Estimating spatiotemporal patterns of aboveground biomass using Landsat TM and MODIS images in the Mu Us Sandy Land, China

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A B S T R A C T

Aboveground biomass (AGB) in areas of desertification cannot only represent the status of vegetation but can also provide evidence to evaluate the effects of ecological restoration and help land managers realize sustainable development of desert ecosystems. Current research estimating AGB by remote sensing has mainly focused on forest, grasslands and crops, and has infrequently been applied to desert ecosystems. We used Landsat Thematic Mapper (TM) images and Moderate Resolution Imaging Spectro-Radiometer (MODIS) data to estimate AGB and its spatiotemporal patterns from 2000 to 2012 in the Mu Us Sandy Land of China. Results showed that: (1) AGB varied from 2000 to 2012 and total AGB showed an increasing trend of 0.1743 Tg per year. The lowest total AGB was observed in 2000 and 2001 and the highest in 2012, with slightly less in 2007. (2) AGB spatial extent (percent of ground covered) had a decreasing trend of 5.37% during the study period and AGB was mainly in the southwestern and eastern parts of the study area. AGB had no change in 2.23% of this area, and areas of no change were mainly in the northwestern and southwestern parts. There was an increasing AGB trend in 92.40% of the area, which was mainly in large areas of the middle, northeastern, and southern parts of the Mu Us Sandy Land. (3) In the sandy land from 2000 to 2012, areas with mild and moderate fluctuations and increasing AGB made up the largest part of the study area. Those two types of fluctuations accounted for 74.60% of the total area, and were widely distributed in the northeastern, eastern, central, and southern portions of the sandy land. Areas with severe and extremely severe fluctuations and decreasing AGB were relatively small. These two types represented 0.86% of the total area and were scattered in the northwestern and western parts of the sandy land. (4) With the increase of temperature and precipitation, total AGB tended to increase from 2000 to 2012, somewhat in agreement with precipitation (r = 0.595). However, precipitation was not the only factor affecting AGB. Human factors such as population, livestock, and particularly positive policies also impacted the spatiotemporal patterns of AGB.

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1. Introduction

Since the start of the 21st century, the world’s social economy has developed rapidly with improvement in many people’s standard of living; the human impact on the earth’s ecosystems has reached a new level. The great social progress made by civilization is also associated with a series of ecological problems, such as desertification, soil erosion, and environmental pollution. Among these problems, desertification is one of the most serious threats to arid and semiarid environments and has seriously inhibited the development of local economies and improvement of people’s living conditions (Bakr et al., 2012; Helldén and Tottrup, 2008; Kassas, 1995; Reynolds et al., 2007; Rubio and Bochet, 1998). China is one of the most seriously desertified countries in the world. A bulletin related to the status of desertification and sandification in China issued by State Forestry Administration, P. R. China in 2011 showed there was 2623,700 km² of desertified land by the end of 2009, which accounted for 27.33% of the national territory. In the new century, desertification is still the most critical factor restricting sustainable social, economic, and environmental development in China. The Mu Us Sandy Land lies on the farming-pastoral ecotone of northern China, in a forest–grassland–desert transition zone. Affected by natural and anthropogenic factors, the Mu Us Sandy Land has been considered as an important ecological barrier in China, whose environment is very sensitive and vulnerable to ecological changes. Studying the spatiotemporal patterns
of vegetation from 2000 to 2012 is vital for land managers to understand the process of desertification and to comprehensively evaluate carbon sinks in the Mu Us Sandy Land in the new century.

Biomass has been widely used to evaluate productivity and is an important indicator in carbon cycle studies related to vegetation growth (Burrows et al., 2003; Crow, 1997; Fang et al., 2001; Houghton et al., 2000). Monitoring AGB dynamically in desertified areas can not only show the status of the growth of local vegetation but also provide evidence that ecosystem managers and scientists can use to evaluate the effects of ecological restoration in desertified areas, as well as to study the carbon cycle and to realize sustainable development of desert ecosystems. In the past, traditional methods for estimating AGB mainly involved field inventory, which suffered from many shortcomings such as having many areas poorly represented and being time consuming, labor intensive, and inefficient. Remote-sensing technology has the advantages of having a macro scale, providing dynamic data, and being economic and efficient, and lacks the inadequacies of more traditional methods. Estimation of AGB has been done for many years using remote-sensing reflectance and various vegetation indices (Boyd, 1999; Hame et al., 1997; Huete et al., 2002; Moreau et al., 2003; Todd et al., 1998; Zhang et al., 2007). Ikeda et al. (1999) used Landsat TM observations in 1984–1990 and climate data to estimate AGB with a growth model, as well as revealed that TM2/TM3 was more successful at accurately estimating biomass than the normalized difference vegetation index (NDVI), and that the ratio TM4/TM5 performed best. Curran et al. (1992) applied TM data to study the linear relationship that existed between NDVI and the leaf area index (LAI), demonstrating the potential use of TM data for studying seasonal dynamics in the forest canopy. Todd et al. (1998) used TM images to show the relationship between biomass and the tasseled cap green vegetation index (GVI), brightness index (Bl), wetness index (WI), NDVI, and the red waveband (RED) on grazed and ungrazed rangelands in north-central Colorado. Zheng et al. (2004) coupled AGB values in Wisconsin, USA, with various vegetation indices derived from Landsat Enhanced Thematic Mapper Plus (ETM+) data through multiple regression analysis. They found that AGB for pine forests was strongly related to the corrected NDVI, and that separating hardwoods from pine forests substantially improved the AGB estimations compared with those obtained with overall regression. Muukkonen and Heiskanen (2005, 2007) applied Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) satellite data to estimate the biomass of boreal forest stands in Finland. They put forward a method coupled with standwise forest inventory data, ASTER, and MODIS satellite data to estimate biomass and verify the possibility of using remote sensed data to conduct carbon inventories. Verbesselt et al. (2006) used Systeme Probatoire d’Observation de la Terre (SPOT) vegetation data to construct a time series designed to monitor herbaceous biomass in South Africa. Propasit et al. (2012) chose ground biomass data and net primary production (NPP) data calculated from the sea-viewing wide field-of-view sensor (SeaWiFS) to test the reliability of their modified light use efficiency (LUE) model in the grasslands of Kazakhstan. Claverie et al. (2012) used Formosat-2 data to simulate a time series of green area index (GAI) and dry aboveground biomass (DAM) of maize and sunflower; actual crop biomass was estimated very well especially considering that biomass measurements were not used for calibration. Yan et al. (2013) used Landsat TM/ETM+ images from 1988 to 2007 and 283 in situ AGB samples in August 2007 to estimate the AGB for the Mu Us Sandy Land of China over the past 30 years. By reviewing current international research studies on biomass estimation by remote-sensing techniques, we found most studies mainly focused on forest, grasslands, and crops, with relatively few applications for desert ecosystems. Although vegetation is sparser in a desert ecosystem than in forest, grassland, and crop ecosystems, total AGB of deserts is still considerable across vast areas. Estimating AGB in desert ecosystems is of great significance for the comprehensive evaluation of the global carbon cycle. Hence, in this research we chose the Mu Us Sandy Land, located on the farming-pastoral ecotone of China, as an area to study methods for estimating AGB using MODIS and TM data. Also, spatiotemporal patterns of AGB from 2000 to 2012 were analyzed, providing data that expand our scientific knowledge of desert ecosystem recovery and deserts as carbon sinks.

