Predicting plant diversity based on remote sensing products in the semi-arid region of Inner Mongolia

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Abstract

Changes in species composition and diversity are the inevitable consequences of climate change, as well as land use and land cover change. Predicting species richness at regional spatial scales using remotely sensed biophysical variables has emerged as a viable mechanism for monitoring species distribution. In this study, we evaluate the utility of MODIS-based productivity (GPP and EVI) and surface water content (NDSVI and LSWI) in predicting species richness in the semi-arid region of Inner Mongolia, China. We found that these metrics correlated well with plant species richness and could be used in biome- and life form-specific models. The relationships were evaluated on the basis of county-level data recorded from the *Flora of Inner Mongolia*, stratified by administrative (i.e., counties), biome boundaries (desert, grassland, and forest), and grouped by life forms (trees, grasses, bulbs, annuals and shrubs). The predictor variables included: the annual, mean, maximum, seasonal midpoint (EVI_{mid}), standard deviation of MODIS-derived GPP, EVI, LSWI and NDSVI. The regional pattern of species richness correlated with GPP_{SD} ($R^2 = 0.27$), which was also the best predictor for bulbs, perennial herbs and shrubs ($R^2 = 0.36$, 0.29 and 0.40, respectively). The predictive power of models improved when counties with >50% of cropland were excluded from the analysis, where the seasonal dynamics of productivity and species richness deviate patterns in natural systems. When stratified by biome, GPP_{SD} remained the best predictor of species richness in grasslands ($R^2 = 0.30$), whereas the most variability was explained by $NDSVI_{max}$ in forests ($R^2 = 0.26$), and $LSWI_{avg}$ in deserts ($R^2 = 0.61$). The results demonstrated that biophysical estimates of productivity and water content can be used to predict plant species richness at the regional and biome levels.
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1. Introduction

Predicting biological diversity at broad spatial scales based on remotely sensed land surface properties has become viable in the modern scientific community because of the increasing variety and availability of remote sensing products. Several studies have shown the increasing accuracy and confidence in this method. Waring et al. (2006) explored the empirical relationships between MODIS enhanced vegetation index (EVI) and tree species distribution in the contiguous United States and found that various expressions of EVI can explain up to 60% of the tree species diversity. Seto et al. (2004) explored the linkages between Landsat-derived normalized difference vegetation index (NDVI) and the spatial variance of bird and butterflies in the Great Basin of western North America. Whether the choice of remote sensing products is based on species richness–vegetation heterogeneity relationships at the landscape level (Seto et al., 2004), climatic conditions (Waring et al., 2006), or potential biophysical regulations of species

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distribution (Gavin & Hu, 2006), species prediction models will greatly enhance our knowledge and support effective management of species at broader spatial scales, as an increasing amount of earth observation satellite data and associated products are made available in the public domain.

Plant species richness studies have been conducted in semi-arid regions at the local scale (e.g., Mediterranean region, Osem et al., 2002), at the landscape level (Jørgenson & Nøhr, 1996), and the regional scale (e.g., Kenya, Oindo & Skidmore, 2002). Some studies considered a direct remote sensing approach to determine species richness, where species assemblages are regressed with spectral reflectance values (Carter et al., 2005; Muldavin et al., 2001). However, such methods that work well at the landscape level might not be a good choice at the regional level due to prohibitive cost of hyper spectral and high-resolution imagery. The indirect method of remote sensing offers an alternative approach and involves the use of primary productivity, climate variables and habitat structure to determine spatial variations of species richness (Turner et al., 2003).

Species richness research at regional scales is traditionally based on NDVI as an indicator of productivity but its use in the semi-arid environment has been questionable owing to its sensitivity to soil background signature in areas with sparse ground cover (Huete et al., 1997, 2002). In addition to replacing NDVI with EVI, the inclusion of vegetation water content indices (Ceccato et al., 2002a,b; Qi et al., 2002; Xiao et al., 2005) has been suggested as more appropriate predictor variables for semi-arid environments such as Inner Mongolia (Qi et al., 2002).

Inner Mongolia is divided into three biomes: the arid deserts in the west, grasslands in the center, and forests in the northeast region (Fig. 1). The grasslands in China (mostly in Inner Mongolia) make up 41% of the land area, and are especially prone to the loss of biodiversity owing to the warming tends (~1.5 °C) in northeast Asia over the last 50 years (Lee et al., 2002; Yu et al., 2003). The area has been subjected to intensive land use practices (Chase et al., 2000; Kang et al., 2007). Climatic changes have not only influenced ecosystem dynamics, productivity, and stability of the Eurasian steppes, but have also accelerated the impacts of land use that are associated with the rapid socio-economic growth (Jiang et al., 2006; Kang et al., 2007). The degradation of the semi-arid grassland has resulted in the replacement of dominant plant life forms (e.g., herbaceous grass) by invasive shrubs, which are less efficient in water use (Zheng & Huang, 1992; Yang et al., 1994; Cheng et al., 2001a,b, 2007; Zhang, 1994). These degraded arid and semi-arid
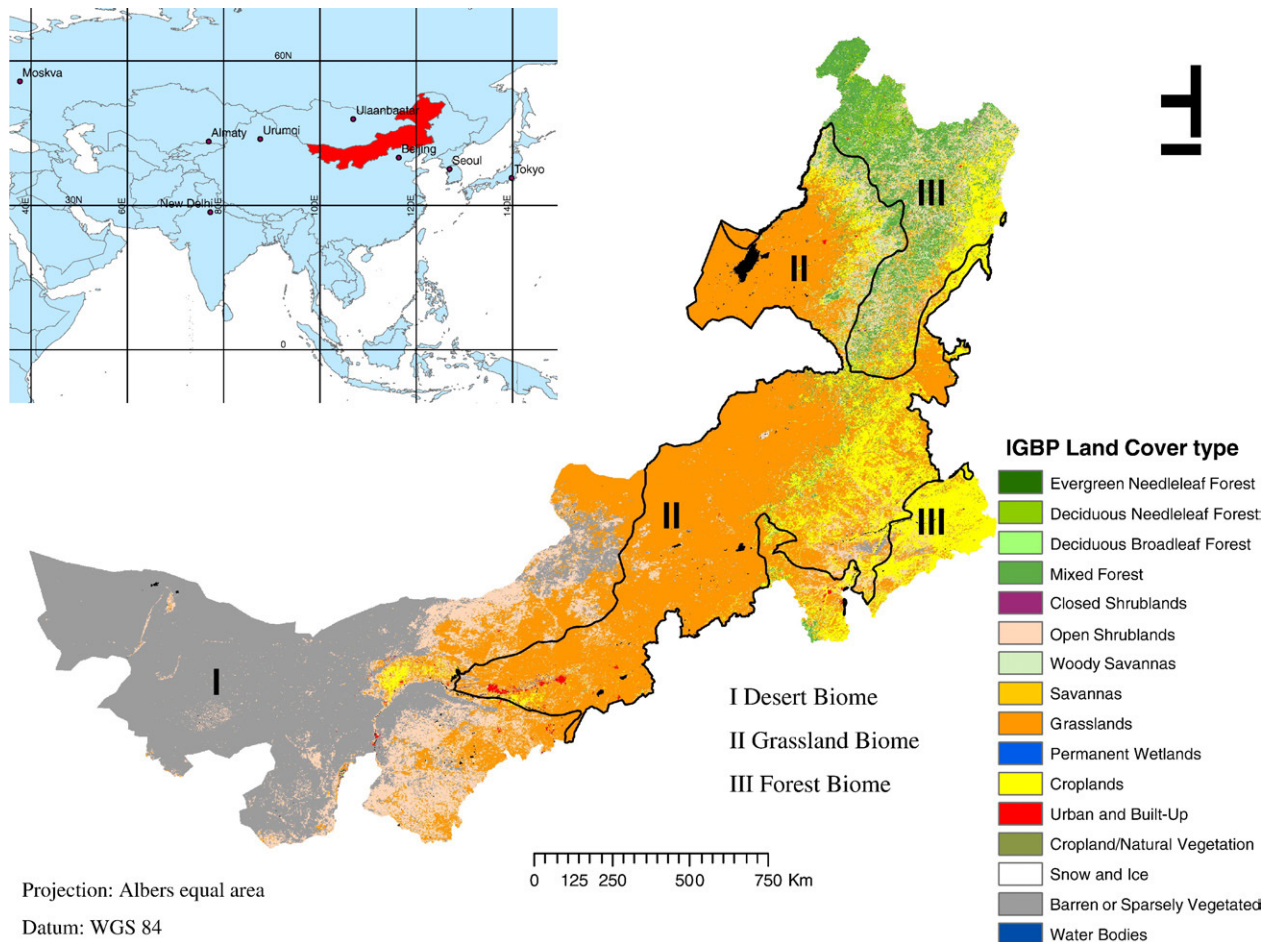

