breakpoints with frequency ranging from 1-5 were extracted to derive breakpoint distribution maps representing for forest abrupt changes. The output of magnitude in BFAST has two directions, the positive numbers mean breakpoints with sudden increasing trends of NDVI in such forest abrupt changes, the negative numbers mean breakpoints with sudden decreasing trends of NDVI in such forest abrupt changes. Moreover, the breakpoints with a bigger absolute value of the magnitude indicate these pixels presented forests with greater or severe forest abrupt changes.

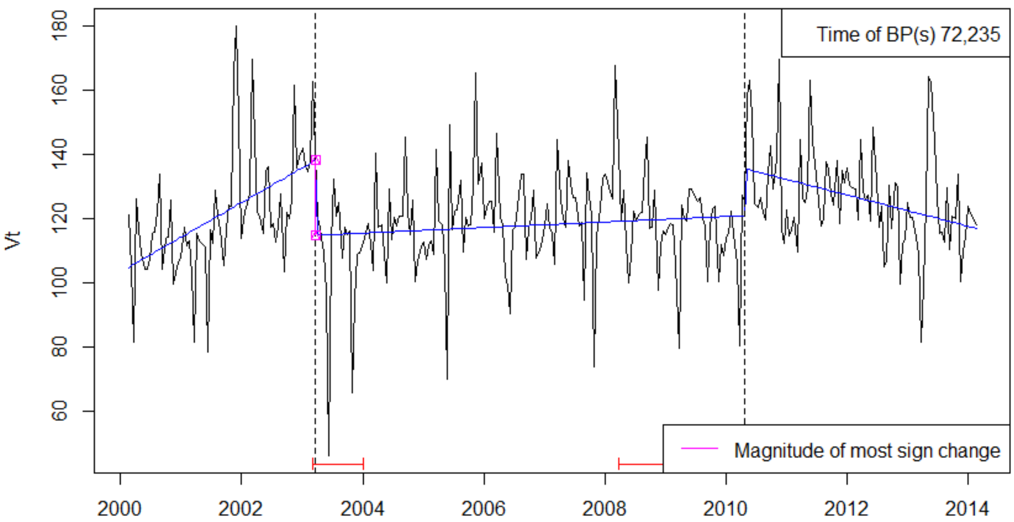

Figure 7. The breakpoints detected in trend component, the example showing 2 breakpoints detected and with the change magnitude marked with a pink line.

2.3.3. Forest change hot spot analysis

With the performance of BFAST in each extracted forest cover pixel, change trend of forest gradual change was calculated, breakpoints of the abrupt changes can be found either with a positive or negative magnitude, the number of breakpoints was also recorded as frequency of abrupt change. Hot spot analyses were performed on these BFAST produced results using Optimized Hot Spot Analysis from spatial statistics tool in ArcGIS. Firstly， hot spot analysis with change trend for both direction, pixels with extreme positive trend were recognized as with signals of high possibility of forest increase in the long term, on the other hand, pixels with significant negative trend were analysed as high forest loss risk area in the long term; Similarly, by analyzing the frequency and the magnitude of breakpoints, hot spots of high rate abrupt changes (high frequency) and hot spot of violent forest abrupt changes (high frequency) were derived. All the performances followed the ArcGIS manual, using count incidents within fishnet polygons aggregation methods. Objective inputted forest change points were counted within derived polygon with appropriate cell size. As a single high value would not be recognized as hot spot, z-core and *p*-value were measured, and multiple high value clustered cells were recognized as hot spot. In the output of the results, the default value in Gi_Bi field of +3 represented the confidence interval of 99% with most significant hot spot aggregation areas, and -3 represented the most significant cold spot aggregation areas of 99% of confidence level. The areas with value +2 and +1 had the lower significance of hot spot clustering than +3 value areas. The areas with negative values had less significance of cold spot clustering with the smaller numbers. The results can be comparable to other forest change outcomes to be a part of validation of the forest change trend analysis. Here we did hot spot analysis using Hansen *et al.* (2013)'s forest gain and forest map of 2000-2013, the hot spot derived were compared with the results of the research.

2.4. Disturbances and forest cover change correlation analysis

Simple linear regression has been widely used for correlation analysis assuming variables are independent of each other. Some of the studies proposed the possibility that vegetations in semi-arid area are sensitive to droughts with long period of high temperature and without precipitation especially under climate change (Liu *et al.*, 2013). However, forest changes will also be driven by human factors. In our study, urbanization is one of the main concerns. In order to detect how forest cover change was driven by climate factors (temperature and precipitation) and human disturbance (urbanization) at the temporal scale, a partial correlation analysis between forest changes (presented by indexes derived from NDVI time series within forest landscape mask as described in previous steps) and both climate and human factors were performed.

Here we analyzed the linear relationship between gradual forest changes and abrupt changes with the two aspects of driven factors derived from the night-time light indicator of each county using correlation analyses within each county. Since climate factors especially temperature differs with the variation of elevation and other terrain factors, we assumed the precipitation and temperature records are reliable to represent the climate within 5km buffer of the meteorological station. Coincidently, precipitation and temperature indices were correlated and regressed with mean values of forest cover change indices, which were calculated with all pixels within 5km buffer of the meteorological station. The Pearson correlation analyses with correlation coefficient (r) were calculated using SPSS. The value of r varies between -1 and 1 shows the strength of the relationship between forest cover changes and the corresponding variables.

Then, on the scatter diagrams of each group, simple linear regression lines were drawn. For each group of the variable and independence, R^2 of the regression were calculated, with the R^2 bigger and much closer to 1, the regression is more significant. Also by performing F-test statistics, the significance and the coefficient level of each regression group can be estimated by p-value. For p-value<0.01, means the regression is significant at the 0.01 level (2-tailed), for 0.05<p-value<0.01 means the correlation is significant at the 0.05 level (2-tailed). Then the strength of correlation and regression between forest change and disturbance factors were compared according to r, R^2 and p-value.

3. RESULTS

3.1. Forest change trend

The forest change trend was detected in all pixels during the study period from 2000 to 2013. The slope of the linear regression of the time series per pixel was recorded as gradual change trend of each study pixel, the result has positive and negative directions, which means forest trend of positive number representing the pixels with growing NDVI value in the long time-series, oppositely the negative value of forest trend representing the pixels showing a decline of NDVI in long term. The result of change trend recorded in raster with a spatial resolution of 250m as is shown in Figure 8, the statistical analysis for each of the county is shown in Figure 9.

In left map of Figure 8, forest change trend with positive direction in blue color occurs actively in most northern and southern part of the forest landscape and in eastern fragmental areas along the edge of the forest landscape. As forest NDVI change trends detected in BFAST had positive and negative two directions, and the significance of the change trend per pixel was calculated by comparing to zero trend, pixels were grouped into three classes by significant positive, significant negative or null. The results within 99% of the coefficient level of significant forest change trend are, significant positive change trend pixels with NDVI change trend > 0.055 and significant negative change trend pixels with NDVI change trend <-0.052. Pixels with significant change trend were extracted and shown in the right side of Figure 8.

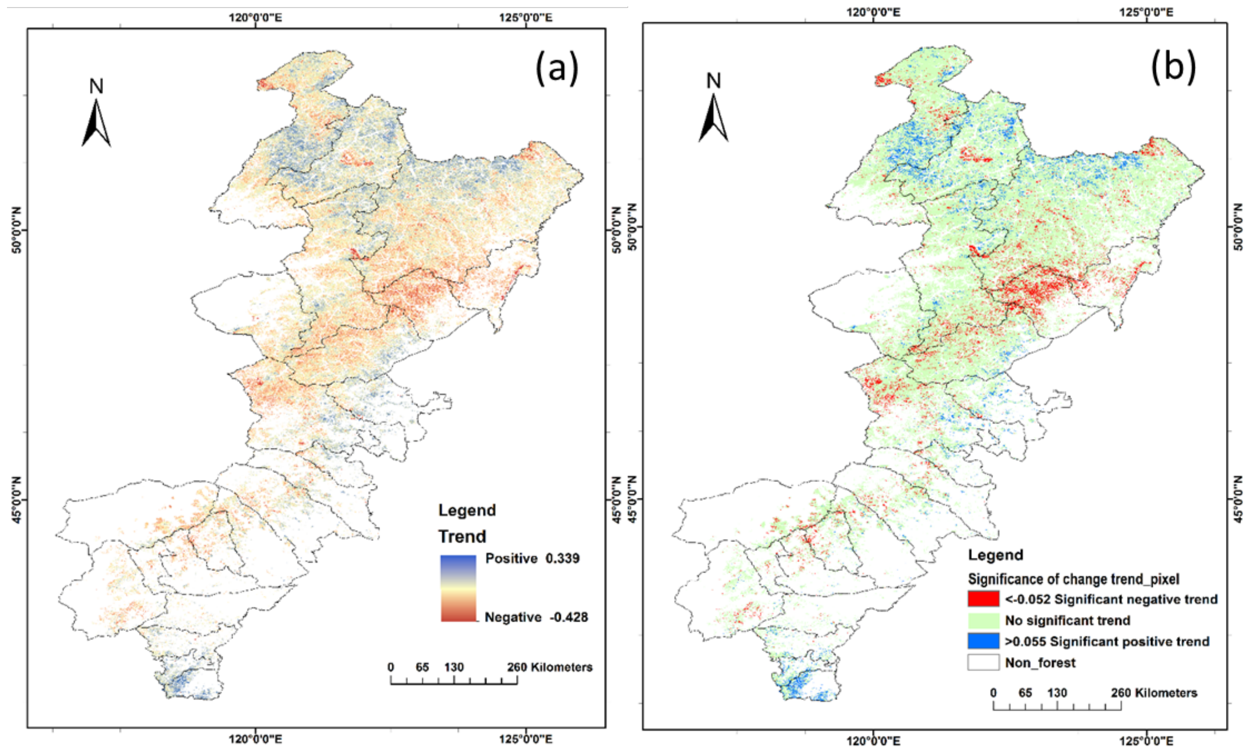

Figure 8. Long-term change trend map of NDVI within forest cover 2000-2013, (a) long-term forest gradual change trend with 250m resolution at pixel level; (b) significant positive and negative forest NDVI change trend map at pixel level.

The character of statistics of forest change trend in each county is shown in Figure 10. The histogram shows the maximum and minimum change trend pixel value occurred in each county, and the black line represents the mean value of change trend of all pixels in the county and with the mean number marked out. In Figure 10, counties were grouped into five classes with five different mean gradual change level. Combining the statistical results in Figure 11 with Figure 10, the pixels with most violent forest cover NDVI change increasing trends among 2,337,140 pixels locate in county P, the most fierce forest change declining pixels locate in county E. Counties with most significant negative trends are county E and F locate in the northeast of the study area. On the other hand, county K, county W and county X laying in most southern part of the study area are showing significant change trend of increasing. County A and county B in top northern part, county J and county L in the middle and eastern part including county V are showing mild positive NDVI increasing trends of increasing.