The objective of this research was to estimate AGB and its spatiotemporal patterns in semiarid regions using TM images and MODIS data from 2000 to 2012. We therefore analyzed the scale transformation of vegetation index between MODIS and TM, and transferred an AGB estimation model established with vegetation index and in situ AGB samples from TM images (Yan et al., 2013) to MODIS data. Then, the MODIS data of 2000–2012 were used to estimate AGB, and trend and fluctuation were used as indicators of AGB spatiotemporal patterns in the Mu Us Sandy Land of China. Finally, we thoroughly analyzed the causes of AGB variations from natural (e.g., temperature, precipitation, and deficit of precipitation) and human factors (e.g., population and policies).

2. Study area and data

2.1. Study area

This study area lies at 37° 27′–39° 22′ N, 107° 20′–111° 30′ E and includes the southern part of Erdos (Inner Mongolia, China), the northern part of the Yuyang District sandy area (Yulin, Shannxi), and the northeastern part of Yanchi County (Ningxia), covering about 40,000 km² (Fig. 1). Elevations vary from 950 to 1600 m above mean sea level. The climate varies from middle to warm temperate zones with mean annual temperature varying from 6.0 to 8.5 °C, and mean annual precipitation ranging from 250 to 440 mm. Precipitation in the Mu Us Sandy Land is mainly concentrated from July to September, and especially in August, which accounts for 60–75% of annual precipitation. Precipitation varies in a southeast-to-northwest direction from 440 to 250 mm, respectively. The soil and vegetation types of the Mu Us Sandy Land show a transitional pattern: in the northwest a semi-desert calcic brown soil zone occurs, while to the southeast in Yanchi County a semi-desert sierozem zone is found; also, to the southeast in the Loess Plateau,
a grey cinnamonic soil occurs with a warm temperate climate in a forest-steppe zone. The main vegetation cover type is sandy grassland, which covers more than 80% of the sandy area and Artemisia Ordosica is a dominant species. The other natural vegetation types include steppe, meadow, and shrubs (Zhang, 1994). In addition, there are farmlands distributed along the river or scattered in the sandy grasslands, and artificial forest and shrubs (Wu and Qi, 2002). Grassland in the northwestern part of the Mu Us Sandy Land is mainly used for grazing and in the eastern and southern parts of the sandy land, some grassland areas are reclaimed into farmland. Land use forms complex patterns across the landscape with staggered distributions of different types being very common and agricultural land taking the largest proportion.

2.2. Data

In this research, MODIS and Landsat TM satellite data were used to estimate AGB in the Mu Us Sandy Land. MODIS is a key instrument aboard the Terra and Aqua satellites, which provides high radiometric sensitivity (12 bit) in 36 spectral bands ranging in wavelength from 0.4 to 14.4 μm, covers a 2300-km wide swath, and provides global coverage every 1–2 days (http://modis.gsfc.nasa.gov). Compared with other frequently used data such as TM, ETM+, and National Oceanic and Atmospheric Administration (NOAA)–Advanced Very High Resolution (AVHRR) images, MODIS data have higher spectral and temporal resolutions. Both MODIS vegetation index products (MOD13Q1 (DOY: 209) from 2000 to 2012) and MODIS surface reflectance products (MOD09GQ (DOY: 224) in 2007) were ordered from the National Aeronautics and Space Administration (NASA); MOD13Q1 and MOD09GQ data are provided at a 250-m spatial resolution in a Sinusoidal projection with 16-d and 1-d temporal resolutions, respectively (https://lpdaac.usgs.gov/products/). The Modis Reprojection Tool (MRT) was used for the MODIS titled land products to perform subset and projection transformation. Albers Conical Equal Area (ellipsoid is Krasovsky, longitude of central meridian is 105°E, latitude of standard parallels are 25°N and 47°N) map projection was employed. Aside from the MODIS data, two Landsat 5 TM images with the path/rows 127/33 and 127/34 acquired on August 12, 2007 (DOY: 224) were also used. After applying atmospheric correction by the Fast Line-of-Sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) atmospheric correction model from ENVI software, the digital number (DN) of the TM image was converted to surface reflectivity. Then, topographic maps at a scale of 1:50,000 were used to spatially locate the ground control points for geometrically correcting the satellite images, and the mean error after geometric correction was controlled within 0.5 pixel.

Historical record of monthly temperature and precipitation (1980–2012) of nine meteorological stations located in the Mu Us Sandy Land, including the stations of Uxin Ju, Shenmu, Uxin, Yulin, Ogot Qian, Hengshan, Henan, Dingbian and Jingbian (Fig. 1), were used to calculate the average annual temperature and precipitation and standardized precipitation index (SPI).