Fig. 1. Location map of study region, province of Inner Mongolia, P.R. China and land use/land cover (LULC) map of Inner Mongolia obtained from MODIS-derived 1 km (MOD12Q1) IGBP classification, overlaid with biomes derived from WWF terrestrial eco-region boundaries (http://www.worldwildlife.org/science/data/terreco.cfm).

ecosystems are prone to wind erosion and considered to be the cause of frequent sandstorms with subsequent loss of biodiversity (Ye et al., 2000). The total annual emission rate of these dust storms in Northern China is about 25 million tons (Xuan et al., 2000). Small dust particles from these sandstorms can cause severe respiratory problems with complications, such as bacterial infections (Karasov, 2000). Clearly, predicting plant species distribution across the region is fundamental to a comprehensive understanding of the ecosystem function and feedbacks to the human disturbances and climatic change. Conventionally, species richness is quantified through ground surveys — a daunting task for a large province like Inner Mongolia, which covers an area of 1.18 million km^2. Research on species richness–productivity relationships has been conducted on 24-year datasets in Inner Mongolia (Bai et al., 2004) showing a positive relationship between richness and ecosystem stability as well as on the effects of land use on species richness and productivity (Zhou et al., 2006), but there are no reported results at the regional level. A practical, objective, and cost-effective method to successfully map plant distribution is to use the Earth Observation (EO) data that provide regional coverage with high temporal resolution (Ceccato et al., 2001; Fensholt & Sandholt, 2003).

Climatic factors like temperature, precipitation and evapo-transpiration (ET) have long been the predictors of choice to successfully explain spatial variations in species richness (Francis & Currie, 2003; Sarr et al., 2005). Additionally, ecosystem productivity has shown good correlation with species diversity, as it is the integrative expression of factors such as, topography, land use, disturbance, and soil nutrients (Tilman, 1996). Hawkins et al. (2003) found that productivity was better than annual climatic predictors for predicting species richness. NDVI has been widely used as a surrogate measure of net primary production (NPP) and proven to be useful within the context of species richness–energy hypothesis (Oindo & Skidmore, 2002). Other authors questioned the use of NDVI alone in understanding ecosystems composition and functions and called for breaking with the traditional NDVI-based doctrine by including other biophysical variables such as EVI, surface temperature, moisture, vegetation chemistry (Huete et al., 2002; Qi et al., 2002; Fensholt &Sandholt, 2003; Xiao et al., 2005; Ollinger et al., 2005). However, the greatest challenge in developing predictive models comes from availability of spatial databases for species distribution. For this study, we created a spatial database based on records of vascular plant species from the Flora of Inner Mongolia (Ma, 1989, 1990, 1993, 1994, 1998).

In recent times, the ability to predict plant species richness at the regional level has improved owing to the availability of satellite derived biophysical variables from sensors such as NASA's Moderate Resolution Imaging Spectroradiometer (MODIS). MODIS-derived biophysical variables have global coverage and are readily available online (MODIS EVI/GPP productivity estimates, Huete et al., 2002; Running et al., 2004). In addition, water content indices such as the Land Surface Water Index (LSWI) and Normalized Difference Senescence Index (NDSVI) can be calculated from surface reflectance (Ceccato et al., 2002a,b; Xiao et al., 2005). We evaluate the use of metrics derived from growing season composites of MODIS EVI, MODIS-derived gross primary production (GPP) as well as water content indices to explain spatial distribution of species in Inner Mongolia, for different biome types. We expected that these metrics would result in improved predictive models of species diversity, which increases with variation in vegetation heterogeneity and water availability.

Recent studies that used MODIS EVI to predict species richness did not find a parabolic relationship at the regional level (Waring et al., 2006), owing to annual compositing of predictors, suggesting that such unimodal relationship can be found at finer spatial scales (Swenson & Waring, 2006). The current study demonstrated that species richness counts at the regional levels as well as in the grassland biomes showed linear relationships with biophysical predictor variables that differed by biome and life form. The species richness in the desert biome showed negative linear relationships with productivity and water content estimates for plant life forms such as shrubs and perennial herb species as compared to the grassland and forest biomes.

2. Methods

2.1. Study area

Inner Mongolia lies between 37°01′–3°02′N and 95°02′–123°37′ E and is the third largest province in China (Fig. 1) with elevation that varies between 86 and 3522 m. The province is characterized by an arid to semi-arid continental climate (Yu et al., 2003) with strong climatic gradients and varied land use practices (Fig. 1). The principal mountain ranges are the Greater Hingaan Mountains in the east and the Yinshan and Langshan in the central part. Deserts include the Gobi desert in the northwest, Mu Us and Hobq deserts, south of the Yellow River, and the Tengger and Badain Jarian desert in the west, which cover 40.03% of the province (Table 2). Precipitation decreases and temperature increases as one moves from east to west. The precipitation in the northeast exceeds 400 mm (Ellis, 1992) and is a transitional zone where the steppes meet the Greater Hingaan Mountains (Yu et al., 2003), which are covered by deciduous forest (0.23 million km^2, 19.7% of the region). It is presently dominated by irrigated agriculture (Yu et al., 2003) in some areas. The north central region of Inner Mongolia borders the Gobi desert and is dominated by the semi-arid steppe with annual rainfall less than 100 mm (Yu et al., 2003). The annual mean, minimum and maximum temperature in the temperate grasslands (40.23%) are 1.6, −18.3, and 18.7 °C, respectively, with an annual precipitation of 385 mm of which 67% falls between June and August (Zhou et al., 2006). The growing season for perennial species in Inner Mongolia runs from April to September, whereas the annuals germinate from April to July depending on the soil moisture content, and following rain events (Bai et al., 2004).

Typical steppes and meadow steppes are the major types of the grassland ecosystems found in Inner Mongolia, and are most commonly used for grazing and animal production (Kang et al., 2007). Typical steppe developed under semi-arid conditions with annual precipitation under 350 mm, is capable of drought tolerance, and includes *Stipa grandis*, *Leymus chinensis*, and multiple species of *Artemisia* and *Festuca*. Meadow Steppe,

which is more productive than typical steppe (Yu et al., 2003) developed in areas with moist fertile soils rich in organic matter with annual precipitation of 450 mm, include *Stipa baicalensis*, *L. chinensis*, and *Cleistogenes mucronata* (Kang et al., 2007). The desert steppe is the most arid ecosystem, with the least biomass (Yu et al., 2003) and is found in areas with annual precipitation between 150 and 200 mm and has a typical continental semi-arid climate (Kang et al., 2007). Some of the species found include perennials such as *Stipa krylovii*, *Stipa bungeana*, and *Artemisia ordosica* (Ellis, 1992; Cheng et al., 2001b). Cropland and forest plantations occur along the riversides, but as isolated patches across the sandy steppe matrix (Zhang, 1994).

2.2. Species distribution and richness

Plant distribution in Inner Mongolia is strongly influenced by climate conditions and human disturbances. The only available, yet comprehensive, plant species database available is provided in the *Flora of Inner Mongolia* (Ma, 1989, 1990, 1993, 1994, 1998). These five volumes were developed over a period 40+ years since the 1950s by a research team from several institutions who conducted intensive and frequent field surveys of the entire province (Ma, 1989). Each species is described by its taxonomical characteristics, life form, and distribution by county. From these publications, we entered each species, its life form, and county into a spreadsheet file for each of the 2562 species recorded. Vascular plant species were divided into five life forms based on the position of the apical bud with respect to the surface of the ground (Raunkiaer, 1934), including (1) Phanerophytes: woody plants with the shoot apices exposed around 1–2 m above the ground; (2) Chamaephytes: shrubs whose apical buds are borne close to the ground; (3) Hemi-cryptophytes: perennial herbaceous plants with the apical bud on the surface of the ground; (4) Cryptophytes: other perennial herbaceous plants with underground tissues such as rhizomes, bulbs and tubers; and (5) Therophytes: annuals plant with complete life cycle within a season. All abbreviations are provided in Table 1.

2.3. MODIS-derived metrics

The climate of Inner Mongolia results in sparse ground cover for most of the year and an increased canopy background noise that reaches a maximum at intermediate levels (50%) of vegetation (Huete et al., 2002). Previous species diversity studies used NDVI as a surrogate of productivity as the independent variable (Oindo & Skidmore, 2002), but EVI has been proposed as a better choice as it is not sensitive to soil/atmospheric effects and adjusts the red wavelength as a function of the blue wavelength to minimize brightness related soil effect (Huete et al., 1997, 2002). The MODIS 16 day EVI is calculated as:

$$\text{EVI} = G \cdot \frac{\rho_{\text{NIR}} - \rho_{\text{red}}}{\rho_{\text{NIR}} - c_1 \cdot \rho_{\text{red}} - c_2 \cdot \rho_{\text{blue}} + L} \tag{1}$$

by the MODIS Data Processing System, or MODAPS at the NASA Goddard Space Flight Center, where, ρ_{NIR}, ρ_{red}, and ρ_{blue} are atmospherically corrected surface reflectance, L is the canopy background brightness correction factor, c_1 and c_2 are the atmospheric resistance coefficients for red and blue bands, respectively, and G is the gain factor. The coefficients adopted in the EVI algorithm (Huete et al., 2002) are: $L=1$, $c_1=6$, $c_2=7.5$, and G (gain factor)$=2.5$.