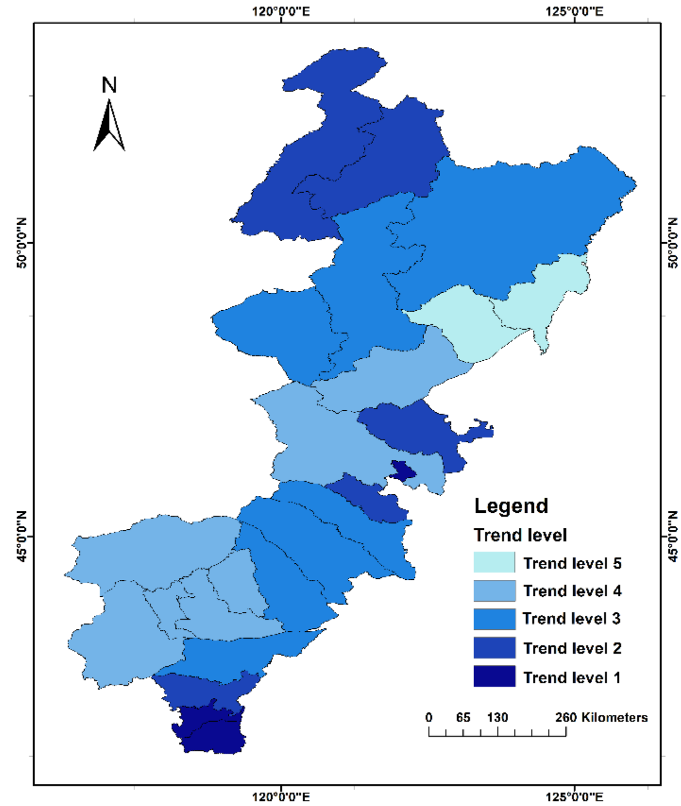

Figure 9. Forest gradual change trend classes of mean trend value at county level.

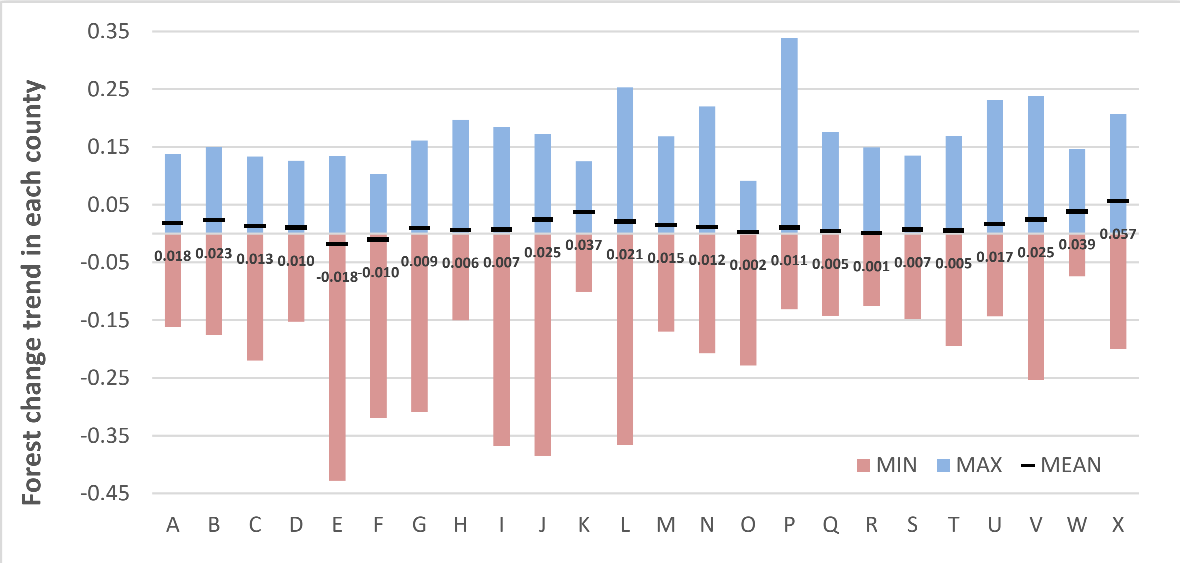

Figure 10. Total forest NDVI change trend mean value of each county with pixel maximum and minimum values during 2000-2013.

Figure 11 shows the mean value of significant negative and positive change trend in each county, the counties with highest mean change trend are county G, county J, county K and county N. Mean values of NDVI change trend of counties with significant positive change trend are shown in boxplot (i) in Figure 11. The boxplot (ii) in Figure 11 shows the mean value of negative forest change trend in each county with standard deviation.

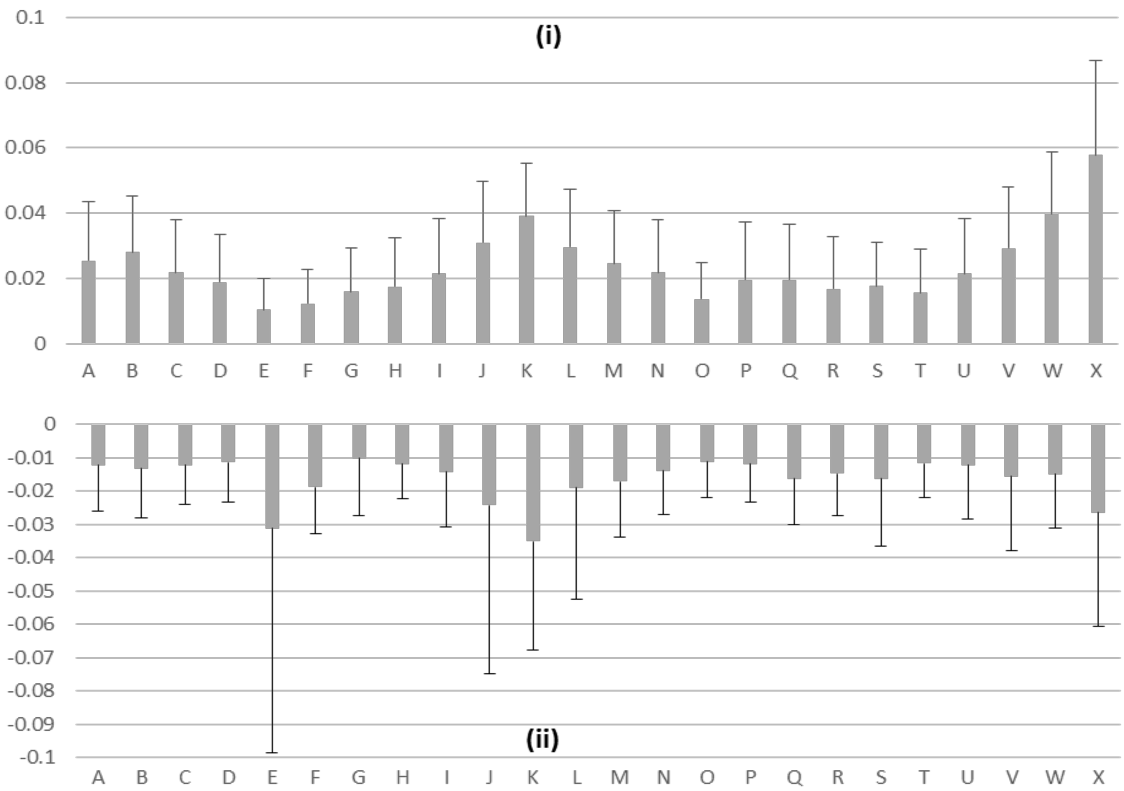

Figure 11. Forest NDVI change trend mean value in both positive and negative direction, (i) mean and standard deviation of significant positive forest change trend per county 2000-2013; (ii) mean and standard deviation of significant negative forest change trend per county 2000-2013.

3.2. Forest change magnitude and frequency

3.2.1. Forest change magnitude

The major breakpoints were recorded with the character of magnitude, either positive or negative. The result shows there are 38.9% of pixels detected with at least one breakpoints, and the total proportion of positive breakpoints is 8.4%, negative breakpoints consists 30.5%. Forest NDVI breakpoints change magnitude derived by BFAST has two directions, the positive and with bigger number ones represent breakpoints with fierce forest NDVI increase, the negative with smaller number ones represent the breakpoints with much fierce forest NDVI decrease.

Figure 12 shows the distribution of all the magnitude of breakpoints either positive or negative. The result shows that most breakpoints of each pixel are with mild positive change magnitude. The histogram (Figure 13) shows the statistical analysis results of mean, maximum and minimum magnitude of breakpoints per pixel in each county. The maximum positive magnitude was in county O and the most fierce negative forest change among the whole study area exists in county B. According to the mean value of breakpoint magnitude, counties were grouped into five breakpoints magnitude level (Figure 15).

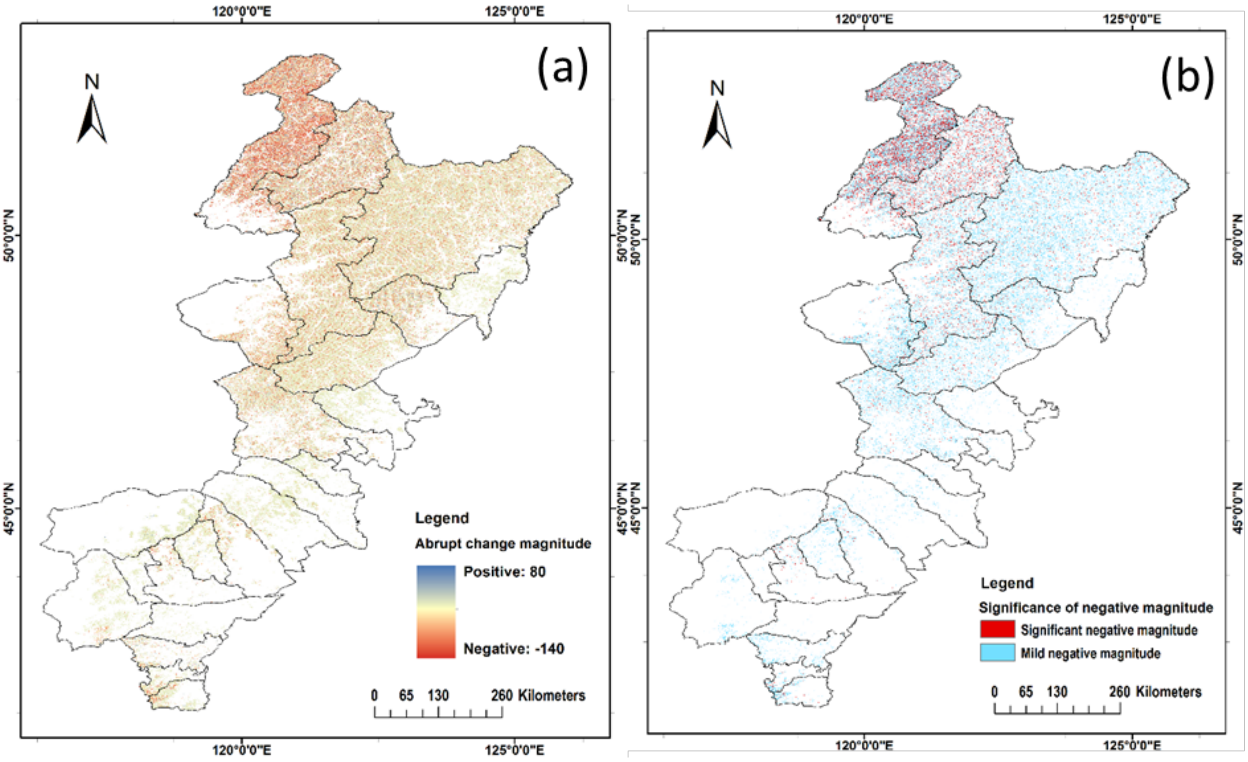

Figure 12. Forest NDVI time abrupt change magnitude during 2000-2013, (a) forest change magnitude at pixel level; (b) significant negative magnitude of forest change at pixel level.

