Geospatial analysis of change in net primary productivity, 1998-2013, Inner Mongolian Desert steppe region, China

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Abstract. Net primary productivity (NPP) is a quantitative measure of the carbon absorption by plants per unit time and space. The NPP is a key indicator to evaluate the productivity of vegetation communities in the natural environment. Consistent data on terrestrial NPP are urgently needed to constrain model estimates of carbon fluxes and hence to refine our understanding of ecosystem responses to climate change. It could also be an indicator to represent certain land cover characteristics. This study analyzed NPP changes from 1998 to 2013 in the Inner Mongolian Desert Steppe region of China through estimation of annual NPP using multiyear 10-day SPOT VEGETATION NDVI data and meteorological observation data from 1998 to 2013 by using a modified Carnegie-Ames-Stanford Approach (CASA) model. ArcGIS and ENVI software was used for spatial data processing; NPP inversion was performed and an integrated program was used for the modified CASA model. We also used related spatial information technologies, such as geographic information system, global navigation satellite system and remote sensing technology, to determine some 1 km$^2$ random sampling pixels and regularly selected four 1m$^2$ quadrats in each pixel, and we measured aboveground net primary productivity (ANPP) for accuracy assessment of modelled NPP. The final results show that the NPP had many obvious geospatial changes during the period from 1998 to 2013 in the Inner Mongolian Desert Steppe region.

1. Introduction
Terrestrial ecosystems play an important role in the global carbon cycle due to their capacity to sequester part of the fossil carbon emitted by anthropogenic activities (Migliavacca et al., 2009). Net primary productivity (NPP) is a quantitative measure of the carbon absorption by plants per unit time and space (Liu et al., 2002). NPP is defined as the accumulation of dry matters by green plants per unit time and space (Nayak et al., 2010), and is equal to the difference between gross primary production (GPP) and autotrophic respiration (Ahl et al., 2004). Regional estimates of NPP are very useful in modelling regional and global carbon cycle (Li et al., 2013). The NPP is a key indicator to evaluate the productivity of vegetation communities in the natural environment. Consistent data on terrestrial NPP are urgently needed to constrain model estimates of carbon fluxes and hence to refine our understanding of ecosystem responses to climate change (Scurlock et al., 2002). It also could be an indicator to represent certain land cover characteristics.

Three groups of models have been used to estimate NPP for large areas (Donmez et al., 2011), namely:

- satellite sensor based models such as Carnegie-Ames-Stanford Approach (CASA) (Potter et al., 2003, 2004); Global Production Efficiency Model (GLO-PEM) (Prince and Goward, 1995; Cao et
al., 2004); Simple Diagnostic Biosphere Model (SDBM) (Knorr and Heimann, 1995; Rayner et al., 2005); Simple Interactive Biosphere Model (SIB2) (Sellers et al., 1996) and Terrestrial Uptake and Release of Carbon (TURC) (Ruimy et al., 1996);

- models that simulate carbon fluxes using a prescribed vegetation structure such as Biome BioGeochemical Cycles model (BIOME-BGC) (Running et al., 2004), CENTURY (Parton et al., 1993); and

- models that simulate both vegetation structure and carbon fluxes such as BIOM3 (Haxeltine and Prentice, 1999), DOLY (Woodward et al., 1995) and HYBRID (Esser et al., 1999).

Remote sensing models are based on the principle of light use efficiency (LUE) (Li et al., 2013). NPP estimation based on productivity efficiency approach was first introduced by Monteith (1972). The positive relationship between NPP and absorbed photosynthetically active radiation (APAR) is the basis for the light use efficiency (LUE) model (Ahl et al., 2004; Monteith, 1972). A common approach is to incorporate information about vegetation type and/or temperature/water availability conditions in LUE calculation. One such technique is the Carnegie-Ames-Stanford Approach (CASA) model that is a widely recognized NPP model for estimating NPP from remote sensing data (Bradford et al., 2005). Monteith (1977) and Potter et al. (1993) observed that plant productivity is correlated with the amount of photosynthetically active radiation absorbed or intercepted by green foliage (APAR) and included their findings in the CASA model (Yuan et al., 2006).