MODIS-derived 16-day composite vegetation indices (MOD13A1) at 500 m resolution were acquired from the EOS data gateway (http://edcimswww.cr.usgs.gov/pub/imswelcome/), between March and November of 2005. The 8-day composites of GPP (MOD17A2) as well as surface reflectance (MOD09A1) were also downloaded for the same period, and covered the entire province of Inner Mongolia. The 500 m resolution, surface reflectance product consists of seven spectral bands that include visible, near infrared, and short wave infrared wavelengths. These data were reprojected from the native Sinusoidal projection to the Albers equal area projection using the MODIS reprojection tool and nearest neighbor method resampling. Growing season (average) composites of MODIS 16 day EVI and 8 day GPP products were produced to further smooth inter-annual variation. The seasonal midpoint metric, which represents the active growing season and is sensitive to site-specific changes in EVI range and local variations in LAI and chlorophyll concentration, was obtained by calculating the annual maximum, mean and minimum EVI and then adding the annual mean to the minimum (Waring et al., 2006).

2.3.1. Productivity and vegetation metrics

GPP is the fixation of light energy into chemical compounds by plants – the primary producers – and should be affected by community or biome species composition. The MODIS sensor has enabled the generation of the first global GPP datasets based on the premise that solar radiation and vegetation biophysical parameters can determine GPP (averaged to 8 days at 1 km resolution, Running et al., 2004). We used the growing season composites of MODIS-derived 8-day MOD17A2 GPP product (Running et al., 2004) and the 16-day EVI (MOD13A1) as direct and indirect measures of productivity, respectively.

The standard deviations of GPP (GPP$_{\text{SD}}$) and EVI (EVI$_{\text{SD}}$), across the province (i.e., spatial variation), were used as surrogate measures of vegetation heterogeneity (Oindo & Skidmore, 2002), whereas the mean and maximum values were used to represent primary productivity. A positive relationship between species richness (SR) and productivity has been reported (Tilman, 1996), although the relationship may differ among ecosystems and is dependent of spatial scales

Table 1
List of variables and abbreviations used in this study

Full name	Abbreviations
Enhanced vegetation index (0–1)	EVI
Seasonal midpoint (0–1)	EVI$_{\text{mid}}$
Gross primary production (kg C m^{-2})	GPP
Land Surface Water Index (−1 to 1)	LSWI
Normalized Difference Senescent Vegetation Index (0–1)	NDSVI
International Geosphere Biosphere Program	IGBP
Land use/land cover	LULC
Standard error	SE
Standard deviation	SD
Species richness	SR

(Mittelbach et al., 2001). At local scales, the SR–productivity relationship can be considered to be 'unimodal', with maximum species richness at intermediate levels of productivity while other studies report a positive or negative linear relationship between species richness and productivity at broad, regional scales (Waide et al., 1999). Published results have suggested that SR–productivity relationships varied among ecosystems, taxonomic groups, and are often scale dependent (Cardinale et al., 2000; Huston, 1999).

2.3.2. Land surface water content

Water availability, especially in the arid and semi-arid regions, plays an important role in limiting plant biological (Ellis et al., 2001) and ecosystem processes (e.g., carbon fixation, plant growth, respiration, production, Sala et al., 1997; Ehleringer et al., 1999; Dube & Pickup, 2001). In semi-arid regions, different plant life forms use water from different soil layers, with different intensity (Schlesinger & Ehleringer, 2001; Schenk & Jackson, 2002). Herbaceous plants in arid environments compete for water resources in upper soil layers, while woody plants have a greater proportion of roots in deeper layers, and therefore take up a greater amount of water (Schenk & Jackson, 2002; Snyder & Williams, 2003). As a result of drought and frequent overgrazing, the grasslands are invaded by desert shrubs which are less water efficient than the herbaceous cover (Schlesinger et al., 1996). Inner Mongolia is largely an arid and semi-arid region ($> 80\%$) with degraded grassland ecosystems (Jiang et al., 2006) and it is therefore critical to include water content indices in predicting species richness. The MODIS-derived GPP and EVI (Waring et al., 2006) provide good estimates of productivity in the forest and grassland biomes, but may not be a good indicator of productivity for the arid desert and semi-arid grasslands as they are based on light use efficiency (Monteith, 1972), but not water stress (Fensholt & Sandholt, 2003).

Land Surface Water Index (LSWI), recently used in mapping forest cover in China along with NDVI (Xiao et al., 2002) and EVI in the mapping temperate grasslands in East Asia (Boles et al., 2004), is calculated to emphasize the water influence on species diversity. As leaf water content increases, reflectance in the NIR and SWIR bands decreases due to absorption (Ceccato et al., 2001). The spectral response in the short wave infrared band increases when the vegetation senesces due to loss of water in leaf tissue (Tucker, 1980). Research efforts to estimate leaf water content usually employ vegetation indices that combine spectral reflectance data in two or more wavelengths (Ceccato et al., 2002a,b). Some of these include the normalized difference water index (NDWI), which was developed to quantify leaf equivalent water thickness (Gao, 1996), LSWI (Jurgens, 1997; Xiao et al., 2005), and NDSVI (Qi et al., 2002). The MODIS surface reflectance data have one near infrared band (1230–1250 nm) and two short wave infrared or SWIR bands (1628–1652 nm and 2105–2155 nm) that are sensitive to leaf water content and soil moisture. Recent studies explored the potential of SWIR (e.g., band 6, 1628–1652 nm) for vegetation water content (Ceccato et al., 2001; Ceccato et al., 2002a,b; Zarco-Tejada et al., 2003; Fensholt & Sandholt, 2003; Maki et al., 2004). LSWI was calculated from surface reflectance as a

normalized ratio between band 2 (841–876 nm) and band 6 (1628–1652 nm), was developed for vegetation equivalent water thickness (Xiao et al., 2005):

$$\text{LSWI} = (\rho_{\text{red}} - \rho_{\text{swir}})/(\rho_{\text{red}} + \rho_{\text{swir}}) \qquad (2)$$

where ρ_{swir} and ρ_{red} are atmospherically corrected surface reflectance in the red (620–670 nm), shortwave infrared (SWIR1: 1628–1652 nm) wavelength, respectively (Xiao et al., 2005). In addition to LSWI, the Normalized Difference Senescence Vegetation Index was also obtained from surface reflectance and calculated as

$$\text{NDSVI} = (\rho_{\text{swir}} - \rho_{\text{red}})/(\rho_{\text{swir}} + \rho_{\text{red}}) \qquad (3)$$

where ρ_{swir} and ρ_{red} are atmospherically corrected surface reflectance in the shortwave infrared (SWIR1: 1628–1652 nm) and red wavelength (620–670 nm), respectively (Qi et al., 2002). The 8-day LSWI and NDSVI products, sensitive to vegetation water content, were composited through the growing season (March to November) to smooth inter-annual variation (Table 2).

2.4. Statistical analyses

Statistical models were developed using stepwise linear regression technique (S-Plus 6.1) with species richness (SR) at the county level as the dependent variables and a total of 13 independent variables (Table 2). The species richness was further studied as a function of life forms (Table 3). To improve the predictive power of statistical models, the species richness was stratified by proportion of land use/land cover (LULC) by using the MODIS-derived IGBP classification (MOD12Q1) and biome boundaries (Fig. 1) obtained from the World Wildlife Funds (WWF) terrestrial eco-region dataset (Olson et al., 2001). Due to intensive farming in southeastern part of Inner Mongolia, croplands were excluded from the models for a repeated regression analysis. We removed counties with $> 50\%$ of croplands for exploring the influence of this important land use practice.

In addition to stepwise linear regression, a spatial regression technique called Conditional Autoregressive (CAR) model was used to account for spatial autocorrelation (S+ Spatial Stats module). The technique fits a linear model with spatial dependence among neighboring counties.