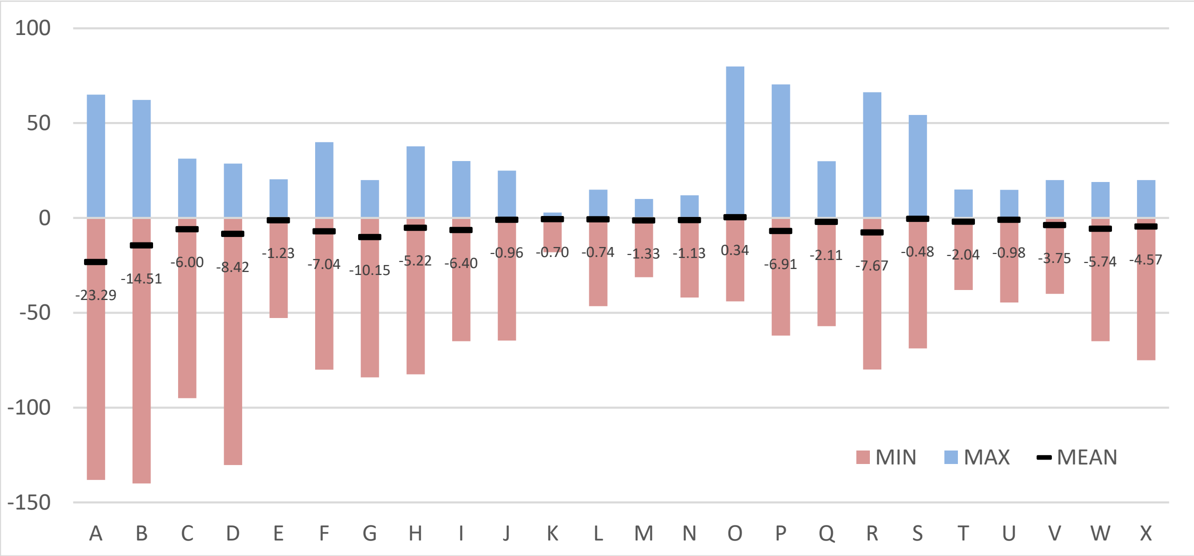

Figure 13. Forest change magnitude in each county_2000-2013

Major breakpoints with negative change were extracted and compared with the magnitude of zero to test the significance of negative change tension level. They were grouped into significant violent negative change and mild negative change classes (Figure 12). As we can see, the significant violent forest abrupt changes occur in county A and B. The boxplot (Figure 14) shows the mean values and standard deviation of magnitude for all the negative abrupt change pixels. In Figure 15, different level of forest NDVI abrupt change is derived according to the mean value of negative magnitude in each county. The most fierce abrupt forest change areas are county A and county B locate in the top northern part of the study area, country C locates in north-eastern part and county S. Other parts show mild negative abrupt changes.

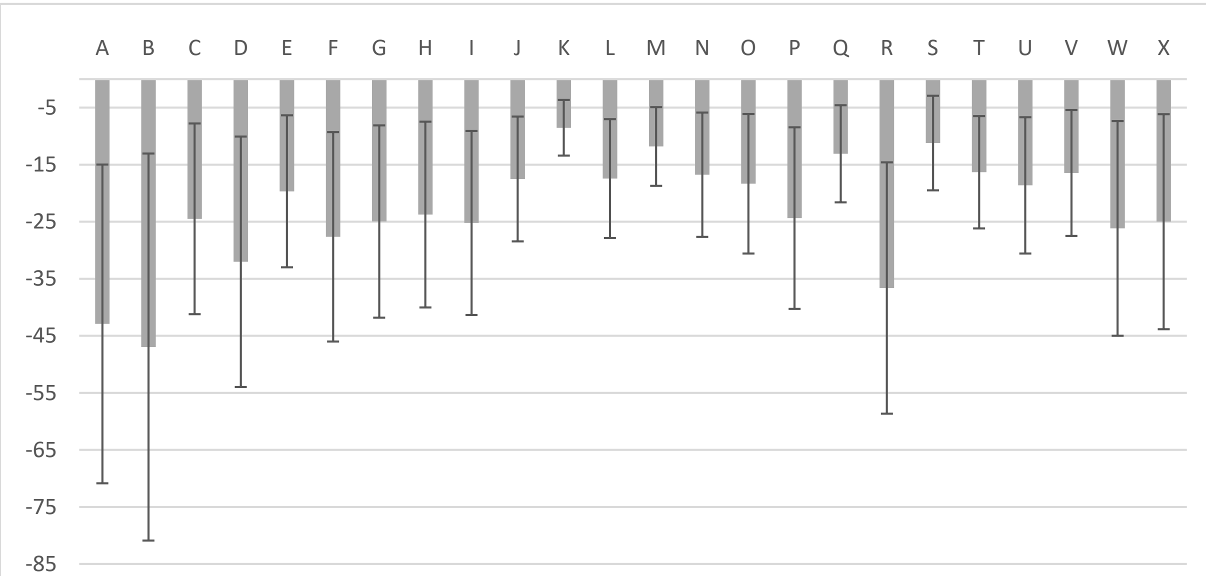

Figure 14. Mean value of forest NDVI abrupt change magnitudes with negative direction in each county

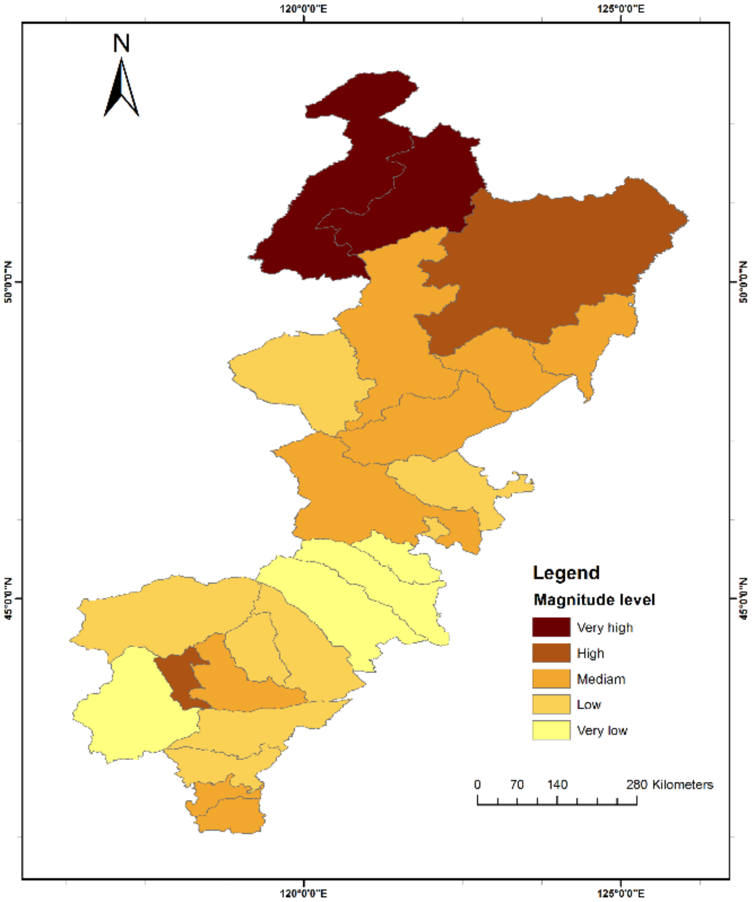

Figure 15. Mean magnitude levels of forest abrupt changes with negative direction in each county during 2000-2013

3.2.2. Forest change frequency

The breakpoints number intended to be detected can be adjusted by setting parameter of 'max.iter' also determined by 'h' which restricts the minimum time gap between two breakpoints. Here in our case, the breakpoints number per pixel detected ranged from 0-5, according to which we derived the frequency map of forest NDVI abrupt change at pixel level (Figure 16). The number 0 represents pixels with breakpoints detected which is the same meaning to the magnitude value of 0. The number 5 means five breakpoints of abrupt changes detected in BFAST, but not mean exactly five times the abrupt change has happened in the field. We grouped the change frequency into three level, the level 1 with none or one abrupt change occurred, level 2 with two or three times of abrupt changes detected, and level 3 with four or five times of abrupt change detected in BFAST. As we can see in the left map of Figure 16, pixels with a high level of forest NDVI abrupt change frequency mainly locate in the northern part of the study area, and pixels with lower frequency level mainly spread in north and east fragmental forest landscape areas.

The boxplot (Figure 17) shows statistical analysis results of mean value and standard deviation of breakpoints number per pixel. Accordingly, counties with five classes of forest abrupt change frequency is shown in right map of Figure 16. Most frequently forest abrupt changes appear in County A, county B and county G.

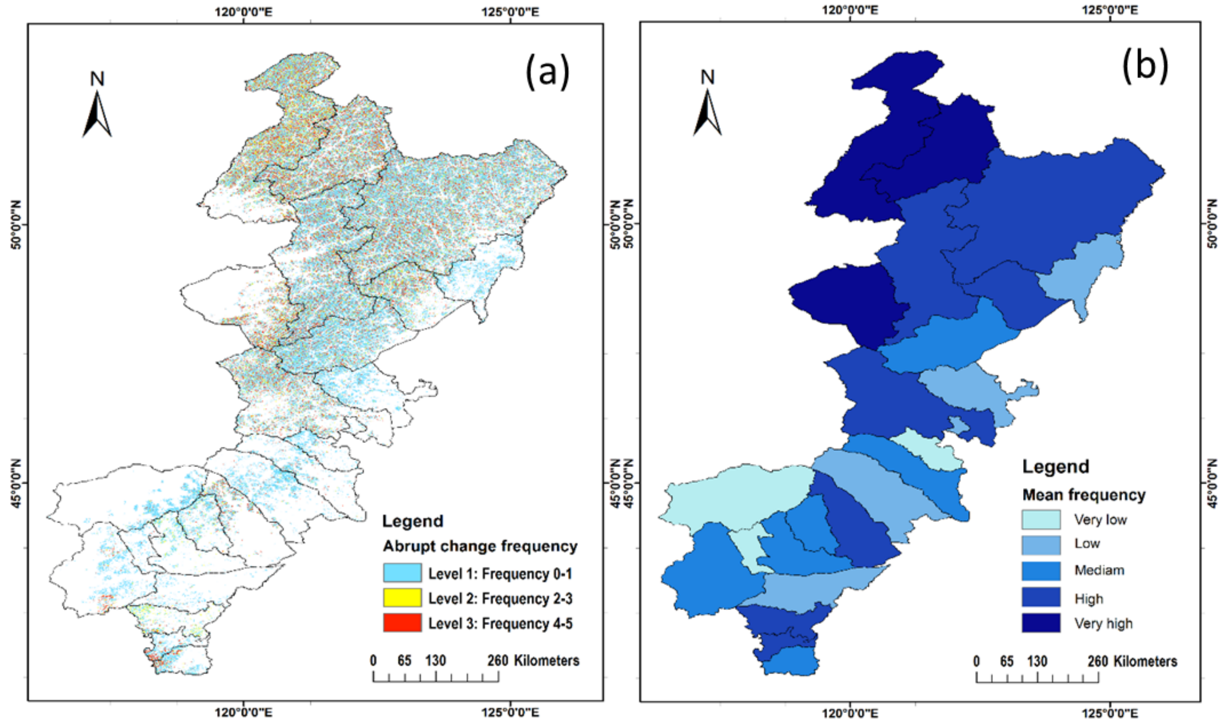

Figure 16. Forest abrupt change frequency level during 2000-2013, (a) frequency levels of forest NDVI abrupt change at pixel level; (b) mean frequency levels of forest NDVI abrupt change at county level.