In this paper, we implemented a modified Carnegie-Ames-Stanford Approach (CASA) model (Zhu et al., 2005) to estimate net primary productivity in Inner Mongolian Desert Steppe region, China, using 10-day SPOT VEGETATION NDVI data and meteorological observation data from 1998, 2006 and 2013.

2. Method

2.1. Study area

The study area is the Inner Mongolian Desert Steppe region (IMDSR). It is located in the western part of the Inner Mongolia Autonomous Region, China, between 105°07´E and 115°12´E, and 37°37´N and 45°08´N (figure 1). The IMDSR has an arid-semiarid, temperate continental climate. The annual mean air temperature is 3 to 9°C and the annual mean precipitation is 150 to 300 mm, with most of precipitation (60 to 70 per cent) occurring between July and September. According to the Chinese Soil Classification System, the soil of the IMDSR is mainly classified as a brown calcic soil, which is

Figure 1. Location of the study area, the Inner Mongolian Desert Steppe region (IMDSR)
equivalent to orthid and argid in the United State Soil Taxonomy (Ren et al., 2012). The dominant species of IMDSR include *Stipa klemenzii*, *Stipa breviflora*, *Stipa gobica*, *Stipa glareosa*, *Cleistogenes songorica*, *Allium polyrhizum* (Wei et al., 2013).

### 2.2. Data acquisition and processing

Data sources include remote sensing data, meteorological observation data and basic geographical data. Remote sensing data used is SPOT/VEGETATION 1 km 10-day NDVI (Normalized Difference Vegetation Index) data in 1998, 2006 and 2013, downloaded through products distribution portal of Proba-V (http://proba-v.vgt.vito.be/content/data). Using ENVI software and ArcGIS software, SPOT/VEGETATION NDVI data has undergone geospatial processing for creating image subsets of the study area, monthly composites by maximum NDVI value, and reprojection within a uniform spatial structure, suitable for input and integration into the modified CASA model (Zhu et al., 2005 and 2007). The uniform spatial structure is defined as input raster data with the same spatial extent of the IMDSR study area, same 1000 m spatial resolution, same Albers Map Projection with central meridian of 110° E, latitude origin of 0°, first standard parallel of 39°N, second parallel of 43°N, and same reference spheroid of WGS1984.

Meteorological data was obtained from the Meteorological Information Center of the Inner Mongolia Meteorological Bureau. Data sets included monthly total precipitation and monthly average air temperature for 65 observation stations (figure 2), and monthly total solar radiation for five stations (figure 2) within or around the study area, collected in 1998, 2006 and 2013. The monthly meteorological data (precipitation, air temperature and solar radiation) has also undergone geospatial processing as suitable input for the modified CASA model.

### 2.3. Model description

An NPP simulation model, the modified Carnegie-Ames-Stanford Approach (CASA) model has been developed (Zhu et al., 2005). We estimated grassland NPP in the IMDRS using this modified CASA model. The NPP estimation theory of the CASA model (Potter et al., 1993) is determined by two variables of absorbed photosynthetically active radiation (APAR) and light utilization efficiency ($\varepsilon$).

$$NPP(x, t) = APAR(x, t)\varepsilon(x, t)$$

where $NPP$ is new production of plant biomass at grid cell $x$ in month $t$, $APAR$ is the absorbed photo-

![Figure 2.](image-url)

**Figure 2.** Location of meteorological stations for observation of precipitation and temperature (a), and solar radiation (b).
synthetically active radiation by green vegetation at grid cell x in month t, and ε is the light utilization efficiency at grid cell x in month t.

\[ \text{APAR}(x, t) = \text{PAR}(x, t) \times \frac{\text{SOL}(x, t)}{\text{PAR}(x, t)} \times 0.5 \times \text{FPAR}(x, t) \]

(2)

where PAR is total incoming photosynthetically active radiation on grid cell x in month t, SOL is the total solar radiation incident on grid cell x in month t, the factor 0.5 accounts for the fact that approximately half of the incoming solar radiation is in the PAR waveband (0.4-0.7 μm), and FPAR is calculated as a linear function of the AVHRR simple ratio (SR); and

\[ \epsilon(x, t) = T_{\epsilon_1}(x, t) T_{\epsilon_2}(x, t) W(x, t) \epsilon^* \]

(3)

where \( T_{\epsilon_1} \) and \( T_{\epsilon_2} \) account for effects of temperature stress, \( W \) accounts for effects of water stress, and \( \epsilon^* \) is the maximum light utilization efficiency. Here, the value of \( \epsilon^* \) is 0.389gC/MJ, and \( \epsilon \) is affected by phenological stage, temperature, water condition, atmospheric CO2 concentration and essential nutrient in soil.