3. Methodologies

3.1. Relationship between vegetation indices and AGB

Vegetation index derived from satellite data by combining two or more spectral bands is one of the primary sources of information for operational monitoring of the earth’s vegetation cover (Gilbert et al., 2002). A good relationship exists between the amount of biomass on the ground and the spectral vegetation index since biomass can be reflected by the index (Tucker, 1979). A vegetation index is generally defined as mathematical transformations of surface reflectance from sensors mainly using red and near infrared spectral bands. To quantitatively study vegetation coverage and growth, dozens of vegetation indices have been designed. Among these, the NDVI, Ratio Vegetation Index (RVI), Difference Vegetation Index (DVI), Soil Adjusted Vegetation Index (SAVI) and Modified Soil Adjusted Vegetation Index (MSAVI) have been commonly used (Table 1).

Table 1

<table>
<thead>
<tr>
<th>Index</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>NDVI = (NIR – R)/(NIR + R)</td>
<td>Rouse et al. (1973)</td>
</tr>
<tr>
<td>RVI = NIR/R</td>
<td>Pearson and Miller (1972)</td>
</tr>
<tr>
<td>DVI = NIR – R</td>
<td>Jordan (1969)</td>
</tr>
<tr>
<td>SAVI = (1 + L)/(NIR – R)/(NIR + R + L)</td>
<td>Hsueh (1988)</td>
</tr>
<tr>
<td>MSAVI = (NIR + 1)/(2NIR + 1)</td>
<td>Qi et al. (1994)</td>
</tr>
</tbody>
</table>

Definitions: NDVI, normalized difference vegetation index; RVI, ratio vegetation index; DVI, difference vegetation index; SAVI, soil adjusted vegetation index; MSAVI, modified soil adjusted vegetation index; NIR and R, the reflectance of near infrared and red bands, respectively; L, a soil adjustment factor (Qi et al., 1994).

Among dozens of available vegetation indices, MSAVI has been widely used as a remote-sensing technique to study vegetation in various research studies (Epting et al., 2005; Rogan and Yool, 2001; Veraverbeke et al., 2012; Wu et al., 2007; Yan et al., 2013; Zheng et al., 2004), because it has been shown to increase the dynamic range of the vegetation signal while further minimizing the influence of soil as background data, resulting in greater sensitivity to the signal received from vegetation (Qi et al., 1994). Yan et al. (2013) chose the Mu Us Sandy Land of China as a study area and analyzed correlations between situ AGB samples and multiple vegetation indices derived from Landsat 5 TM and found correlations of AGB-MSAVI was relatively higher than those of the SAVI, DVI, RVI, and NDVI. And as a result, an AGB-MSAVI model (Eq. (1)) for estimating AGB in August in the Mu Us Sandy Land of China was established. In this study we continued to use Eq. (1) to estimate a time series of AGB from 2000 to 2012.

\[
\text{AGB} = 12.733 \times \text{MSAVI} - 1.315 \left( R^2 = 0.612 \right)
\]

3.2. Scale transformation of vegetation index between MODIS and TM

Landsat 5 TM and MODIS data were used for estimating AGB in our study. Compared with MODIS, TM has higher spatial resolution (30 m) but a longer revisit period (16 days) and a smaller swath (185 km). The availability of TM images is often limited by weather conditions and the longer revisit period across large areas. While MODIS has some advantages such as the shorter revisit period (at least 2 times/day), the larger swath (2330 km) and moderate spatial resolution (250, 500, and 1000 m) can make up for the inadequacies of TM images. Scale transformation must be carried out during the course of estimating AGB by MODIS data with Eq. (1) derived from TM, because of differences in spectral and spatial resolutions in the two sensors.

Scale transformation is the process of transforming information and knowledge among different scales. In remote sensing, one basic characteristic of an image is the spatial resolution or the size of an area on the ground from which the measurements that compose the image are derived (Woodcock and Strahler, 1987). Some pixel-based scale transformation methods have been proposed such as mathematical statistical analysis, fusion, and classification transformations (Aman et al., 1992; Berterretche et al., 2005; Braswell et al., 2003; Feng et al., 2012; Gao et al., 2006; Kim and Barros, 2002; Mayaux and Lambin, 1995; Teillet et al., 1997; Xu and Zhang, 2013). Gao et al. (2006) used a spatial and temporal adaptive reflectance
fusion model (STARFM) to predict Landsat-scale reflectance using the 500-m daily surface reflectance product (MOD09GHK) with Landsat and MODIS images. Hilker et al. (2009) applied method of STARFM to map seasonal changes in vegetation at a Landsat spatial resolution and 8-day time intervals with Landsat and MODIS (MOD09GHK) images. Berterretche et al. (2005) compared different methods to predict leaf area index (LAI) in a boreal forest and found aspatial orthogonal regression analysis (reduced major axis) was the most practical option for regional NPP modeling with coarse resolution inputs. Feng et al. (2012) adopted a simple linear regression model to measure the agreement between Landsat and MODIS images and assessed the quality of Landsat surface reflectance products using MODIS data. Xu and Zhang (2013) used a cross-comparison method based on relationship between sampled pixels of ASTER data and those of corresponding ETM+ data to assess consistency in forest-dominated vegetation observations. Among the pixel-based scale transformation methods, mathematical statistical analysis bases on a function of pixel-based parameters, does not need to input too much weight on the physical mechanism of remote sensing. And it has been widely used for transformation among different remote sensed images with different pixel-scales (Berterretche et al., 2005; Feng et al., 2012; Xu and Zhang, 2013). In this research, we chose mathematical statistical analysis transformations method to transform MSVI values between Landsat TM and MODIS images.