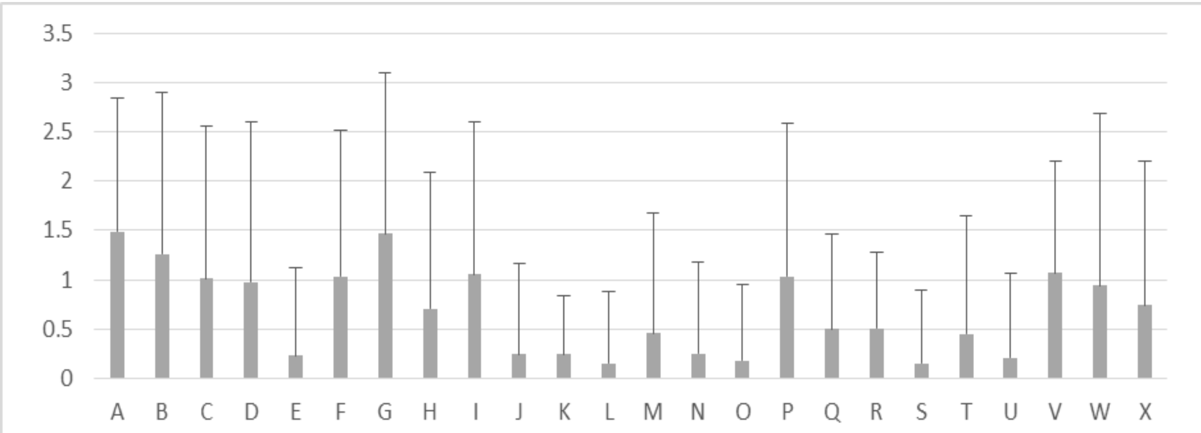

Figure 17. Mean value of forest NDVI abrupt change frequency from 2000-2013 at county level

3.3. Hot spot of forest change

Based on forest NDVI change detection results in BFAST, hot spot analysis were performed using ArcGIS function. Hot spots of extreme negative and positive forest gradual change areas, high-frequency abrupt change areas and negative violent abrupt change areas are shown.

Both hot spots of extreme negative and positive forest gradual change areas are shown in Figure 18. Hot spot areas with negative forest change trend mainly locate in the middle of the study area. By doing hot spot analysis using significant negative forest NDVI change trend pixels, extreme negative forest gradual change areas locate in county A, county B, county C, county D, county E, county F and county G, with the mostly clustered in county F. For the positive forest change trend part, hot spot analysis results performed with extreme numbers of positive forest change trend. Hot spots of forest change trend increasing areas locate in county A, county B and northern part of county C, and southern part covering most region of county W and county X.

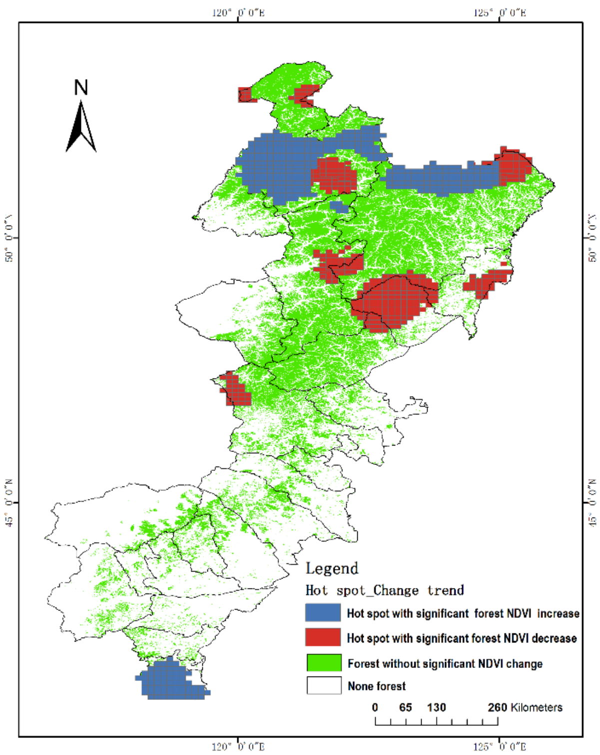

Figure 18. Hot spots of extremely negative and positive forest change trend derived from 2000-2013 NDVI time series

We derived the hot spots of Hansen *et al.* (2013)'s forest loss and forest gain which compared forest presence of 2000 and 2013, as is shown in Figure 19 for discussion.

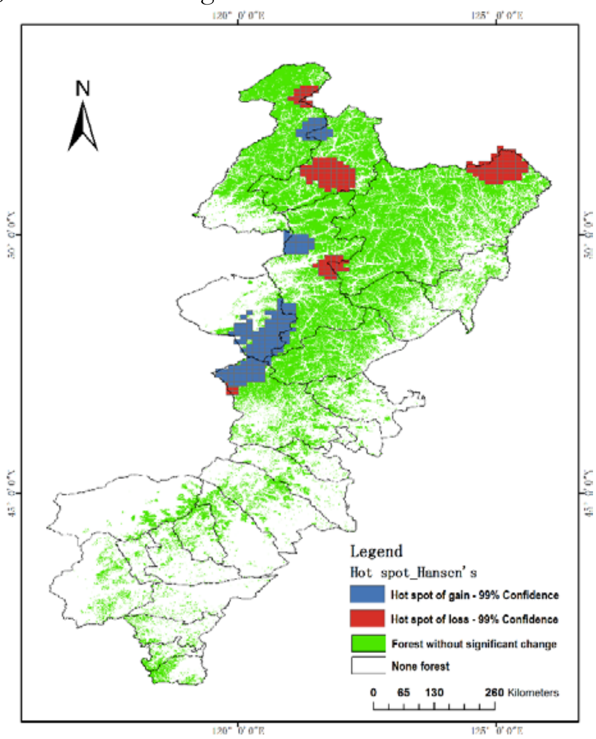

Figure 19. Hot spots of forest change trend from 2000-2013 based on Hansen's forest loss and forest gain map

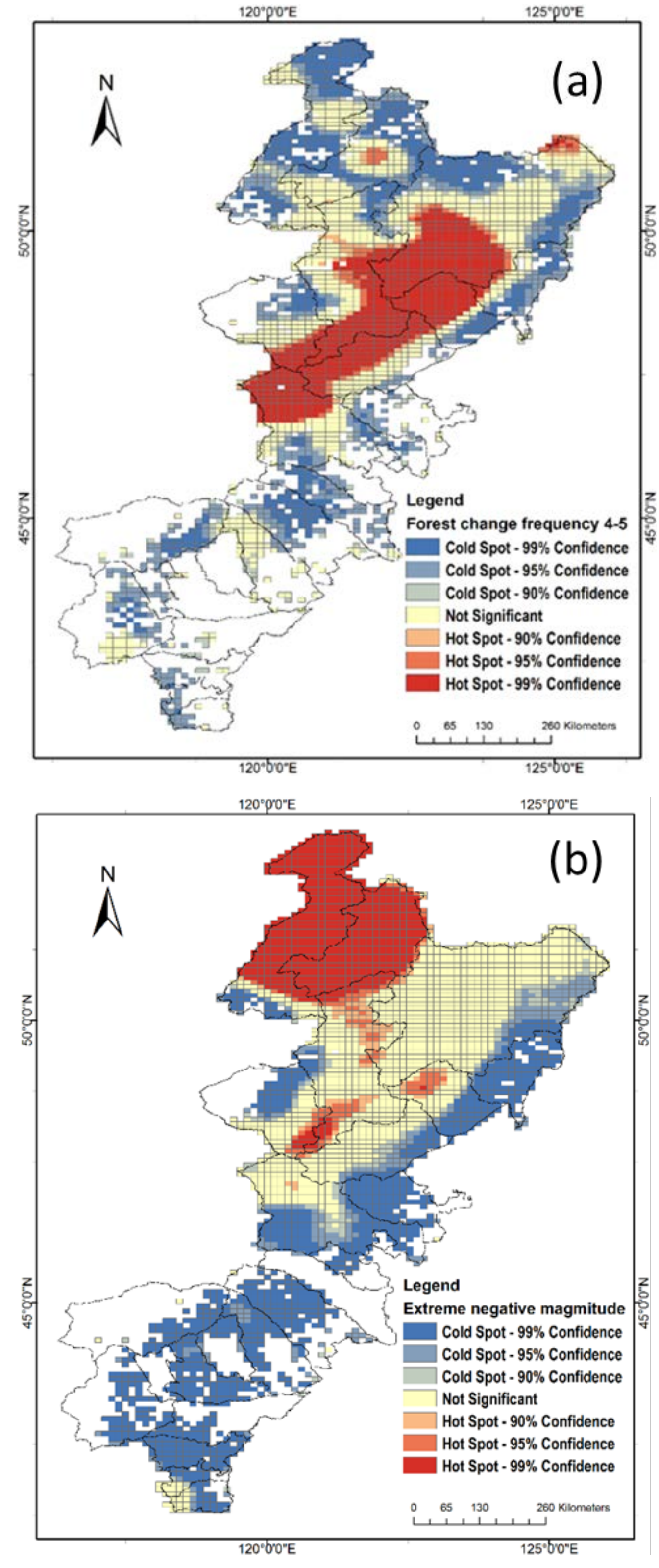

Figure 20. Hot spots of extreme abrupt forest change areas from 2000-2013, (a) hot spots of forest abrupt changes with high frequency; (b) hot spots of forest abrupt change areas with extreme negative magnitude.

Figure 20 demonstrates the results of clustering breakpoints frequency 4 and 5. Red areas represent hot spot with high frequency of forest abrupt changes, which mainly spread among the middle part of the study area covering county E, county F, county G and southern part including county C, county D, and a very little northern part of county I. The distribution is very similar to the distribution of negative forest gradual change.