In this modified CASA model, the maximum light utilization efficiency \( \epsilon^* \) is has been considered as a variable that depends on the ecosystem type and can be determined by the user of the model (Zhu et al., 2005). On the other hand, the calculation method of estimated evapotranspiration and potential evapotranspiration has been simplified and differs from the original CASA model in the calculation of \( W(x,t) \), given by equation (4) and equation (5):

\[ \text{EET}(x, t) = \frac{P(x, t) \times R_n(x, t) \times (P(x, t)^2 + R_n(x, t)^2 + P(x, t) \times R_n(x, t))}{[P(x, t) + (P(x, t)^2 + R_n(x, t)^2)]} \]

(4)

where \( EET(x,t) \) is estimated evapotranspiration at grid cell x in month t, \( P(x,t) \) is precipitation at grid cell x in month t, and \( R(x,t) \) is net solar radiation at grid cell x in month t (Zhu et al., 2005; Zhou et al., 1996); and

\[ \text{PET}(x, t) = [\text{EET}(x, t) + \text{PET}^0(x, t)] \]

(5)

where \( \text{PET}(x,t) \) is the potential evapotranspiration at grid cell x in month t, \( \text{PET}^0(x,t) \) is local potential evapotranspiration calculated by Thornthwaite’s method for calculating potential evapotranspiration and climatic classification at grid cell x in month t (Zhang, 1989).

3. Results and discussions

3.1. Comparison of modelled NPP and field based NPP

We used spatial information technologies, such as Geographic Information System (GIS), Global Navigation Satellite System (GNSS) and remote sensing technology, to determine 100 1km² random sampling pixels for the geographical study of the IMDSR (figure 3).

Figure 3. Distribution map of random points for field investigation.
Table 1. Comparison of modelled NPP and field based NPP by random points in IMDSR.

| Number of random points | Longitude | Latitude | Modelled NPP (gCm⁻²yr⁻¹) | Field NPP (gCm⁻²yr⁻¹) |
|-------------------------|-----------|----------|---------------------------|------------------------|
|                         |           |          | 1998          | 2006    | 2013 | 2015    |           |          |
| 003                     | 107°46'03.64" | 39°18'07.99" | 154.12 | 122.42 | 164.97 | 119.27 |
| 032                     | 111°05'34.93" | 42°00'37.70" | 186.99 | 96.37 | 202.94 | 129.84 |
| 045                     | 112°53'54.60" | 42°34'54.19" | 196.64 | 98.70 | 189.86 | 116.78 |
| 049                     | 107°20'37.76" | 38°52'10.10" | 124.88 | 72.18 | 130.44 | 117.96 |
| 060                     | 112°53'02.89" | 43°43'05.82" | 146.88 | 108.41 | 98.49 | 70.95 |
| 068                     | 110°46'46.07" | 42°02'56.30" | 168.52 | 95.38 | 154.99 | 102.22 |
| 069                     | 111°39'24.27" | 42°19'40.40" | 157.53 | 66.86 | 174.91 | 141.05 |
| 071                     | 108°21'37.21" | 41°39'11.12" | 84.43 | 83.17 | 113.31 | 116.36 |
| 099                     | 112°43'57.46" | 42°47'38.70" | 170.40 | 111.55 | 119.31 | 32.05 |
| 100                     | 113°44'43.281" | 44°06'36.18" | 218.67 | 148.34 | 157.94 | 408.33 |

Table 2. Comparison for estimated annual NPP of IMDSR in 1998, 2006 and 2013

| Year | Minimum (gCm⁻²yr⁻¹) | Maximum (gCm⁻²yr⁻¹) | Mean (gCm⁻²yr⁻¹) | Standard deviation (gCm⁻²yr⁻¹) | Total (MtCyr⁻¹) |
|------|---------------------|---------------------|-----------------|---------------------------------|-----------------|
| 1998 | 0                   | 451.37              | 141.7           | 45.75                           | 13.40           |
| 2006 | 0                   | 431.54              | 90.7            | 33.82                           | 8.56            |
| 2013 | 0                   | 480.97              | 138.67          | 53.20                           | 13.11           |

Figure 4. Maps of IMDSR estimated annual NPP in 1998 (a), 2006 (b) and 2013 (c).