Fractional vegetation cover (FVC) refers to the percentage of the vertically projected area covered by vegetation as a fraction of the entire area under study (Gitelson et al., 2002; Purevдорж et al., 1998); FVC is an important parameter used to characterize land surface vegetation cover and growth conditions. With the development of remote sensing, several FVC retrieval methods have been proposed, such as empirical, vegetation index, and sub-pixel unmixing models (Asrar et al., 1992; Choudhury, 1987; Zhou and Robson, 2001) and the pixel decomposition method has also been widely used (Gutman and Ignatov, 1998; Mu et al., 2013; Tømmervik et al., 2003; Zhang et al., 2013). The pixel decomposition method assumes that each pixel consists of vegetation and bare soil and the spectral value is a linear combination of the two parts. So, FVC can be expressed as

\[ FVC = \frac{NDVI - NDVI_{\text{min}}}{NDVImax - NDVI_{\text{min}}} \]  

(2)

where \( NDVI_{\text{min}} \) is the minimum NDVI corresponding to 0% vegetation cover or bare soil and \( NDVI_{\text{max}} \) is the maximum 100% vegetation cover, respectively. Because of landscape heterogeneity in the sandy land, selecting “pure” bare and vegetation pixels from a lower spatial resolution remote sensing image is very difficult, but relatively pure pixel selection is easy. In this research, an interactive method was used to select such pixels from MODIS images. We first chose a large area of pure pixels from TM data and then used this area to obtain the relatively pure pixels from MODIS images. In the northeastern part of Mu Us Sandy Land is the largest area of original Sabina vulgaris in China, about 9333 ha. As an evergreen dominant shrub, S. vulgaris tends to grow so densely in the sandy land that it can cover sand dunes completely, like “a vast green blanket” (Dong and Zhang, 2000). The relatively pure vegetation pixels were selected near a site (109°17′37.74″E, 38°58′52.65″N) within the S. vulgaris Natural Reserve of Mu Us, Inner Mongolia. Relatively pure soil pixels were selected near a site (107°38′31.20″E, 38°46′48.40″N) covered by large areas of drifting sand. Inserting MODIS surface reflectance product MOD09GC (2007: DOY: 224) data of the Mu Us Sandy Land to NDVI and MSVI equations (Table 1), we calculated those two indices, hereinafter expressed as \( NDVI_{\text{MODIS}} \) and \( MSVI_{\text{MODIS}} \). Then, \( NDVI_{\text{MODIS}} \) was entered in Eq. (2) to calculate FVC.

Reflectivity data of TM3 and TM4 (Path/Row: 127/33 and 127/34) on August 12, 2007 (DOY: 224) were used to calculate MSVI hereinafter expressed as \( MSVI_{\text{TM}} \). Next, the nearest neighbor interpolation method was used to resize the resolution of \( MSVI_{\text{TM}} \) from 30 m to 250 m. FVC (DOY: 224) of the Mu Us Sandy Land was then divided into five grades using a 0.2 step: 300 corresponding samples were randomly selected for each grade from \( MSVI_{\text{TM}} \) and \( MSVI_{\text{MODIS}} \), then spatial scale transformation regression equations were established (see Eqs. (3)–(7)) for each step. Based on the scale transformation method for MSVI from TM and MODIS images, we used reflectivity data derived from MOD13Q1 (DOY: 209) to calculate FVC and \( MSVI_{\text{MODIS}} \) and acquired a time series of \( MSVI_{\text{TM}} \) in 2000–2012.

\[ MSVI_{\text{TM}} = 0.1689 MSVI_{\text{MODIS}} + 0.0748, \]

note: \( R^2 = 0.9143 \) and \( 0 \leq Fc \leq 0.2 \)  

(3)

\[ MSVI_{\text{TM}} = 0.6582 MSVI_{\text{MODIS}} + 0.0104, \]

note: \( R^2 = 0.8462 \) and \( 0.2 < Fc \leq 0.2 \)  

(4)

\[ MSVI_{\text{TM}} = 0.5434 MSVI_{\text{MODIS}} + 0.0227, \]

note: \( R^2 = 0.8352 \) and \( 0.4 < Fc \leq 0.6 \)  

(5)

\[ MSVI_{\text{TM}} = 0.8936 MSVI_{\text{MODIS}} - 0.1599, \]

note: \( R^2 = 0.8275 \) and \( 0.6 < Fc \leq 0.8 \)  

(6)

\[ MSVI_{\text{TM}} = 0.2828 MSVI_{\text{MODIS}} + 0.1932, \]

note: \( R^2 = 0.8437 \) and \( 0.8 < Fc \leq 1.0 \)  

(7)

To evaluate error of AGB estimation caused by scale transformation of vegetation index between Landsat TM and MODIS images, we randomly chose four samples from southern to northern Mu Us Sandy Land, according to TM data coverage (Path/Row: 127/33 and 127/34). The selected samples were mainly in an area with varying degrees of desertification, rather than with homogeneous land cover. The area of each sample was 4.5 km × 4.5 km, exactly corresponding to 18 pixel of MODIS vegetation index product MOD13Q1 and 150 pixel of TM images, (Fig. 1). Transformation relationship from Eqs. (3) to (7) were used to retrieve \( MSVI_{\text{TM}} \) from \( MSVI_{\text{MODIS}} \) and AGB on August 12, 2007 was estimated from TM and MODIS images. Minimum, maximum, mean, standard deviation (SD), and relative error (RE) of the estimated AGB from two sensors were analyzed (Table 2). Results showed that minimum values of AGB based on TM data were 0 t/ha for all four samples, whereas those of AGB based on MODIS imagery were usually larger than 0 t/ha, especially for S1 and S4 samples. Maximum and SD values of AGB based on TM were also larger than those of AGB based on MODIS. These differences are mainly owing to image spatial resolution and landscape heterogeneity in the Mu Us Sandy Land. The spatial resolution of MODIS was coarser than that of TM and it was more difficult to find “pure” pixels from MODIS data. For the mean values, however, there was little difference between each pair of estimated AGB from both TM and MODIS images, which was mainly caused by the method of scale transformation of vegetation index between MODIS and TM. Considering the spatial resolution, we chose TM data as “true” values and calculated RE of the AGB estimated from MODIS imagery. Error analyses showed that the smallest RE values of estimated AGB were in S3 and S1, which corresponded to the minimum and maximum mean values of AGB.
among the four samples. RE values in S2 and S4 (with moderate mean values of AGB) were as high as 3.84% and 3.31%, respectively. According to error analyses of AGB estimation from TM and MODIS images, we found that RE could be generally controlled within 4%. Thus, Eqs. (3)–(7) could be effectively used to estimate AGB from TM and MODIS images of the Mu Us Sandy Land.