3.4. Correlation analysis

Correlation between selected disturbance factors and forest change indicators of 24 counties were performed firstly with Person's correlation to check the significance of the correlation coefficient of Person (*r*), then accordingly with simple linear regression of corresponding pairs. For each pair of the linear regression, the coefficients of determination R^2(r-squared) were calculated and *p*-values of F-test were compared to see the significance of the regression. Indicators at the significance level *p*-value=0.05 were accepted as high simple linear regression pairs.

Urbanization variables

The line chart (Figure 21) shows the trends of mean and sum night-time light DN values of the whole study area through the study period 2000-2013. The mean values and the sum values of night-time light in the study area show similar growing trends from 2000-2013. With statistical analysis of the night-time light time series, indices of two aspects were derived at county level: the mean values of night-time light DN throughout the time series each county and the change trend of night-time light mean values from 2000 to 2013.

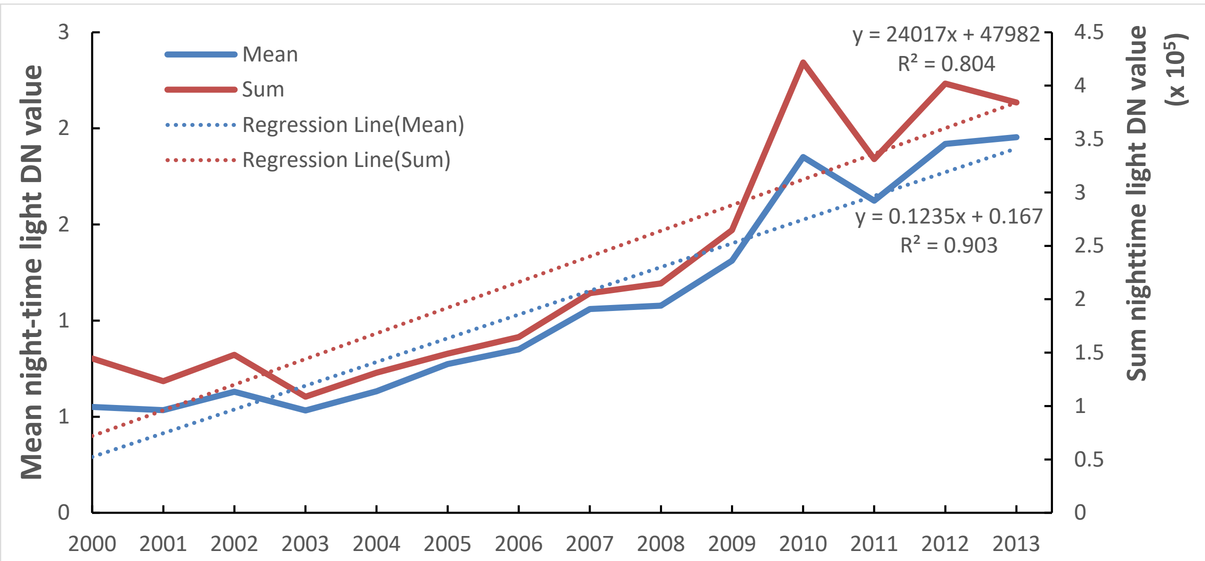

Figure 21. Trend of night-time light DN value in the whole study area from 2000-2013

The mean value of 14-year mean night-time light DN value and the change trend of mean value were selected to represent the urbanization disturbance variation and disturbance change trend among the study area at county level. As is shown in Figure 14, the counties with high mean forest urbanization disturbance factor are county K and other three southern counties. And counties with most significant positive trends of mean night-time light DN value are county K, county V and southern counties of county W and county X according to Table 3.

Table 3. Mean value and trend of night-time light DN values for each county

County ID	Mean light DN value	Trend of light DN value
A	0.139	0.015
B	0.204	0.009
C	0.170	0.015
D	0.373	0.018
E	0.501	0.066
F	0.414	0.061
G	0.477	0.041
H	0.293	0.032
I	0.223	0.032
J	0.421	0.043
K	6.866	0.708
L	0.378	0.036
M	0.181	0.022
N	0.479	0.070
O	0.203	0.044
P	0.153	0.020
Q	0.432	0.049
R	0.229	0.031
S	0.574	0.071
T	0.173	0.031
U	0.299	0.029
V	3.094	0.268
W	1.908	0.199
X	1.642	0.178

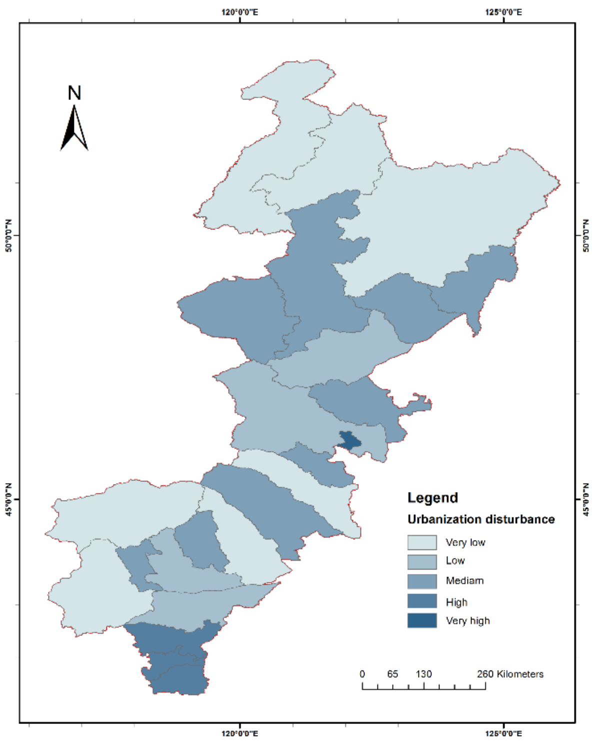

Figure 22. Urbanization disturbance level derived from mean night-time light DN value for each county from 2000-2013

Climate variables

The pixels within each meteorological station buffer were extracted and the mean values of their forest change indices from BFAST were calculated. The characters of these indices are shown in Figure 23, the forest change trend and forest change magnitude in each station buffer are characterized by minimum, maximum, and mean values. Forest change frequency is shown by histogram with mean frequency and standard deviation in the third boxplot of Figure 23. Meanwhile, the sum values of frequency are shown, which represents the total number of abrupt change occurred in each meteorological station buffer.

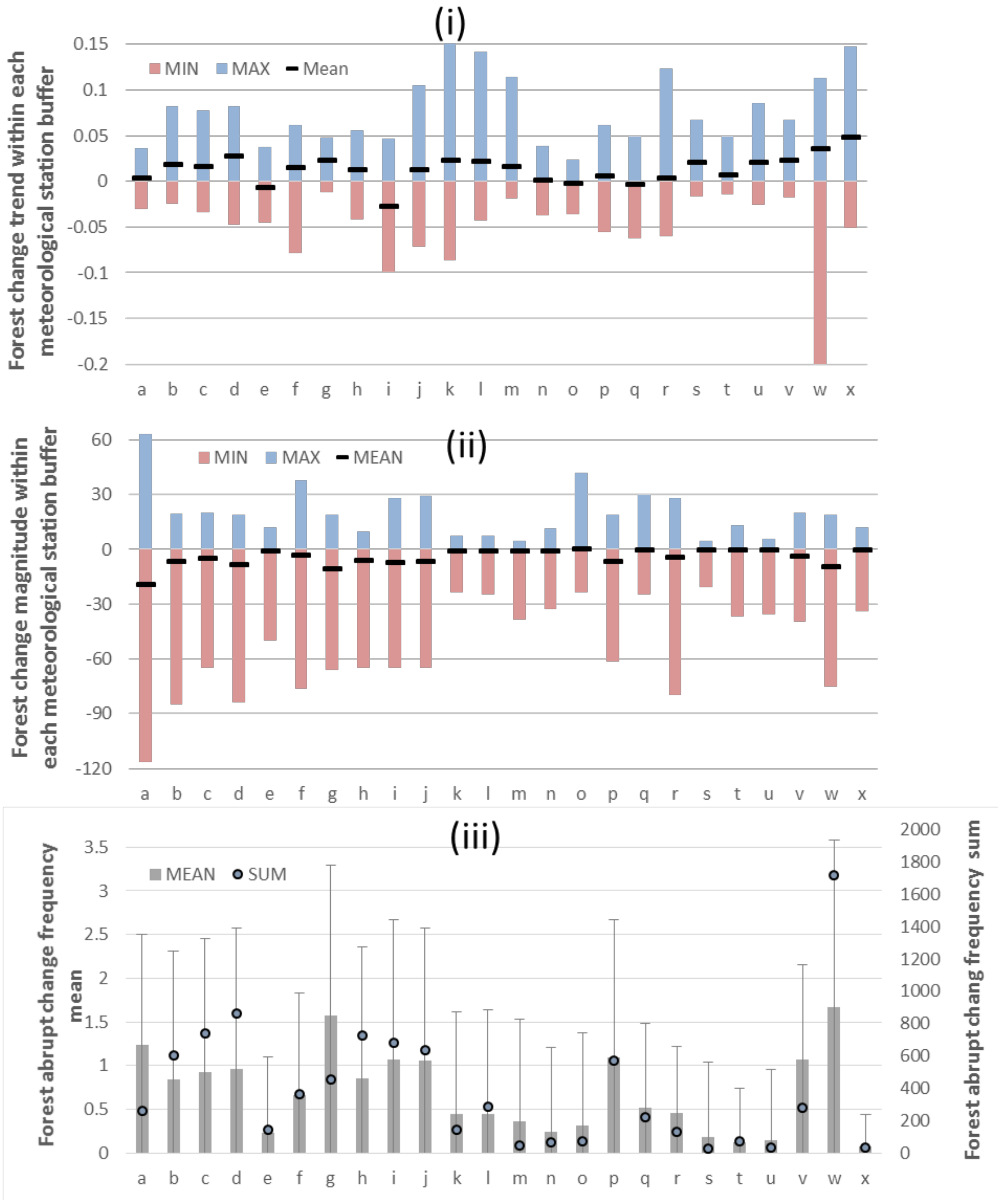

Figure 23. Forest change indices within each meteorological station buffer, (i) forest gradual change trend within meteorological station buffer; (ii) forest abrupt change magnitude within meteorological station buffer; (iii) forest abrupt change frequency within meteorological station buffer.

3.4.1. Correlation between Night-time light and forest change

The result of Pearson's correlation shows significant correlation between mean night-time light with forest change trend and mean night-time light trend with forest change trend, the *r* for each is 0.45 and 0.52. Linear regression between night-time light DN value and forest change indicators were performed at county level, as variables and independents were statistically analyzed in each county. As is shown in the first regression group in Figure 24, there is a significant linear relationship between mean night-time light DN value and forest change trend with R^2=0.276 and *p*-value=0.010. The trend of mean night-time light DN value also shows good linear correlation with forest change trend with R^2=0.244 and p-value=0.014.