3. Results

Bulbs and perennial herbs were found to be the major groups across the region (70%) and within any biome (64.8–74.0%). As expected, the forest biome has 6.98 species per 1000 km^2, while the desert and grassland biome have 2.51 and 3.94 species for the same unit area, respectively (Table 2). Mean species richness of shrubs was the highest in the desert biome and the lowest in the forest biome ($p < 0.001$); while species richness of bulbs and perennial herbs was significantly higher in the grassland and forest than the desert ($p = 0.0001$; $p = 0.0027$). There was no significant difference in species richness of trees

Table 2
Statistical summaries of MODIS-derived metrics (independent variables) and species richness by life form (dependent variables)

	Independent variables					Dependent variables					
	EVI	EVI_{mid}	GPP	LSWI	NDSVI	SR	Shrubs	Bulbs	P. herbs*	Trees	Annuals
Region (N=88) 1,153,181 km²											
Mean	0.163	0.235	0.009	−0.065	0.344	337	9	106	126	24	66
Minimum	0	0	0	−0.309	0	165	0	0	0	0	0
Maximum	0.480	0.701	0.035	0.743	0.610	822	37	328	300	90	117
SD	0.088	0.105	0.007	0.105	0.106	148	8	64	58	18	16
Total						2562	118	834	959	320	331
Of the total (%)						100	4.61	32.6	37.4	12.5	12.9
Desert biome (N=28) area: 461,658 km² (40.03%)											
Mean	0.152[b]	0.141[c]	0.003[c]	−0.091[b]	0.267[c]	277[b]	16[a]	69[b]	100[b]	22[a]	65[a]
Minimum	0	0	0	−0.150	0	187	2	46	65	6	50
Maximum	0.346	0.516	0.008	0.229	0.402	390	37	123	139	44	91
SD	0.045	0.052	0.001	0.053	0.040	66	10	18	23	11	11
Total						1161	79	311	441	138	192
Of the total (%)						100	6.8	26.8	38	11.9	16.5
Grassland biome (N=42) area: 464,369 km² (40.27%)											
Mean	0.201[a]	0.278[b]	0.007[b]	−0.073[b]	0.389[b]	342[ab]	6[b]	115[a]	135[a]	23[a]	67[a]
Minimum	0	0	0	−0.125	0	165	0	52	59	4	50
Maximum	0.370	0.701	0.032	0.257	0.522	822	19	328	300	90	117
SD	0.095	0.075	0.002	0.125	0.083	153	4	61	59	18	15
Total						1813	55	639	672	208	239
Of the total (%)						100	3.03	35.3	37.1	11.5	13.2
Forest biome (N=18) area: 227,154 km² (19.70%)											
Mean	0.182[ab]	0.341[a]	0.014[a]	0.012[a]	0.441[a]	408[a]	7[b]	144[a]	154[a]	33[a]	71[a]
Minimum	0	0	0	−0.081	0	178	1	52	63	8	51
Maximum	0.378	0.693	0.026	0.311	0.567	767	17	318	280	71	105
SD	0.142	0.081	0.005	0.184	0.144	193	5	86	70	23	16
Total						1586	41	613	560	178	194
Of the total (%)						100	2.59	38.7	35.3	11.2	12.2

*Perennial herbs.

and annual herbs among the biomes ($p=0.0868$; $p=0.386$). Proportion of shrub and annual herb species decreased from desert to grassland and to forest biome, while proportion of bulb

Table 3
Statistical evaluation of different biophysical indicators and their metrics to predict species richness (SR) in Inner Mongolia at the county level and with counties with >50% cropland removed from the analysis

Inner Mongolia	Species richness			Life form		
	SR	Shrubs	Bulbs	Perennial herbs	Trees	Annuals
All counties (N=88)	GPP_{SD} $LSWI_{max}$	EVI_{mid} GPP_{SD}	GPP_{SD} $NDSVI_{SD}$	GPP_{SD} $LSWI_{max}$	GPP_{SD} EVI_{SD}	$LSWI_{max}$ $NDSVI_{max}$
R^2	0.27***	0.40***	0.36***	0.29***	0.16**	0.11**
SE	128	6	51	48	16	13
SE [a]	128	6	51	48	16	13
Counties w/ >50% cropland (N=75)	GPP_{SD}	EVI_{mid} GPP_{SD}	GPP_{SD} $LSWI_{SD}$	GPP_{SD} $LSWI_{max}$	GPP_{SD}	GPP_{SD}
R^2	0.28***	0.41***	0.43***	0.34***	0.13**	0.1**
SE	129	6	50	47	16	13
SE [a]	126	6	49	46	16	13

**$p<0.01$, ***$p<0.001$.
[a] Standard error of spatial conditional auto regressive (CAR) model.

species increased (Fig. 2). No significant difference was found for the proportion of tree species among the three biomes. As for MODIS-derived metrics, the regional mean (SD) EVI and GPP values were 0.163 (0.088) and 0.009 (0.007); and the regional mean (SD) LSWI and NDSVI (i.e., surrogates for water content) values were −0.065 (0.105) and 0.344 (0.106), respectively (Table 2). However, there were significant differences in EVI among the biomes with the highest values in the grassland biome and the lowest in the desert ($p=0.0028$). LSWI was significantly higher in the forest biome than in the grassland and desert ($p<0.0001$). GPP, EVI_{mid} and NDSVI increased from desert to grassland and to forest biome ($p<0.0001$).

The most important variables for species richness prediction (for all counties, $N=88$) were GPP_{SD} and $LSWI_{max}$ (Fig. 4a), which showed positive, linear relationship ($R^2=0.27$, $p<0.001$). Excluding counties with >50% cropland ($N=75$) resulted in a positive linear relationship (Fig. 5a; $R^2=0.28$, $p<0.001$) between species richness and GPP_{SD} (Table 3.). The spatial CAR regression model fit for all counties returned the same results (Table 3).

The predictive models were improved significantly when the species richness was divided by life forms. The variation in species richness of shrub species was negatively correlated (Fig. 4b) with seasonal EVI_{mid} and a positive linear relationship

with GPP$_{SD}$ ($R^2 = 0.40$, $p < 0.001$). The bulb richness was positively correlated (Fig. 4c) with GPP$_{SD}$, and NDSVI$_{SD}$ ($R^2 = 0.36$, $p < 0.001$). The variation in species richness of perennial herbs was explained by a positive linear relationship (Fig. 4d) with GPP$_{SD}$ and LSWI$_{max}$ ($R^2 = 0.29$, $p < 0.001$). However the species richness of trees and annual herbs could not be explained as well as other life forms ($R^2 = 0.16$ and 0.11 respectively, $p < 0.01$). The tree species had a positive linear relationship with GPP$_{SD}$, and EVI$_{SD}$ whereas annual herbs had a positive linear relationship with LSWI$_{max}$ and NDSVI$_{max}$ (Fig. 4e,f).

Predicting species richness by life form improved when agricultural land was excluded from the analysis. Species richness of shrubs showed a negative linear relationship (Fig. 5b) with EVI$_{mid}$ and a positive linear relationship with GPP$_{SD}$

($R^2 = 0.41$, $p < 0.001$). Bulb species richness was explained by a positive relationship (Fig. 5c) with GPP$_{SD}$ and LSWI$_{SD}$ ($R^2 = 0.43$, $p < 0.001$). The predictive models for perennial species were improved slightly ($R^2 = 0.34$, $p < 0.001$) with species richness being positively related to GPP$_{SD}$ and LSWI$_{max}$ (Fig. 5d). The model for species richness of trees and annual herbs did not improve (Table 3) after agricultural land had been removed and could not be explained as well as other life forms ($R^2 = 0.13$ and 0.11 respectively, $p < 0.01$). The spatial CAR model fit after counties with >50% croplands were excluded showed minimal change for all species as well as different life forms (Table 3).