### 3.3. Trends and fluctuations of AGB

Trends of a series of numbers in chronological order can be expressed as the slope of a line. For measurements of AGB, a positive slope indicates that the series tends to increase, and a negative slope indicates decreasing AGB. For the present study of AGB trends in the Mu Us Sandy Land, a sequence of AGB spectra from 2000 to 2012 was expressed as a 13-dimensional AGB data matrix. Linear fitting by the least-squares method was performed for this matrix at pixel level (see Eq. (8)) and the spatial distribution of AGB slope was calculated.

\[
\text{slope} = \frac{\sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^{n} (x_i - \bar{x})^2} \quad (i = 1, 2, 3 \ldots n)
\]

where slope is the slope of the line with the best linear fit, \(x\) is the independent variable (in this study is year), \(i\) and \(n\) are the numbers of years from 2000 to 2012, and \(y\) is the dependent variable (in this study is AGB).

SD and coefficient of variation (CV) were used to portray fluctuations of AGB in the sandy land. SD and CV are important and widely used indicators for quantitative evaluation of an array’s degree of dispersion. SD represents the deviation between a set of data and their mean value. CV is defined as the ratio of SD, and the mean value and can be used to eliminate influences of different units or averages on comparison of the dispersion of two or more sets of data. SD and CV are expressed in the following equations:

\[
\sigma = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (x_i - \bar{x})^2} \quad (i = 1, 2, 3 \ldots n)
\]

\[
CV = \frac{\sigma}{\mu}
\]

where \(\sigma\) is SD, \(\mu\) is the mean value of an array, \(x\) is the array (in this study is AGB), \(i\) and \(n\) are the numbers of years from 2000 to 2012.

### 4. Results and discussion

#### 4.1. Temporal variations of AGB

By inserting scale-transformed MSAVI derived from MODIS products from 2000 to 2012 into Eq. (1), we calculated a series of AGBs in the Mu Us Sandy Land. Statistical results of area percentages of various AGB levels showed that these areas fluctuated dynamically since 2000 (Table 3). Areas with AGB percentage not more than 1.5 t/ha occupied more than 57.8% of the total sandy land in each year. The percentage of area with 0 ≤ AGB ≤ 0.5 t/ha peaked at 54.44% in 2000 and was smallest in 2012, at 10.37% of the total study area. The percentage of area with 0.5 t/ha < AGB ≤ 1.0 t/ha maximized in 2006 (32.22%) and was smallest in 2012 (16.23%). The percentage of area with 1.0 t/ha < AGB ≤ 1.5 t/ha peaked in 2010 (39.70%) and was smallest in 2000 (13.94%). The percentage of area with 1.5 t/ha < AGB ≤ 2.0 t/ha maximized in 2012 (21.93%) and was smallest in 2000 (3.17%). The percentage of area with AGB > 2.0 t/ha peaked in 2012 (20.31%) and was smallest in 2000 (3.39%).

Total AGB in the sandy land from 2000 to 2012 (Fig. 2) was lower than average in 2000, 2001, 2004, 2005, 2006, and 2008. There were minima in 2000 and 2001, at 2.26 and 2.54 Tg, respectively. Total AGB was greater than average in 2002, 2003, 2007 and 2009–2012, peaking in 2007 and 2012 with values 4.70 and 5.62 Tg, respectively. Overall, from 2000 to 2012, total AGB in the entire sandy land increased by 0.1743 Tg annually, indicating generally improved conditions for vegetative growth.

#### 4.2. Spatial variations of AGB

##### 4.2.1. Characteristics of trends and fluctuations

Statistical results of AGB trends showed that its average annual growth rate was from −39.5 to 38.5. The peak value of the slope distribution histogram is 3.62, accounting for 4.40% of the total area.

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**Table 2**

<table>
<thead>
<tr>
<th>Sample</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
<th>SD</th>
<th>RE (%)</th>
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<tr>
<td>S1</td>
<td>0.362</td>
<td>0</td>
<td>4.054</td>
<td>7.622</td>
<td>2.360</td>
</tr>
<tr>
<td>S2</td>
<td>0</td>
<td>0</td>
<td>3.755</td>
<td>8.091</td>
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<tr>
<td>S3</td>
<td>0</td>
<td>0</td>
<td>2.258</td>
<td>7.880</td>
<td>0.589</td>
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<tr>
<td>S4</td>
<td>0.248</td>
<td>0</td>
<td>3.960</td>
<td>7.410</td>
<td>1.366</td>
</tr>
</tbody>
</table>

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**Table 3**

<table>
<thead>
<tr>
<th>Year</th>
<th>Area percentage (%)</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>AGB = 0</td>
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<tr>
<td>2000</td>
<td>26.31</td>
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<tr>
<td>2001</td>
<td>24.32</td>
</tr>
<tr>
<td>2002</td>
<td>11.42</td>
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<td>2003</td>
<td>8.65</td>
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<td>2008</td>
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<td>5.95</td>
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<tr>
<td>2010</td>
<td>4.72</td>
</tr>
<tr>
<td>2011</td>
<td>5.16</td>
</tr>
<tr>
<td>2012</td>
<td>4.39</td>
</tr>
</tbody>
</table>
Table 4
Classification system for spatial patterns of AGB.

<table>
<thead>
<tr>
<th>Fluctuation characteristic</th>
<th>CV</th>
<th>Trend characteristic</th>
<th>Trend</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0 &lt; CV ≤ 0.3</td>
<td>Mild</td>
<td>Slope &gt; 0</td>
</tr>
<tr>
<td></td>
<td>0.3 &lt; CV ≤ 0.6</td>
<td>Moderate</td>
<td>Increasing</td>
</tr>
<tr>
<td></td>
<td>0.6 &lt; CV ≤ 0.9</td>
<td>Severe</td>
<td>Slope &lt; 0</td>
</tr>
<tr>
<td></td>
<td>CV &gt; 0.9</td>
<td>Extremely severe</td>
<td>Decreasing</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>y = 0.1743x + 2.7657</th>
<th>R² = 0.5736</th>
</tr>
</thead>
</table>

Fig. 2. Variations of total AGB from 2000 to 2012.