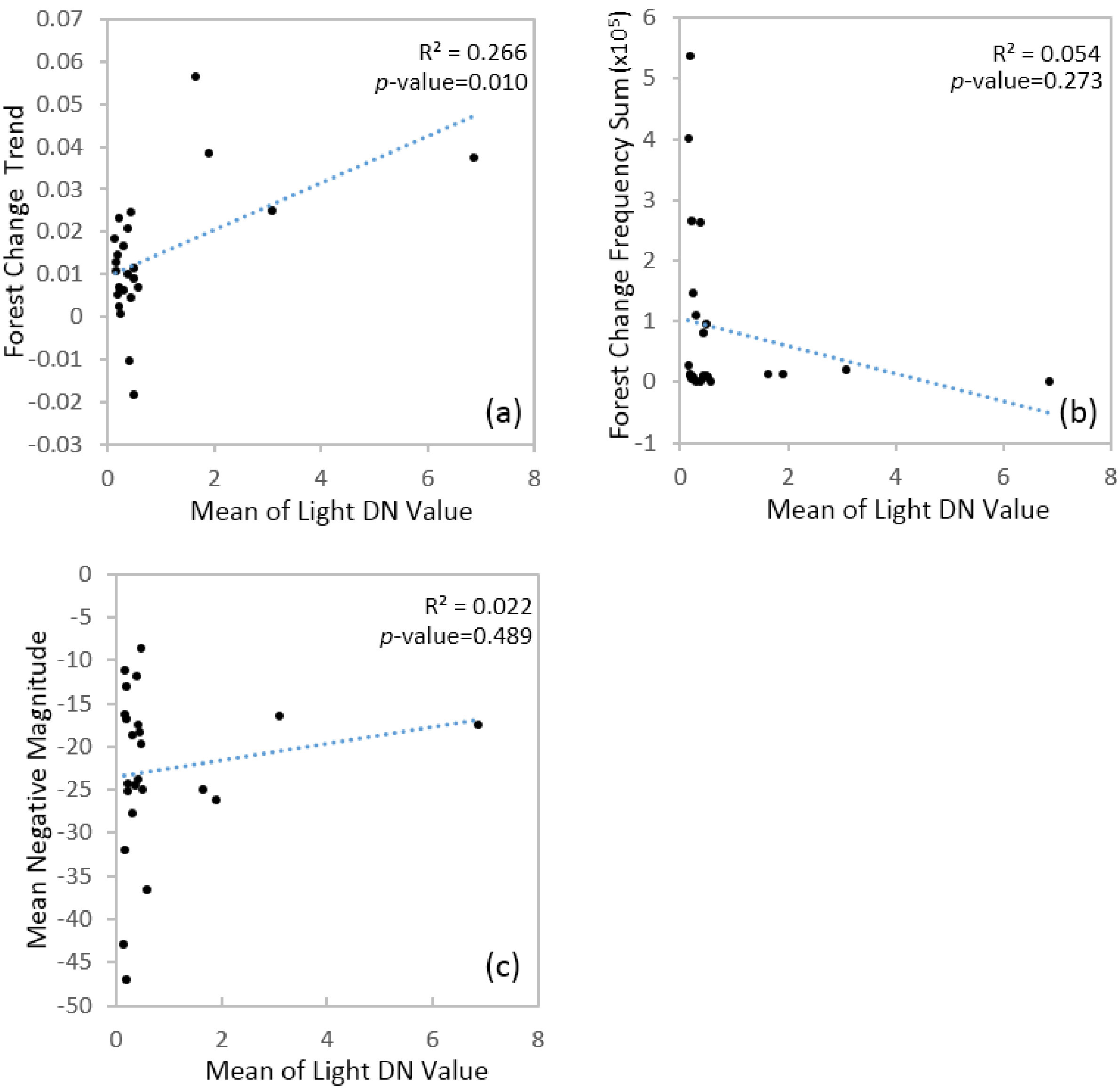

Figure 24. Correlation of forest change trend with mean night-time light data from 2000-2013, (a) the regression between mean night-time light and forest gradual change trend; (b) the regression between mean night-time light and forest abrupt change frequency; (c) the regression between mean night-time light and mean value of negative abrupt forest change magnitude.

The result showed weaker linear relationship between dynamics derived from night-time light image time-series (trend and mean) and forest breakpoints change indicators (magnitude and frequency) as is shown in Figure 25.

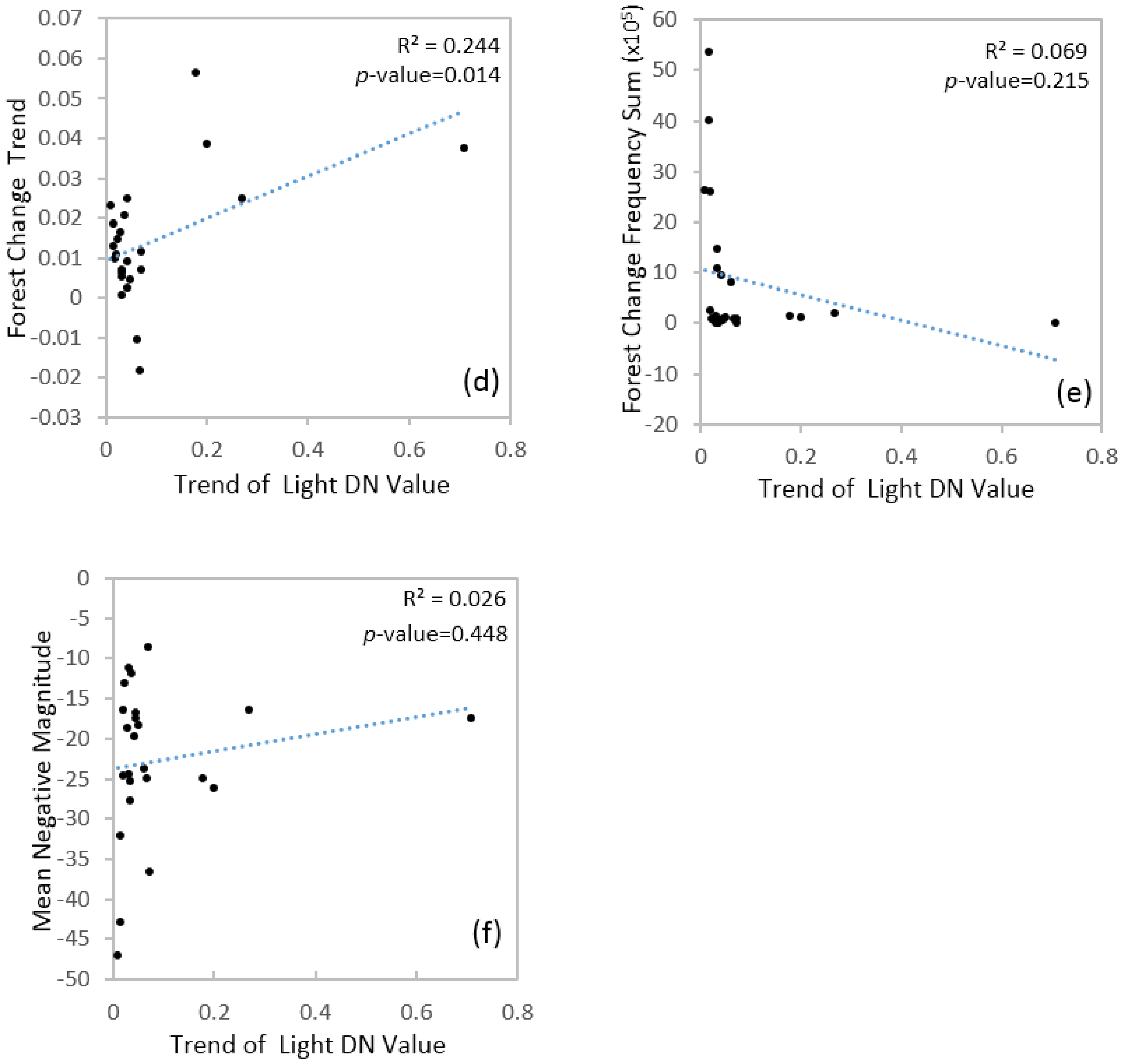

Figure 25. Correlation of forest change trend with trend of night-time light data from 2000-2013, (d) the regression between the trend of night-time light and forest gradual change trend; (e) the regression between the trend of night-time light and forest abrupt change frequency; (f) the regression between the trend of night-time light and mean value of negative abrupt forest change magnitude.

3.4.2. Correlation between climate variables and forest change

Correlation between climate variables (precipitation and temperature) and forest change indicators were performed.

The selected indicator, DLP (the Days of the Longest Period Continuously without Precipitation) represented by each meteorological station, were tested with 5km station buffer statistical value of forest change trend, mean of negative forest change magnitude and sum of forest change frequency. The results in Figure 26 indicate that the forest change trend has no significant linear relationship with precipitation (R^2=0.001, *p*-value=0.993), but has a significant regression coefficient with forest abrupt change indicators has high significance (*p*-value<0.01). Only pixels with extreme negative forest change magnitude were selected and the mean value was recorded to carry out, the linear regression with precipitation indicator. The result shows a higher linear relationship (R^2=0.502, *p*-value≈0) between DLP and extreme forest abrupt change than DLP and normal forest abrupt change (R^2=0.355, *p*-value=0.002).