Our predictions were further improved (Table 4) by stratifying the species richness by biome (Fig. 1). In the desert biome, species richness count was explained by a negative
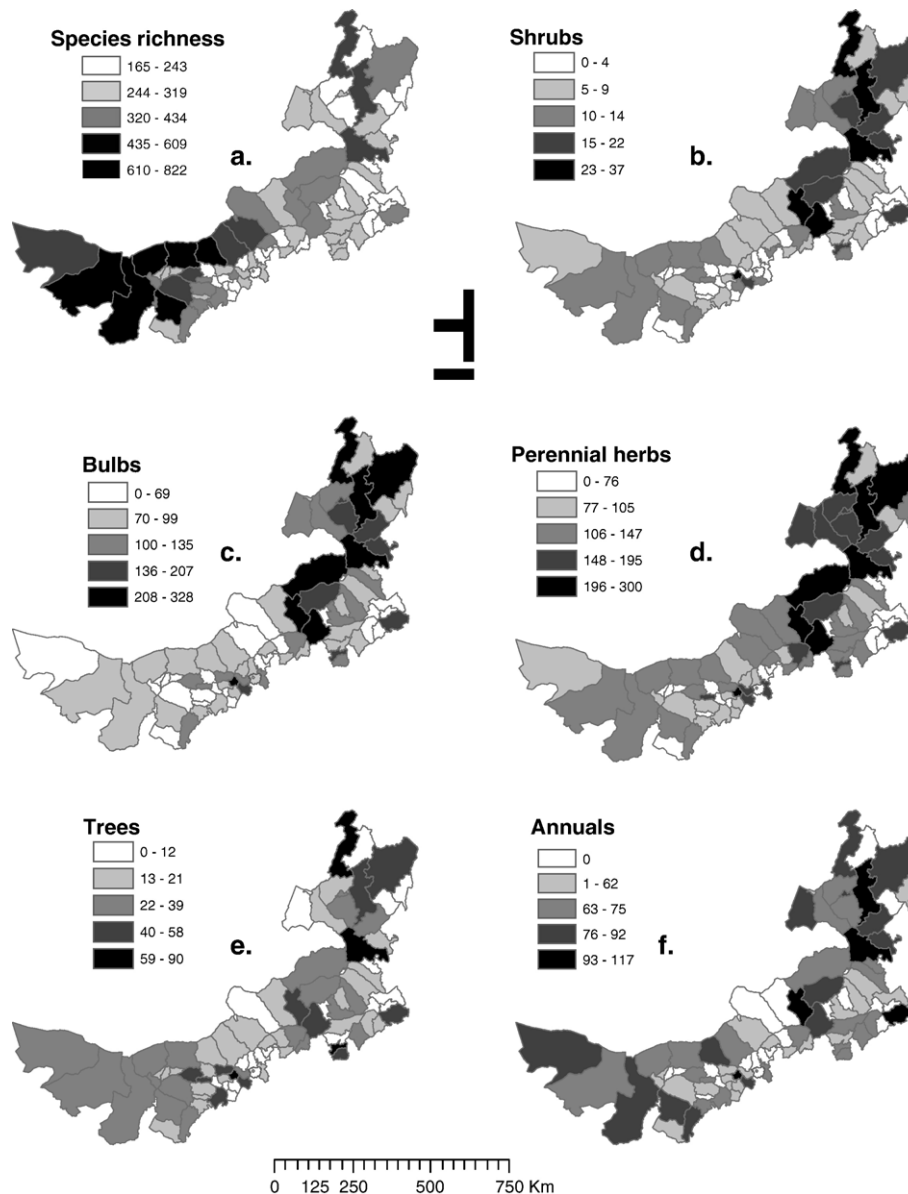

Fig. 2. Species richness distributions at county level include: a) all species, b) shrubs, c) underground bulbs/corms, d) perennial herbs, e) trees, and f) annuals. These maps were developed based on species distribution database at county level from *Flora of Inner Mongolia* (Ma, 1989, 1990, 1993, 1994, 1998).

relationship (Fig. 6a) with $LSWI_{avg}$, and positive linear relationship with GPP_{max} ($R^2 = 0.61$, $p < 0.001$). The variation in species richness by life form in the desert biome was best explained by a negative relationship (Fig. 6b) with seasonal midpoint in shrub species and a positive relationship (Fig. 6d) with $NDSVI_{max}$ in bulb species ($R^2 = 0.53$, and 0.22 respectively, $p < 0.01$). Species richness of perennial herb species was explained by negative linear relationships ($R^2 = 0.46$, $p < 0.01$) with EVI_{SD} and EVI_{max} (Fig. 6c). The spatial CAR model fit for the desert and grassland biome showed minimal change for all species as well as different life forms (Table 4).

In the grassland biome (Fig. 7a), species richness was explained by a positive linear relationship with GPP_{SD} and negative relationship with GPP_{avg} (Fig. 7a; $R^2 = 0.30$, $p < 0.01$). When species richness was studied by life form, perennial herb species showed a positive relationship with GPP_{SD} and negative relationship with GPP_{avg} (Fig. 7c; $R^2 = 0.34$, $p < 0.001$). The annual herb species richness showed a positive linear relationship, with GPP_{SD} (Fig. 7d; $R^2 = 0.20$, $p < 0.01$), while bulb species richness was explained by a positive linear relationship with GPP_{SD} and a negative relationship with EVI_{mid} (Fig. 7b; $R^2 = 0.40$, $p < 0.01$). The species richness of shrubs was positively
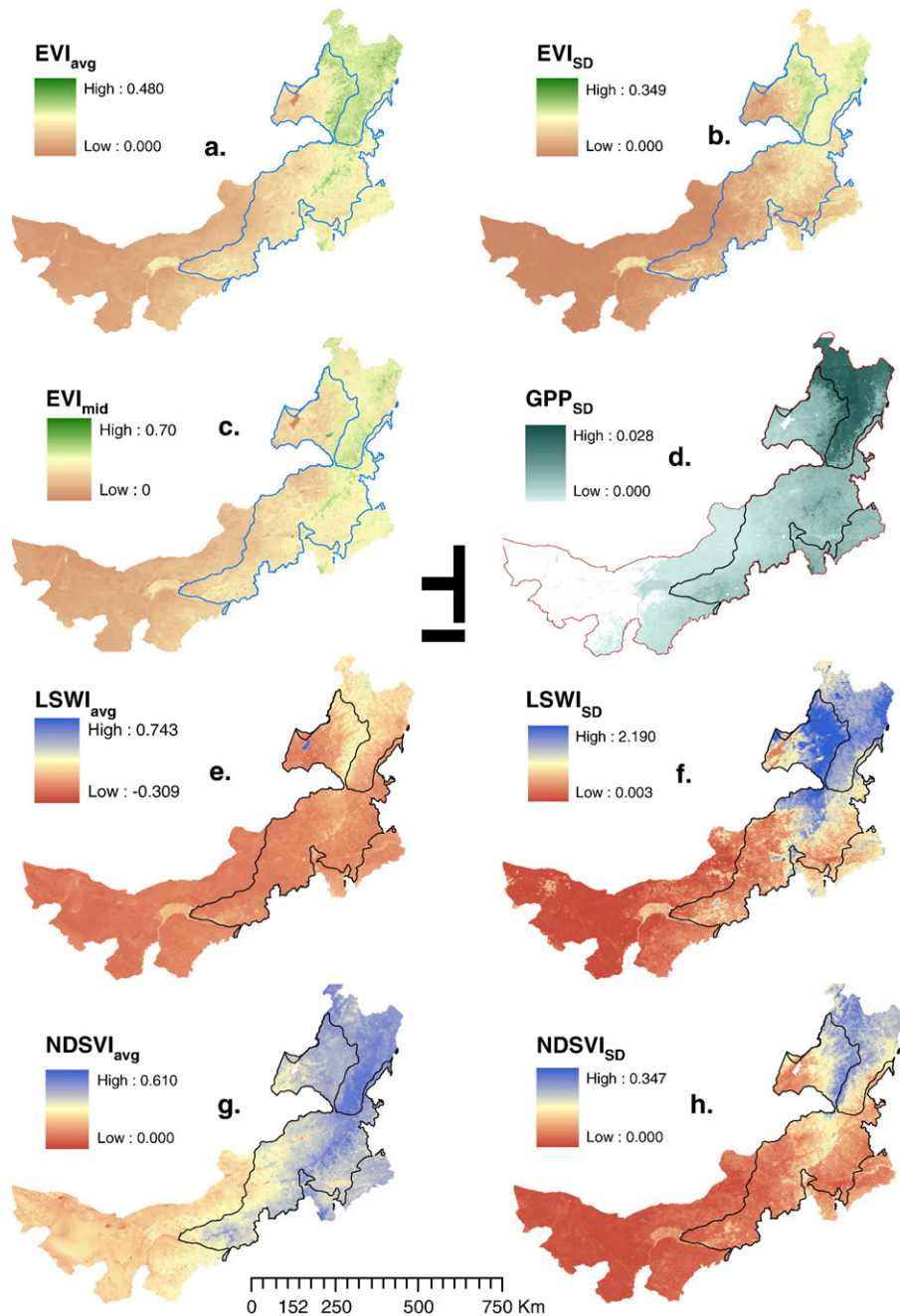

Fig. 3. Metrics of MODIS-derived biophysical variables obtained from annual composites in 2005 include: a) annual mean EVI, b) standard deviation of EVI, c) seasonal midpoint EVI, d) standard deviation of GPP, e) annual mean LSWI, f) standard deviation of LSWI, g) annual mean NDSVI, and h) standard deviation of NDSVI.

correlated with GPP_{SD} ($R^2 = 0.27$ respectively, $p < 0.01$, Fig. 7e). In the forest biome, variation in species richness was explained by a positive linear relationship (Table 4) with $NDSVI_{max}$ ($R^2 = 0.26$, $p < 0.01$). Species richness of trees and perennial herbs showed positive linear relationships with $NDSVI_{max}$ ($R^2 = 0.28$ and 0.31, respectively, $p < 0.01$).