Of that area, 5.37% or 2059.31 km² had a decreasing AGB trend with negative slope; this area was mainly in the southwestern (eastern Otog Banner and southwestern Uxin Banner) and eastern (central Yuyang District) parts of the Mu Us Sandy Land (Fig. 3). In an area of 856.63 km² or 2.23% of the study area, AGB showed no significant change with zero slope; this area was primarily in the northwestern (northwestern Uxin Banner, eastern and southeastern Otog Banner) and southwestern (southeastern of Otog Qian Banner) parts of the sandy land. AGB tended to have an increasing trend with positive slope over a large area of 35,460.00 km², or 92.40% of the study area. This included most areas of the central, northeastern, and southern parts of the sandy land.

To enhance the comparability of degree of AGB fluctuation in various areas, we used the CV as an indicator to quantitatively evaluate those fluctuations in the sandy land. During analysis of the distribution of the CV of AGB from 2000 to 2012 (Fig. 4), we found that CV was mainly in the range of 0–0.9 at pixel level from 2000 to 2012, representing 91.72% of the study area. The maximum CV was 0.28 and the area with 0 ≤ CV < 0.3 constituted 34.47% of the total area. Regions with 0.3 ≤ CV < 0.6 and 0.6 ≤ CV ≤ 0.9 made up 46.85% and 10.40% of the total area, respectively. The area of CV > 0.9 embraced 8.28% of the area and was mainly in northwestern (northwestern Uxin Banner and southeastern Otog Banner) and southwestern (southern Otog Qian Banner) parts of the sandy land.

4.2.2. Spatial pattern

Trend characteristics may reveal the entire trend of AGB development in the future, which is equivalent to the direction of a space vector. AGB fluctuations may show the dispersion of an AGB array, which is equivalent to the module of the space vector. The combination of trend and fluctuation characteristics can express both the direction and module at the same time, and is able to describe the characteristics of AGB variation very well. In this research, we coupled the two characteristics to quantitatively classify spatial AGB patterns in the Mu Us Sandy Land from 2000 to 2012 (Table 4). In the regions with CV = 0 or slope = 0, AGB was never less than zero, although the mean annual AGB was zero. The corresponding land surface was generally water bodies, drifting sandy land, bare soil, and artificial construction. Hence, both CV = 0 and slope = 0 were not considered in the classification system of AGB spatial pattern. In that system, given that CV was mainly between 0 and 0.9 for 91.72% of areas with measured CV, we divided the degree of AGB fluctuation in the study period into mild, moderate, severe, and extremely severe, or four levels at steps of 0.3. Positive and negative slopes indicated increasing and decreasing AGB trends, respectively. Using the classification system, the AGB spatial patterns were calculated and classified (Fig. 5).
Table 5

Areas and percentages of different AGB variation character from 2000 to 2012.

<table>
<thead>
<tr>
<th>Number</th>
<th>Type</th>
<th>Area (km²)</th>
<th>Percentage (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>−4</td>
<td>Decreasing with extremely severe fluctuation</td>
<td>214.00</td>
<td>0.56</td>
</tr>
<tr>
<td>−3</td>
<td>Decreasing with severe fluctuation</td>
<td>115.88</td>
<td>0.30</td>
</tr>
<tr>
<td>−2</td>
<td>Decreasing with moderate fluctuation</td>
<td>72.81</td>
<td>1.83</td>
</tr>
<tr>
<td>−1</td>
<td>Decreasing with mild fluctuation</td>
<td>1025.63</td>
<td>2.67</td>
</tr>
<tr>
<td>0</td>
<td>No change</td>
<td>856.63</td>
<td>2.23</td>
</tr>
<tr>
<td>1</td>
<td>Increasing with mild fluctuation</td>
<td>11356.06</td>
<td>29.59</td>
</tr>
<tr>
<td>2</td>
<td>Increasing with moderate fluctuation</td>
<td>17274.00</td>
<td>45.01</td>
</tr>
<tr>
<td>3</td>
<td>Increasing with severe fluctuation</td>
<td>3874.44</td>
<td>10.10</td>
</tr>
<tr>
<td>4</td>
<td>Increasing with extremely severe fluctuation</td>
<td>2955.50</td>
<td>7.70</td>
</tr>
</tbody>
</table>

AGB spatial patterns were analyzed, including the development of statistics related to the area and percentage of the sandy land with various AGB trends and fluctuations (Table 5). The results show that areas with extremely severe or severe fluctuations and decreasing trends of AGB covered 214.00 and 115.88 km², respectively, or 0.56% and 0.30% of the study area. These areas were scattered in the northwestern (southeastern Otog Qian and northwestern Uxin) and western parts of the sandy land. Areas of moderate fluctuations and decreasing trends of AGB covered 703.81 km² (1.83% of study area), which were mainly in the southwestern (central and eastern Otog Qian and northern Dingbian) parts of the sandy land. Areas with mild fluctuations and decreasing trends of AGB covered 1025.63 km² (2.67%), which were largely in the northern (southern Ejin Horo and western Shenmu), eastern (western Yuyang), and southwestern (eastern Otog Qian and southwestern Uxin) parts of the sandy land. Areas with no change covered 856.63 km² (2.23%), mainly in the northernmost (southeastern Otog and northwestern Uxin) and southwestern (central and southern Otog) parts. Areas with mild fluctuations and increasing trends of AGB covered 11,356.06 km² (29.59%), primarily in the northeastern (southern Ejin Horo, western Shenmu, and northern Yuyang), central (eastern and central Uxin), and southern (northern Dingbian and northern Jingbian) parts. Areas with moderate fluctuations and increasing trends of AGB covered 17,274.00 km² (45.01%), mainly in the western, southwestern, southeastern, and northeastern parts of the sandy land. Areas with severe fluctuations and increasing trends of AGB covered 3874.44 km² (10.10%), mainly in the western (southern Otog), southeastern (northern Jingbian), and eastern (northern Hengshan) parts. Areas with extremely severe fluctuations and increasing trends of AGB covered 2955.50 km² (7.70%), largely in the northwestern (southeastern Otog and northwestern Uxin) and southwestern (southern Otog Qian) parts. Among the various AGB spatial patterns across the entire sandy land, the largest area had a combination of moderate fluctuations and increasing trends of AGB. The second largest area had mild fluctuations and increasing trends. Combined, these two types of areas made up 74.60% of the study area. The smallest coverage was for areas with severe and extremely severe fluctuations and decreasing trends of AGB. These two types of areas constituted only 0.86% of the total area and were scattered across the northwestern and western parts of the sandy land.