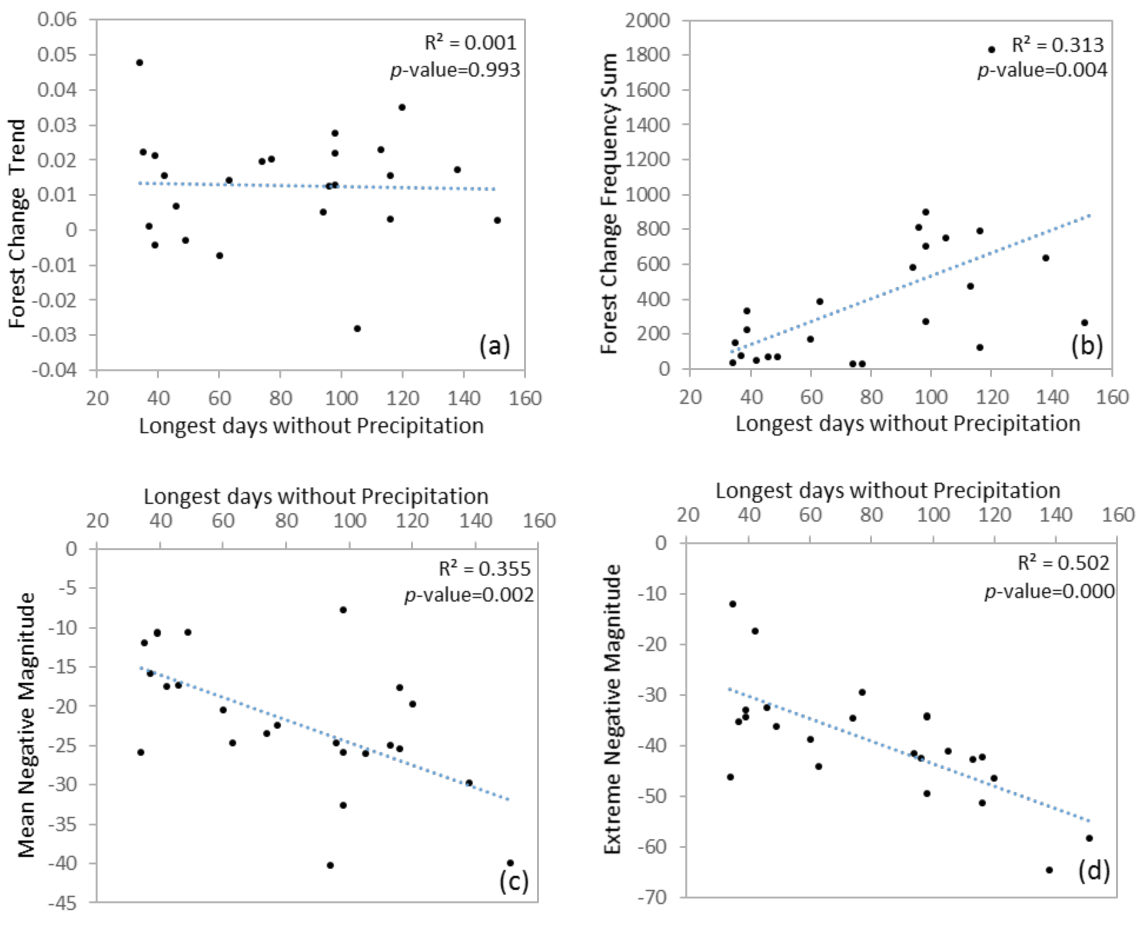

Figure 26. Correlation between forest change and precipitation from 2000-2013, (a) correlation between DLP and forest gradual change trend; (b) correlation between DLP and forest abrupt change frequency sum value at county level; (c) correlation between DLP and mean value of negative forest abrupt change magnitude at county level; (d) correlation between DLP and mean value of extreme negative forest abrupt change magnitude at county level.

The indicator of temperature here selected is DLT35 (the mean value of Days of the Longest Period Continuously with Maximum Temperature Above 35℃ each year), and the linear regression shows similar results with precipitation indicator. The indicator of extreme temperature shows no significant correlation with forest gradual change trend (R^2=0.001, *p*-value=0.993), but shows a strong linear relationship with forest abrupt change indicators (frequency and magnitude) shown in Figure 26. However, the relationship between significant negative forest abrupt change and the extreme temperature is weaker than forest change with precipitation according to R^2 and *p*-value.

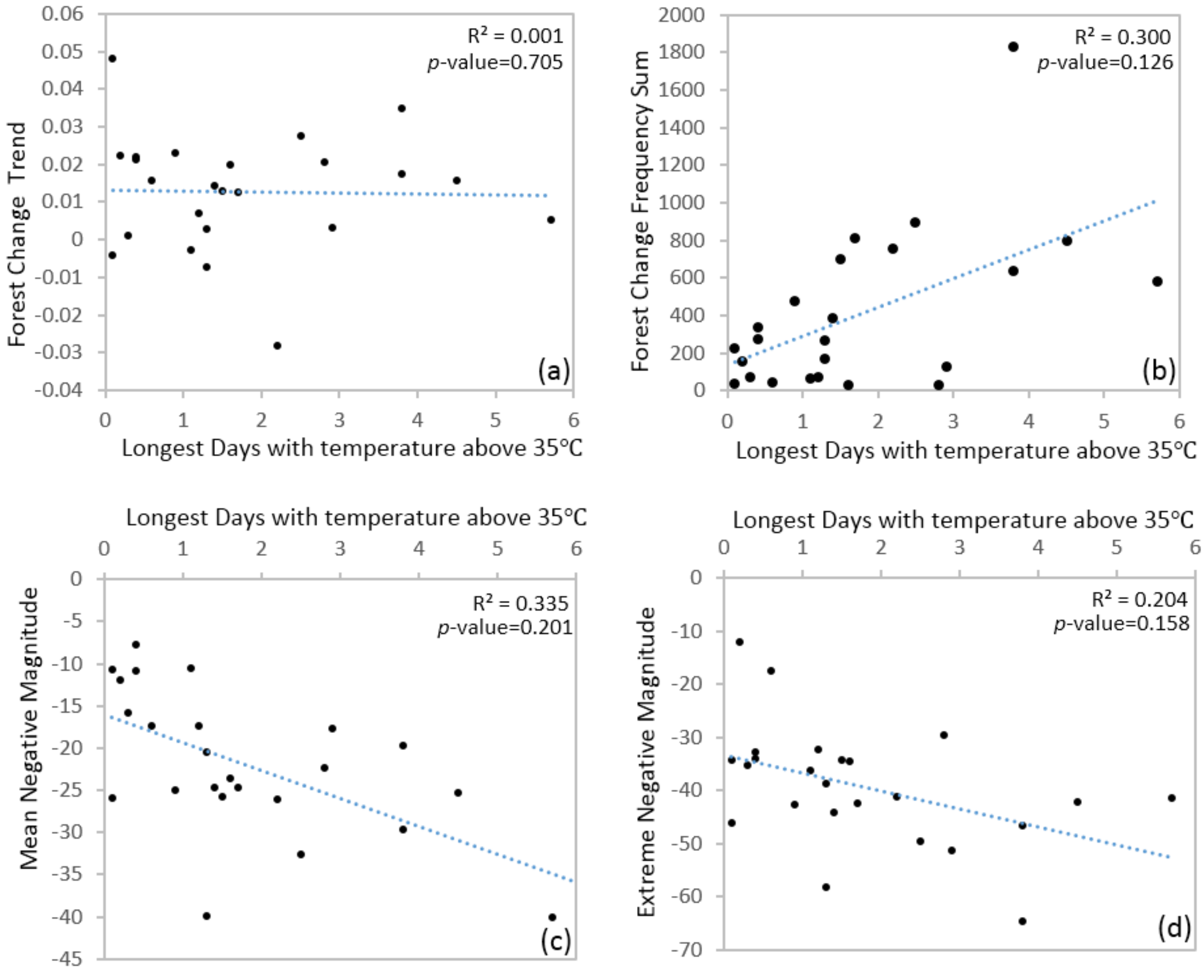

Figure 27. Correlation between forest change and temperature from 2000-2013, (a) correlation between DLT35 and forest gradual change trend; (b) correlation between DLT35 and forest abrupt change frequency sum value at county level; (c) correlation between DLT35 and mean value of negative forest abrupt change magnitude at county level; (d) correlation between DLT35 and mean value of extreme negative forest abrupt change magnitude at county level.

4. DISCUSSION

4.1. Distribution of forest changes and validation issues

A lot of studies and field work have found forest loss events in the eastern section of semi-arid region in China (Liu *et al.*, 2013). However, we assumed that the total forest gradual trend in this area was increasing during 2000-2013, considering the Chinese governments' efforts in forest conservation and afforestation in recent decades.

According to the proportion of forest change trend directions of all the pixels, 71.6% forest pixels are with positive change trend direction and 28.4% with negative change trend direction. When considering the mean value of forest change trend including all the forest pixels, the overall forest NDVI in the whole study area had gradually increased 0.014 from 2000 to 2013. By performing forest change trend analysis, each of the pixel within forest cover was detected with forest change trend either positive or negative, by comparing to no trend value 0, both pixels with significant forest increase and pixels with significant forest decrease trend were found over the 14 years between 2000 and 2013. The results show similar forest gradual change pattern from 2000-2010 with Deng *et al.* (2010)'s work.

It is widely recognized that it is difficult to validate changes detected by change detection of dense time series straightforwardly. Usually, the ground truth data cannot fully validate the changes because it needs references of potential changes detected within the time interval, and it is not possible to record every change happen in reality (Verbesselt *et al.*, 2010). What's more, the ground observations used for reference were always performed within forest stand and were always presented by trees in small plots. Recently, use other satellite images like Landsat products give a solution for upscaling of ground observations according to Lambert *et al.* (2013).

This study can be partly validated by comparing the change detection results of hot spot area under negative forest change trend with the forest loss map derived from Landsat (Hansen *et al.*, 2013), and comparing the hot spot areas detected under significant positive trend with the forest gain map by Hansen. The two forest negative trend maps are comparable to some extent as the majority of hot spots in the two maps overlay. In our study, forest pixels with a positive gradual change trend >0.039 and marked with significant forest increase trend consist of 11.68% of the total forest area. Forest pixels with a negative gradual change trend<-0.018 and marked with significant forest decrease trend, consist of 7.29% of the total forest area. The results of hot spot analyses on significant forest increase and decrease trend are shown in the left map of Figure 28. Hot spots with an increasing forest gradual change trend mainly cover the areas in county A, county B, northern part of county C, and southern part of the study area covering most parts of county W and county X; hot spot with an extreme negative forest gradual change trend locate in northern part of the counties, and the most clustered one is mainly spread in county F. Forest decreasing trend is consistent with Hansen's work displayed in the right map in Figure 28, but the increasing part is not. It may be because of that the specific study period is a bit different as Hansen's work using the images mainly in growing season. What's more, Hansen only considered bi-temporal changes, here we examined the linear trend of the whole time series. However, this simple comparison is not convincible enough to evaluate the accuracy of the results forest abrupt changes. Some satellite images such as free data of Sentinel or other images like Google-Earth Images and the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) are potential data sources to provide forest change areas for validating the forest abrupt changes caused by fire or other disturbances to certain extend.