4. Discussion

Land use/cover changes as well as climate change constitute two major threats to biodiversity (Higgins, 2007), which together compound the threat to biological systems. Anthropogenic modification in urban, rural and agricultural areas create migratory barriers to plant species, which might need to move on account of that climate change. The shifting of species ranges in response to climate change means that there would be a redistribution of biological systems in light of new land use patterns resulting in new orientation of species ranges. It is important to consider the implications of future redistribution of climate and land use patterns, as it will be critical to determine how biological diversity respond to future change. Recent studies have documented such change as species ranges have already begun to move in response to the climate changes of the past century (Parmesan & Yohe, 2003). As greenhouse gas emissions continue, there will be an increasing pressure on biological systems to move in order to adapt to increasing extreme changes in climate (Higgins, 2007). The classical methods for studying regional patterns of species richness have constraints that produce a disagreement between the scale of the study and the parameters measured (Levin, 1992). Remote sensing data might be better suited to bridge the gap between the scales of the processes and the observations especially at regional scales (Fairbanks & McGwire, 2004).

Previous remote sensing studies on predicting species richness were often based on image classification (i.e., identifying habitat
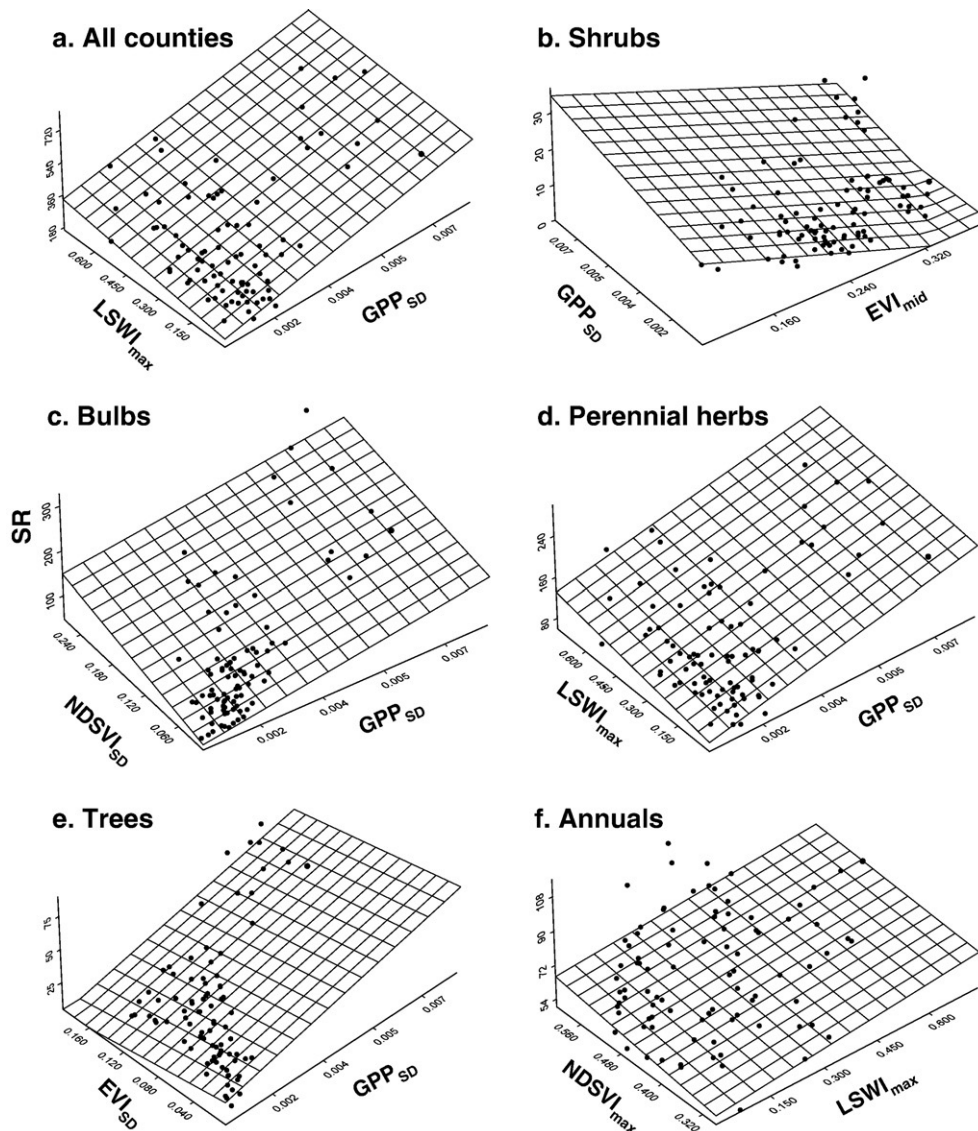

Fig. 4. Species richness as a function of MODIS-based productivity (GPP, GPP_{SD}, EVI_{mid} and EVI_{SD}) and surface water content ($LSWI_{max}$, $NDSVI_{max}$ and $NDSVI_{SD}$) metrics across all species, (a) and for each functional group, b) shrubs, c) underground bulbs/corms, d) perennial herbs, e) tree species, and f) annuals. The driving factors were identified with a stepwise linear regression, with $\alpha < 0.05$ entry requirement.

type) followed by a correlation of species richness with class types (Behera et al., 2005; Saveraid et al., 2001). These methods, based on habitat relationships, can be effective if intensive empirical models exist for all patch types, but might not be efficient owing to classification accuracy, context of class types (Seto et al., 2004), or potential mismatch between species and a habitat (Pulliam, 2000). Recent efforts have included development of empirical models between species richness and continuous measures of land surface properties and their dynamics (e.g., maximum, mean and standard deviation of NDVI; Seto et al., 2004), species richness and vegetation heterogeneity (Oindo, 2002; Oindo & Skidmore, 2002), and of phenology metrics (EVI$_{mid}$; Waring et al., 2006). The latter approaches allow us to examine the relationship continuously across space (i.e., full coverage of the region), while the distinct ecological properties of different biomes are considered for selecting model form and predictive variables (Seto et al., 2004). For example, if species richness were hypothesized to have a positive relationship with ecosystem production (Tilman et al., 1996), then GPP and associated surrogate measures would be the natural choices for depicting variables (Waring et al., 2006).

We found that Inner Mongolia region had a relatively low GPP, EVI, LSWI and NDSVI mean in the desert and grassland. EVI and LSWI mean values in the grassland and desert steppe regions of Temperate East Asia were 0.2 and −0.07 with maximum values of 0.35 and 0.2, respectively (Boles et al., 2004). These values compared well with our values of mean annual EVI for grassland and desert steppe (0.201 and 0.152 respectively, Table 2). The maximum EVI values for the two biomes were 0.346 and 0.370, respectively, and also closely matched published values (Boles et al., 2004). Similarly, our estimates of LSWI in the grassland and desert biomes closely matched the published values mentioned above, with mean annual LSWI for the two biomes being −0.091and −0.073, respectively. The maximum LSWI values for the grassland and desert biomes were 0.257 and 0.229 (Table 2) and were close to the published maximum (0.2) for temperate East Asia (Boles et al., 2004). MODIS GPP annual mean estimates from our study for desert and grassland biome in Inner Mongolia was 3 and 7 g C m^{-2} respectively, with annual maximum estimates being 8 and 19 g C m^{-2}. Published MODIS GPP estimates (Zhao et al., 2005) of the world's grasslands were 396 g C m^{-2} year^{-1}. However, annual MODIS GPP estimates in Inner Mongolia were closer to the published values based on local studies carried out between 15 and 20, August 2004 in Duolun County, Inner Mongolia. The estimates of GPP ranged between 10 and 70 g C m^{-2} and included grazing exclusion sites as well as heavily grazed sites with biomass removal (Zhou et al., 2006). There exists a gradual change in climate as one moves from the southwest to the northeast of the region (Fig. 3). In addition, there also appeared an increasing trend in proportions of species richness in four of the five life forms with shrubs as the only exception (Fig. 2), which decreases as one moves from the desert biome to the grassland and forest biomes.
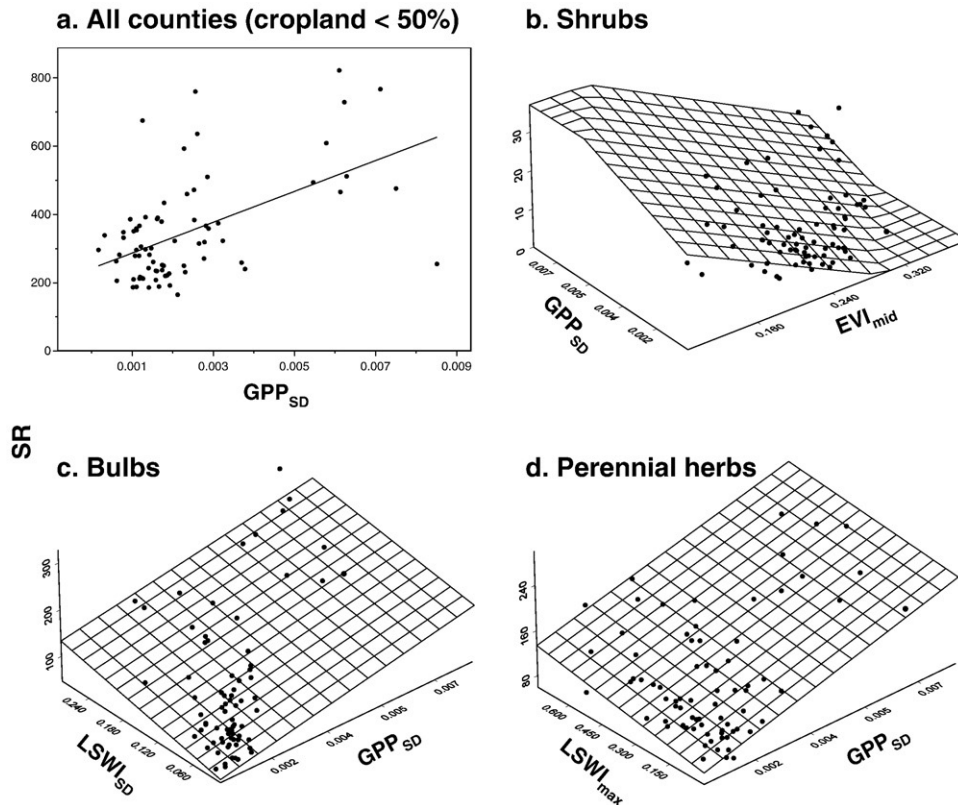