4.3. Causes of variations of AGB

The variations of total AGB in the Mu Us Sandy Land during 2000–2012 were mainly controlled by changes of vegetation growth conditions and vegetation distribution. In semi-arid and arid regions, growth conditions of natural vegetation are mainly affected by temperature and precipitation. For vegetation distribution, in addition to the limitation of climate factors, human activities on the landscape such as grazing and forestation are also important. Thus, causes of AGB variations in the sandy land are mainly addressed with respect to natural and human factors.

4.3.1. Natural factors

Temperature and precipitation are the most important natural climate factors affecting the growth of vegetation in semi-arid and arid regions. In this research, historical records of nine meteorological stations were used to calculate average annual temperature and precipitation for the Mu Us Sandy Land. By analyzing changes of these two variables from 1980 to 2012 (Fig. 6), we found that both gradually increased, at 0.046 °C/a and 1.669 mm/a, respectively. The trend of increasing temperature was more significant...
than that of precipitation. Fluctuations of total AGB and precipitation revealed an almost uniform trend across the sandy land, with their correlation coefficient \( r = 0.595 \) (Fig. 7). Precipitation in the sandy land was 212.5 mm in 2000, which was 38.53% below average and the minimum in the above study period. Precipitation in 1999 was 223.9 mm, which was 35.24% below average. Considering that there is a time lag between vegetation growth and meteorological factors (Nezlin et al., 2005; Roerink et al., 2003; Schmidt and Karrielli, 2000), there were more or less continuous severe droughts in 1999 and 2000. This had a negative effect on the growth of natural vegetation, which is the most important reason for the smallest AGB in 2000. Precipitation in 2001 and 2002 was 426.4 mm and 467.8 mm, respectively, which were 23.34% and 35.31% above average. With the increase of precipitation, total AGB in 2001–2002 was greater than that in 2000. From 2002 to 2005, both precipitation and total AGB had decreasing trends. The same time lag occurred in 2005–2006 when precipitation was 225.7 mm and 262.2 mm, 34.72% and 24.16% below average, respectively. This might have produced the smaller AGB in 2005–2006. Affected by the continuous severe drought, AGB in 2006 was even less than that in 2005. In 2007–2008 and 2009–2012, variations of AGB and precipitation were more stable.

Fluctuations of total AGB and precipitation showed an almost uniform trend. A precipitation deficit somewhat affects levels of vegetation growth and AGB (Zhao and Running, 2010). It was necessary to quantitatively evaluate this deficit for comprehensively understanding AGB spatial variations. Among dozens of drought indices, the standardized precipitation index (SPI) developed by McKee et al. (1993, 1995) has been widely used for agricultural drought, water supply, and water management interests (Caccamo et al., 2011; Ji and Peters, 2003; Narasimhan and Srinivasan, 2005; Quiring and Papakryiakou, 2003). The SPI can be calculated by fitting long-term precipitation data to a Gamma probability distribution function and transforming that distribution to a normal one, which ensures a mean of zero for SPI on any timescale. Positive SPI values indicate greater than median precipitation, and negative ones less than median precipitation. McKee et al. (1993) proposed a seven-category classification for the SPI: extremely wet (2.00 or greater); very wet (1.50 to 1.99); moderately wet (1.00 to 1.49); near normal (−0.99 to 0.99); moderately dry (−1.49 to 1.00); severely dry (−1.99 to −1.50); and extremely dry (−2.00 or less). Considering the locations of the nine meteorological stations and their AGB characteristics, we chose Henan, Uxin, and Uxin Ju, from south to north of the Mu Us Sandy Land, as typical stations. SPI on a 12-month scale for the three stations was calculated to address the causes of AGB spatial patterns from 2000 to 2012 (Fig. 8). Fig. 5 shows that the main AGB spatial pattern around Henan, Uxin, and Uxin Ju stations at a radius of 5 km was increasing, with severe, moderate, and mild fluctuations, respectively. At Henan, SPI values had precipitation classifications (and numbers of corresponding years) as follows: extremely wet (1), very wet (1), near normal (8), moderately dry (1), severely dry (1), and extremely dry (1). Both extremely wet and extremely dry years at Uxin and Uxin Ju were zero. The extremely wet and dry years made Henan the station with the greatest AGB fluctuation of the three. Moreover, near-normal precipitation years at Uxin Ju were 11, the highest among the three stations in 2000–2012. There were two severely dry years, the same as Uxin, which gave the AGB spatial pattern at Uxin Ju an increasing with mild fluctuation character. At Uxin, the precipitation classifications (and numbers of corresponding years) were very wet (2), moderately wet (1), near normal (8), and severely dry (2). Number of near-normal years was the same as that at Henan but less than that at Uxin Ju, respectively. This gave the AGB spatial pattern in the Uxin region an increasing with moderate fluctuation characteristic.

4.3.2. Human factors

Aside from natural driving forces such as precipitation and temperature, human driving forces such as population, production type, policy, and others were also important factors causing variations of AGB (Dai, 2010; Jiang, 2005; Mu et al., 2013; Wang et al., 2006; Zhou et al., 2009). Uxin Banner is the only region in the remotest area of the Mu Us Sandy Land. Statistical data of human factors in Uxin Banner gave a better representation and they could be used to represent the socioeconomic situation of the sandy land.