Figure 5. Maps of IMDSR annual NPP changes for 1998–2006 (a), 2006-2013 (b) and 1998-2013 (c)
In this study, ten 1km² random pixels (figure 3) have been used for field measurement of aboveground net primary productivity (ANPP). We measured the ANPP at four center points of the square quarter part of each selected 1 km² random pixel in area of 1 m² by using the harvesting approach. Final field based NPP in each random pixel given by equation (6) as:

$$\text{FBNPP} = \left( \sum_{i=1}^{4} DW_i \right) \frac{m}{n}$$

where FBNPP is field based estimation value of annual NPP, DW is dry weight of annual aboveground biomass at the center point of a random pixel in area of 1m², i is number of center point of square quarter part of random pixel, m is a conversion coefficient from dry weight to carbon weight, set at 0.45 (Fang et al., 1996), and n is fraction of ANPP in NPP, set as 10/77 (Wang et al., 2010). A comparison of modeled NPP and field based NPP is shown in table 1, indicating that field based NPP of 2015 is lower than modeled NPP in 1998, 2006 and 2013.

3.2. Geospatial analysis for NPP changes in IMDSR

Modeling and mapping results of IMDSR’s NPP in 1998, 2006 and 2013 are shown as figure 4. Pixels representing NPP values from 50 to 100 gCm⁻² yr⁻¹ occupy 13.53 per cent, 63.56 per cent and 23.60 per cent of the total IMDSR pixels in 1998, 2006 and 2013, respectively. Pixels representing NPP values from 100 to 150 gCm⁻² yr⁻¹ occupy 47.78 per cent, 28.42 per cent and 39.90 per cent of the total IMDSR pixels in 1998, 2006 and 2013, respectively; and pixels representing NPP value from 150 to 200 gCm⁻² yr⁻¹ occupy 28.97 per cent, 2.10 per cent and 26.87 per cent of total IMDSR pixels in 1998, 2006 and 2013, respectively. The mean value of NPP is 141.7, 90.7, and 138.67gGm⁻² yr⁻¹ in 1998, 2006 and 2013 respectively (table 2).

According to this data, the IMDRS has obviously experienced grassland degradation from 1998 to 2006 and grassland improvement from 2006 to 2013. These features are represented more clearly in figure 5, showing the spatial distribution maps of NPP differences between 2006 and 1998 (a), 2013 and 2006 (b), and 2013 and 1998 (c), respectively. Due to the occurrence of grassland improvement during the period of from 2006 to 2013, the IMDSR has experienced both of grassland degradation and improvement during the period from 1998 to 2013. Degradation is mainly encountered in the northeastern portion of the IMDSR and the improvement in southwestern portion of the IMDSR.

3.3. Further research

Further research will includes following: (1) acquisition and geospatial processing of meteorological observation data of the IMDSR for the years 1999 to 2005, 2007 to 2012, and 2014 to 2015; (2) NPP estimation for the years 1999 to 2005, 2007 to 2012, and 2014 to 2015; (3) accuracy analysis for modelled annual NPP in 2015 by using field based NPP data from August 27 to September 2, 2015; (4) further modification of the NPP estimation model by adjustment of maximum light utilization efficiency; and (5) further geospatial analysis for the change process of modelled annual NPP.

4. Conclusions

In this study, we estimated annual NPP of the IMDSR by the modified CASA model in 1998, 2006 and 2013. The final modeling results were basically acceptable, and we present the following findings: the IMDRS has obviously experienced grassland degradation from 1998 to 2006 and grassland improvement from 2006 to 2013. Degradation is mainly encountered in the northeastern portion of the IMDSR and the improvement in southwestern portion of the IMDSR. This result appears to coincide with the effort of the Chinese government for the protection and restoration of grassland ecosystem in China. Inner Mongolian livestock numbers increased sharply and led to grassland degradation since 1998. After the year of 2000 the Chinese government issued a series of policies and regulations to protect grassland and initiated “The project for treatment of sandstorm source in Beijing and Tianjin” (Chang et al., 2015).
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