Fig. 5. Species richness as a function of MODIS-based productivity (GPP$_{SD}$, EVI$_{mid}$ and EVI$_{SD}$) and surface water content (LSWI$_{SD}$ and LSWI$_{max,}$) metrics excluding counties with >50% land under agricultural use (a), and for functional groups, b) shrubs, c) underground bulbs/corms, d) perennial herbs. The driving factors were identified with a stepwise linear regression, with α<0.05 entry requirement.

Table 4
Statistical evaluation of different biophysical indicators and their metrics to predict species richness by biome in Inner Mongolia

Biome	Species richness			Life form		
	SR	Shrubs	Bulbs	Perennial herbs	Trees	Annuals
Desert (N = 28)	$LSWI_{avg}$ GPP_{max} $LSWI_{max}$ EVI_{max}	EVI_{mid}	$NDSVI_{max}$	EVI_{SD} EVI_{max}	$NDSVI_{SD}$ $LSWI_{max}$ EVI_{max}	$LSWI_{SD}$ $LSWI_{max}$ EVI_{mid}
R^2	0.61***	0.53***	0.22*	0.46***	0.46**	0.53***
SE	45	7	15	17	8	8
SE [a]	47	5	13	14	7	7
Grassland (N = 42)	GPP_{SD} GPP_{avg}	GPP_{SD} GPP_{avg}	GPP_{SD} EVI_{mid}	GPP_{SD} GPP_{avg}	GPP_{SD}	GPP_{SD}
R^2	0.30**	0.27**	0.40***	0.34***	0.12*	0.20**
SE	131	3	48	49	17	13
SE [a]	128	3	47	48	17	13
Forest (N = 18)	$NDSVI_{max}$	–	$NDSVI_{SD}$	$NDSVI_{max}$	$NDSVI_{max}$	–
R^2	0.26*	–	0.25*	0.31*	0.28*	–
SE	171	–	76	60	20	–
SE [a]	166	–	67	59	16	–

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.
[a] Standard error of spatial conditional auto regressive (CAR) model.

As expected, the grassland biome had the highest species richness among the three biomes with perennial herbs and bulb species as the dominant life forms, which are twice the number of the desert biome, likely owing to water availability (i.e., the major limiting factor in the desert). The tree species in the grassland biomes, however, were more in number as compared to the desert and forest biomes, while annuals were more in number but less in proportion (Table 2). Shrub species were fewer in number as compared to the desert biome. This is likely because the more favorable conditions promote grass species which maintain a higher competitive edge (Cheng et al., 2007). For the forest biome, the LSWI and NDSVI mean values were higher than those in the other biomes (Fig. 3; Table 2). The higher elevation in some areas of the biome (e.g., Greater Hingaan Mountains) suggests greater precipitation and less evapotranspiration. Consequently, the proportions of shrub species and annual herb species were lower compared with other biomes.

The power of the developed models increased significantly (Tables 2 and 3) when the study area was stratified by desert, grassland, and forest biomes. The exclusion of counties with >50% cropland further increased the contrast among the natural cover types. This is not surprising, as deserts, grasslands, and forests have very different climatic and hydrological regimes that have to be explained independently. In addition, the models were improved when the species were studied by life forms, thus supporting the hypothesis that the SR–productivity relationship is taxonomically dependent. As the grain of observation increased, the SR–productivity relationship decreased and this may be accounted for by the confounding effects of biophysical variables that are not separated by biome or functional groups such as life forms. Our initial hypothesis of a strong sensitivity to water availability across the region was rejected when counties with >50% of land under agricultural use were excluded. The water use in irrigated agriculture does

not follow natural biophysical mechanisms (Yu et al., 2003) and therefore the agricultural lands were confounded with the patterns observed in the natural land cover classes.

Water availability did have a significant effect on SR in the desert and grassland biomes (Table 4), but shrubs, trees, corms, and annuals differed in the moisture sensitivity (Fig. 6). In Inner Mongolia, xerophytic grass, herb and shrub species dominate and are characteristic of successional stages of desertified communities (Cheng et al., 2001b; Kang et al., 2007). Though species richness of shrubs (Fig. 2b) counts only 6.80% of all species (Table 2), the desert biome was dominated by open shrubland cover type (Fig. 1). The shrub species showed a negative relation with seasonal midpoint EVI in the desert biome, while trees and annuals increased with water availability but decreased with its variance (Fig. 6b,e,f). This can be attributed to local hydrological and landform influences such as river systems (e.g., Huang he near Baotou, Fig. 1) and oasis (e.g., the Ejina oasis). The bulb species were constrained by water availability (Fig. 6d) and can be explained by the low species richness count within the desert biome as compared to the forest biome and a portion of grassland biome in the north east of the province. In grasslands, the effect of moisture on species richness was significant, but the primary correlates were measures of seasonal variability (GPP_{SD} and EVI_{SD}; Table 4; Fig. 3). This implies moisture limitation on SR, and corroborates with earlier studies that have suggested that inter-annual variation in the timing of precipitation may affect productivity (Xiao et al., 1995, 1996).