(1) Population and livestock

In Uxin Banner, the population was 93,752 in 2000 and 108,797 in 2012, an annual average increase of 7.04%. Total livestock numbers, especially sheep and goats, were 605,465 to 1.34 million head in 2006, and 1.02 million in 2012, an annual average increase of 5.68%. Continuous increases of population and number of breeding animals boosted pressure on the land and water resources. This could have led to the changes of land use and AGB.

(2) Policies

AGB was also affected by the environmental education of local people and by national and regional policies, which resulted in interventions and interest-driven impacts that improved AGB, especially in grazing areas. With the implementation of the Household Responsibility System (HRS) in the 1980s, livestock and pasture were allocated to small operators and farmers, and the length of a grassland contract was extended from an indefinite term to a period of 30–50 years. Stimulated by the HRS, farmers began to plant more trees, shrubs, and grass. In Uxin Banner, tree and shrub planting in 2000 brought the forest area to 225,000 ha, an increase around fourfold from 1975 (Jiang, 2005). In 2012, forest area reached 376,867 ha. Areas of natural and artificial grassland in 2000 were 606,000 and 10,000 ha, respectively. The figures in 2010 were 667,000 and 42,000 ha. Over-cultivation, overcutting, and over-grazing behaviors of farmers have been greatly restricted.
In addition to the HRS, a series of favorable policies were developed and implemented to address environmental degradation in China beginning in the late 1990s, which were very important for afforestation and combating desertification in the Mu Us Sandy Land during 2000–2012. The Grain-to-Green Program (GTGP) began in 1999, which subsidized farmers for afforestation on marginal croplands. Grazing intensity declined under the GTGP program, which led to vegetation recovery and an improvement in the sandy land (Dai, 2010). As the only one in a sandy area among 174 demonstration counties of GTGP in China, Uxin Banner converted 3300 ha grain plots to forestry and grass in 2000. From 2001 to 2005, GTGP areas in Uxin Banner were 2000 ha, 6600 ha, 7330 ha, 8067 ha, and 3667 ha, respectively, which may have greatly improved the ecological environment and provided better growth conditions for vegetation in the Mu Us Sandy Land.

Several other projects had significant impacts in combating desertification and improving vegetation recovery, including the “Two Policies that Limited the Effects of Goat Grazing”, the fourth phase of the “Three-North Shelterbelt” project in 2001, and the “Aerial Seeding Afforestation” project in the Mu Us Sandy Land. With implementation of the “two policies” project, the proportions of goats and sheep were 13.4% and 86.6% in 2003, respectively, and corresponding figures in 2010 were 10.1% and 89.9%. The hog number also increased considerably, from 70,316 head in 2003 to 132,892 in 2010. As a result of the policy, the sheep population showed a steady recovery, hogs had a sharp increase, but goats registered an abrupt decline (Dai, 2010). Adjustment of animal feeding structure can reduce grazing pressure on grassland, which would be favorable for vegetation restoration. With implementation of the Aerial Seeding Afforestation project, the associated afforestation area in Uxin Banner has increased 118,774 ha since 2000. Of this, 17,334 ha was new afforestation in 2007 and 2008. Furthermore, during implementation of the fourth phase of the Three-North Shelterbelt project, 3067 and 7200 ha of afforestation areas were added in Uxin Banner during 2008 and 2009, respectively. This may be the major reason for total AGB increase, despite the decrease of precipitation from 2008 to 2009.

(3) Other human activities

Among human factors, continuously increasing trends of population, cultivated land area, and number of breeding animals have negative effects on the growth of vegetation. However, with the promotion of environmental education and useful policies, AGB in most of the Mu Us Sandy Land still had moderate or mild fluctuations with increasing trends from 2000 to 2012. In contrast, a rapid expansion of urban area, especially in the southern (Dingbian and Jingbian), middle (Uxin), and northeastern (Yuyang and Shenmu) parts of the sandy land, was the main cause of vegetation destruction and AGB decline. Other human factors, such as mining, factories and supporting highways (Shenmu, Yuyang and Hengshan), were also reasons for decreasing trends of AGB in the sandy land.

5. Conclusions

This study explored the use of Landsat TM and MODIS images for estimating AGB in the Mu Us Sandy Land, a farming-pastoral ecotone of northern China. Spatiotemporal AGB patterns over 2000–2012 were also analyzed.

AGB estimation revealed that areas with various AGB levels fluctuated. A relatively low average AGB and percentage of area with less than 1.5 t/ha AGB accounted for more than half the total area each year. Total AGB increased by 0.1743 Tg annually during the study period. Spatial variations of AGB based on time series of retrieved data showed an increasing trend in most of the area (over 92.40% of the total area). The largest and the second largest areas had moderate and mild AGB fluctuations with increasing trends, respectively. These two types of areas constituted 74.60% of the total area and were widely distributed in the northeastern, eastern, central, and southern portions of the sandy sand. Areas with severe and extremely severe fluctuation combined with decreasing AGB made up the smallest portion of the study area, with these two types combined representing only 0.86% of the total area. These areas were scattered in northwestern and western parts of the sandy land.

Under the background of global climate warming with increasing temperature and precipitation, the total AGB tended to increase in 2000–2012, almost in line with precipitation. The relationship between AGB and precipitation (especially precipitation deficit) showed that precipitation was an important natural factor that significantly affected AGB variation. However, precipitation was not the only effect on AGB. Other sources of interference were human, such as population, livestock, and policies. These altered AGB spatiotemporal patterns. Increasing populations of humans and livestock exert more pressure on land and water resources in sandy land ecosystems, which can modify AGB patterns. However, positive policies can somewhat reduce land and water resources pressure and promote vegetation restoration and reforestation. Affected by such positive human factors, although precipitation declined in 2008–2009, total AGB still increased. Positive policies such as the “Aerial Seeding Afforestation” and “Three-North Shelterbelt” projects may be very important in the Mu Us Sandy Land.

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