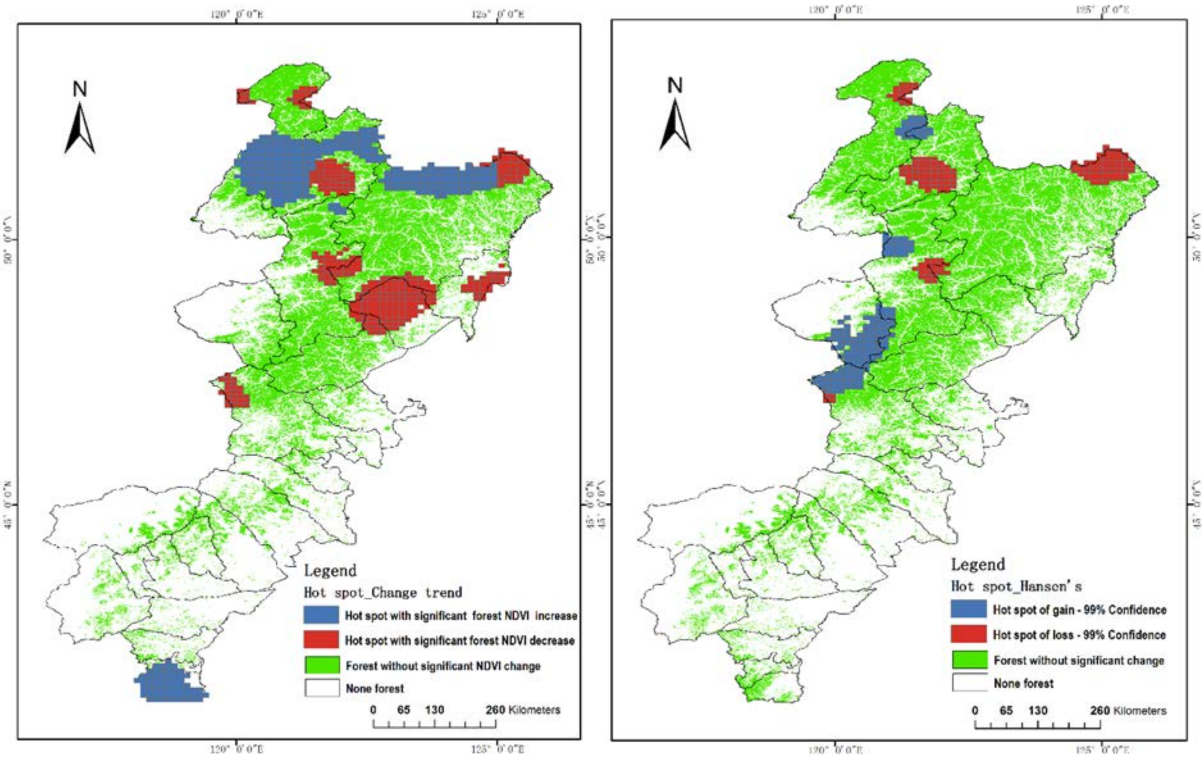

Figure 28. Comparison between the hot spot derived from extreme forest change trend (left) with hot spot derived from Hansen's work (right)

Another alternative data for ground truth validation might be the tree-ring data. Liu et al. (2013) used tree-ring data to demonstrate the forest growth characters and assessed the correlation of the tree-ring data with the droughts in Inner Asia. Wang et al. (2009a) also indicated that tree-ring data as an excellent proxy for representing long-term forest growth responding to the climate change in Northeast China. Regarding this, tree-ring data might be a useful validation data for representing forest changes.

Forest types with different canopy cover have different change characteristics in this area. Deng *et al.* (2010a) used 1-km area percentage data model with Landsat data, demonstrated the forest degradation resulting from the conversions between different forest cover types in northeast China. This study only examed the forest changes within forest landscape which treat all the forest with density over 10% as the same forest cover area (according to the definition from Land Cover and Land use map of China). As a result, this study cannot reveal change characteristics between different forest types and species.

4.2. Correlation between forest change and disturbances

Our study area locates in the eastern section of semi-arid China, a forest-steppe ecotone with high sensitivity to climate change and other human disturbance factors. Previous studies found the vegetation NDVI in this area has vital correlations to climate variables (Zhao *et al.*, 2013; Liu *et al.*, 2013). Deng *et al.* (2010b) also demonstrated forest dynamics in this area in the beginning years of the 21st century, with consideration of more specific variables, such as human density, forest distances to the cities, forest distances to the roads. What's more, the terrain and elevation also need to be discussed as other studies in this area show the geography factors have influences on the forest changes patterns. Wang *et al.* (2009b) considered altitudinal gradient within site to explore the forest dynamics in northeast China, which suggested the importance of including local factors of diverse topography in large-scale forest study.

For estimating the major factor of forest change in this study, correlation and regression analyses between forest change indicators and disturbance variables were carried out. Forest change trend indices and night-time light indices have certain positive correlations, which indicated that the slight forest gradual change trend has a possible correlation with the development and urbanization in the study area. This particular phenomenon can be explained by the successfulness of logging ban promoted by the Chinese government. From 1998, the Chinese government shifted the primary focus of forest management in the country from wood production to protect the sustainability of the forest ecology (Yu *et al.*, 2011), and published Natural Forest Conservation Program and Grain to Green Program (Liu *et al.*, 2007). Liu *et al.* (2008)'s study declared the enormous contributions of these efforts to the increase of forest area in China, which also explained the potential reason of why forest NDVI gradually increased in our study.

However, considering the distance effect of human activities, the night-light might not be the best proxy for estimating the human disturbance in this study. More accurate assessment of human activity influences on forest dynamics may utilize proxies such as the distribution of roads and settlements (Liu *et al.*, 2012).

For the forest abrupt change part, both extreme abnormal precipitation and climate indices show a significant correlation to forest abrupt change indices. The unusual forest mortality events occurred in recent years can be explained by the significant correlation with extreme unfriendly climate factors, especially blame for droughts and high temperature according to the correlation results, which consistent with previous findings of Tong *et al.* (2016). These forest abrupt changes driving factors need more detailed analysis with disturbances such as forest fire and pests. Liu *et al.* (2012) studied the fire occurrence in the boreal forest of northeast China, which indicated that fires could be ignited from both human disturbance as well as the side effect of climate. Forest in China also faced big challenges from various kind of forest pests, including insects and plant diseases (Ji *et al.*, 2011). State Forestry Administration (2010) recorded pests outbreak events which seriously threatened the forest in China. According to the research of Ji *et al.* (2011), different species of beetles are the major threaten for northern forest areas. Liu *et al.* (2013) used tree-ring data to demonstrate the forest decline in Inner Asia, which also revealed the correlation of tree mortality documented from 2007- 2009 responding to fire and insects in northeast China. Forest abrupt changes disturbance analysis can be more convincible if the correlation of forest changes occurrence times and forest fire as well as pests outbreak events are fully discussed.

4.3. Detecting forest changes using MODIS time series with BFAST

Our study area has a characteristic of forest fragmentation, and detection of thin forest change using coarse resolution images is generally difficult (Lambert *et al.*, 2015), using coarse resolution images might underestimate the presence of forest. Here in our study, using MODIS data with fine resolution of 250m which has the same spatial resolution as the forest cover mask, overcomes this problem.

On the other hand, the temporal resolution of MODIS-NDVI data is 16-day, by performing time series analysis with such frequency can reveal abrupt changes between short time gaps. With the advantage of time series analysis using BFAST to detect abrupt changes in the seasonal and trend components, the results can reflect not only the differences between the two time nodes, but also the changes within time series, which reveal much information hidden within long time trajectory of the remote sensing images. In this study, by performing BFAST and hot spot analysis with results of gradual change trend and breakpoints, we can elicit the forest areas with significant negative forest change trend, high rate of abrupt changes and violent abrupt changes as is shown in Figure 20. Although the drawback of difficult to find comparable validation data is obvious, the result is at least convincible by showing different changes within study areas.

What's more, BFAST can record the date of forest change detected, which might be used to compare the occurring time of forest change with other disturbance factors. It might reveal a much deeper correlation between forest changes with potential factors in temporal aspect.

This study only has 24 correlation groups when performing forest disturbances analysis, which need other substantial data for more accurate correlation examination. There is no doubt that the correlation and regression analyses for the results of forest changes from BFAST with other disturbance factors can be improved if indices of disturbance factors with better resolution were acquired. Then the correlation can be analyzed at pixel level which might reveal a much deeper relationship between forest changes and potential factors spatially.

The patterns of forest abrupt changes are very different from long-term forest gradual change. As these forest abrupt change areas need particular attentions of government departments concerning the management of forests such as Forestry Bureau and Land Use Planning Bureau for their policy and decision making. What's more, further studies and filed investigations need to be performed within forest abrupt change hot spots. Historical forest fire, pests outbreak events and tree-ring records are potential data resources besides remote sensing data for validation and accuracy assessment. Further study of driving factors of these changes will contribute to better management of forests and sustainability of forest ecology.

5. CONCLUSION AND RECOMMENDATIONS

5.1. Conclusions

This study is the first time of applying BFAST with MODIS images in such large area. The results revealed that this research fulfilled the goals to detect both forest gradual and abrupt changes within long time series of MODIS-NDVI at pixel level. Forest gradual changes cannot explain some sudden changes within forest NDVI time series. With the performance of BFAST model, forest abrupt changes can be extracted by breakpoint change detection function and characterized by magnitude and frequency. By further hot spot analysis with the results of BFAST model, the spatio-temporal forest gradual change and abrupt change were clearly revealed. By correlation and regression analyses, forest gradual change and forest abrupt change main driving factors were found out. In this research, three main aspects have been explored corresponding to research objectives:

- This case study detected gradual forest change trends and abrupt forest changes among totally 2,337,140 pixels, with the MODIS-NDVI spatial resolution of 250 m. The spatial and temporal distribution of forest change character were shown. From 2000-2013, the total trend of the forest gradual change among the whole study area was generally increasing. Forest NDVI decreasing areas mainly distributed among the boundaries of counties located in the middle part of the study area, forest NDVI increasing areas mainly among counties located in top northern part and southern part of the study area.
- The distribution of forest abrupt change from 2000-2013 showed at pixel level appeared to be more fragmented, but the extreme abrupt forest change characterized by the higher frequency and more violent magnitude can be found with clustering distribution patterns, mostly located among northern part of the study area.
- The hot spot analysis also indicated the major gradual forest negative change happened in counties located in northern part of the study area: county F and northern corner of county A, county C, county J, middle part of county B and county E. The hot spot analysis showed the violent negative abrupt forest changes were clustering in county A, county B located in northern part of the study area and high-frequency abrupt forest changes clustering similarly around the hot spots of negative forest gradual change but with much larger areas.
- The correlation and regression analysis revealed a certain positive correlation between forest long-term gradual change trend and urbanization with two groups, showing the development of human society positively influenced the long-term forest change trend. Forest abrupt changes have significant correlation with extreme precipitation and temperature events, and the main controlling factor is precipitation with linear regression results of $R^2=0.502$, $p\approx 0$. Comparing to other factors, precipitation had overwhelming control on forest growth in the eastern section of semi-arid region in China during 2000-2013.

5.2. Recommendations

Forest changes were statistically analyzed within certain scopes with BFAST to derive variable indices for correlation and regression. The final correlation and regression results were based on 24 groups of comparison. If the meteorological data can be interpolated into certain comparable resolution spatial data, or derived from other climatic remote sensing products, the results of correlation can reveal a much deeper spatial correlation of forest change with these disturbance factors. What's more, BFAST model can record the 'date' where changes happen, if comparable climatic or other disturbance data have date recorded, more variety of the correlation and comparison can be performed to derive more exciting results. These can be the further work of this study.

To some extent, the results of change trends or abrupt changes detected by this model, depended a lot on the parameters set by the users. In this study we dealt with this issue cautiously, we picked harmonic model when dealing with seasonal components in BFAST according to the suggestion that it is most appropriate for fitting natural vegetation (Verbessslt *et al.*, 2010). Other issues should also be paid attention as the sensitivity of change detection depends on the degree of operation like cleaning when doing pre-processing or smoothing with the time series.

On the other hand, BFAST model has already been tested with its capacity of detecting changes not only in time series of remote sensing but also numeric strings. It has high potential in analyzing big data set because it only put numeric strings in arithmetic which boosting the analysis performance. This case study applied all the pixels' time series inside forest mask to BFAST model within R language environment. However, the string needs to be extracted manually, and the output of BFAST are numeric which need to be assigned to the raster images or point shapefile using other R functions or GIS tools. Regarding this, the applicability of BFAST model for users needs improvement.

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