Our study has several limitations that prohibit us from more confident predictions of plant species richness in Inner Mongolia. The foremost constraint is the plant distribution database obtained from the *Flora of Inner Mongolia*. These published volumes are by far, the most comprehensive database in China following 40+ years field surveys lead by a large team
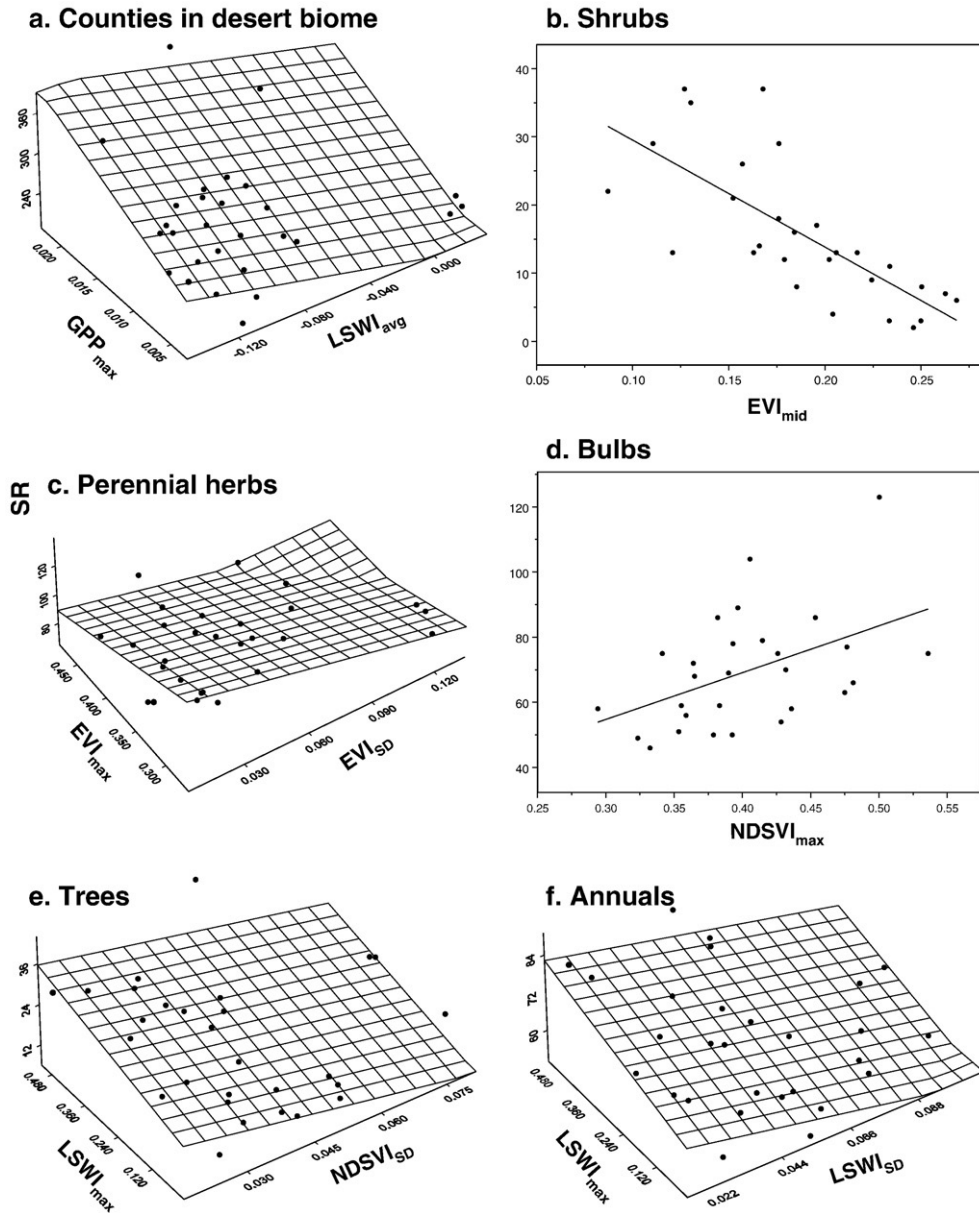
Fig. 6. Species richness as a function of MODIS-based productivity (GPP_{max}, EVI_{mid}, EVI_{max} and EVI_{SD}) and surface water content ($LSWI_{avg}$, $LSWI_{max}$, $NDSVI_{max}$ and $NDSVI_{SD}$) metrics in the desert biome at: a) county level and with life forms that include, b) shrubs, c) underground bulbs/corms, d) perennial herbs, e) trees, and f) annuals. The driving factors were identified with a stepwise linear regression, with $\alpha < 0.05$ entry requirement.

in University of Inner Mongolia (Ma, 1989, 1990, 1993, 1994, 1998). Yet only presence or absence of a species by county was recorded. We suspect some inconsistency in developing the database among counties near the provincial capital; Huhehot, where the university is located, showed higher species richness counts when compared with other counties in the region (Fig. 2). There is also an element of uncertainty whether the species tabulated in the survey are still prevalent or extinct. For example, we were unable to assess the contribution of each species, but assumed all had an equal importance. Finally, availability of remote sensing products, their use (i.e., MODIS data in 2005 only), and some aspects of data analysis are additional pitfalls of this study. We could, however, explore the use of all available MODIS products since 1999 to provide additional long-

term means of remote sensing products that might better match the ground data. Clearly, there exists a mismatch between the time the species richness data (dependent variables) and MODIS data (independent variables) were acquired.

Future research should include the prediction of species richness using remote sensing products in the context of functional groups (e.g., nitrogen fixation). For example, species richness predictive models could be used in monitoring the spread of shrubs with higher water use intensity as well as toxic herbs which replace native grass species in the Ordos plateau (Cheng et al., 2001a,b). Results from these models can assist conservation efforts by identifying areas that contain high species richness, but are not currently protected. This could be achieved in a Geographic Information System (GIS) through
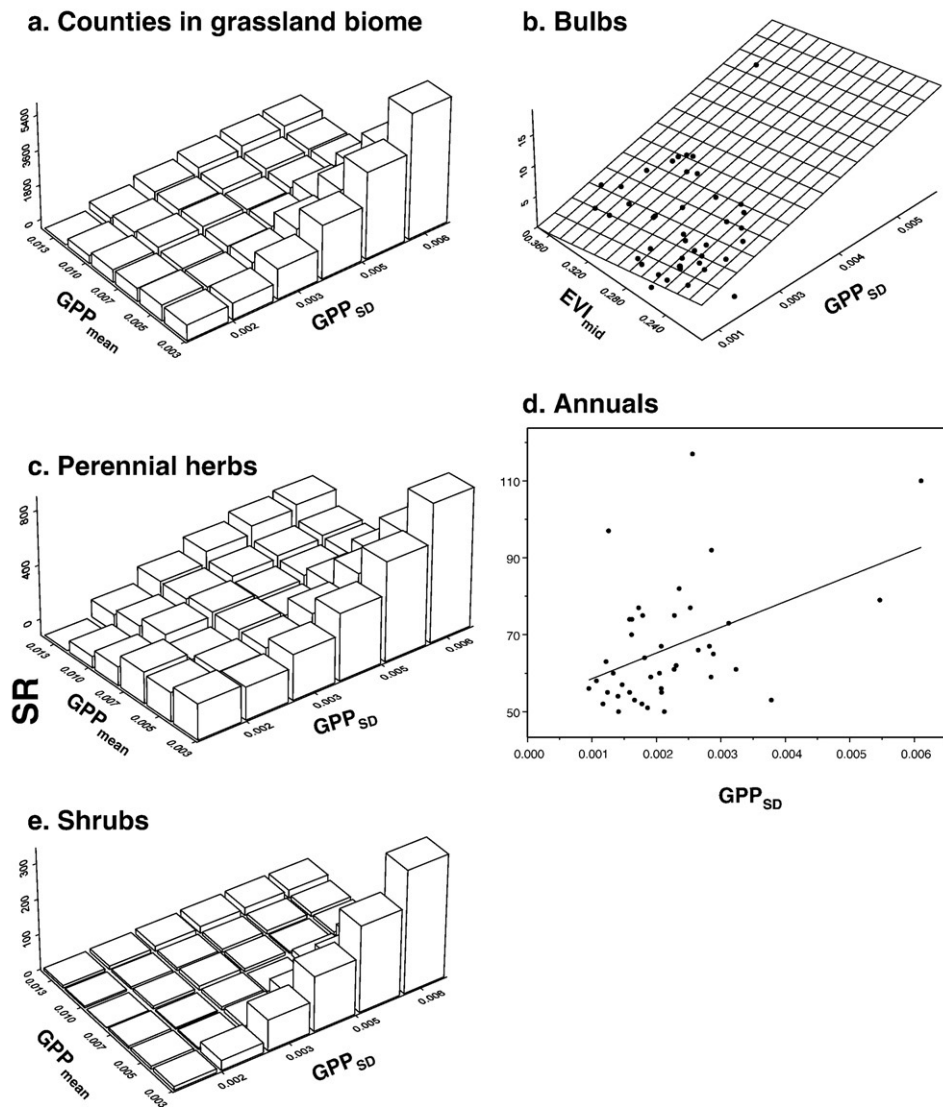
Fig. 7. Species richness as a function of MODIS-based productivity (GPP$_{SD}$, GPP$_{mean}$, EVI$_{mid}$, and EVI$_{SD}$) and surface water content (NDSVI$_{max}$) metrics in the grassland biome at: a) county level, and with life forms that include, b) underground bulbs/corms, c) perennial herbs, d) annuals, and e) shrubs. The driving factors were identified with a stepwise linear regression, with $\alpha < 0.05$ entry requirement.

overlaying current conservation areas and land use data with predicted levels of species richness for different biomes and life forms types. Explorations of long-term MODIS and other remote sensing products in predicting species diversity should be continued to improve confidence in the predictive models. Finally, land use practices (e.g., grazing, cropping, harvesting) and potential influences of climate change have been shown to have unique consequences on different functional of taxonomic groups (Bao et al., 2004) and, hence, must be accounted for in the future species richness studies.

5. Conclusions

Based on the most comprehensive, regional species database and remote sensing products, we conclude that GPP$_{SD}$ and water availability were the two most important variables for predicting species richness in Inner Mongolia, although other MODIS-derived metrics were occasionally selected as significant independent variables. Our confidence levels were further enhanced when models were developed based on biome and life form. The predictive power also increased when species richness was examined when the counties with >50% croplands were excluded. The coherent relationships between the combinations of productivity (MODIS GPP, EVI) and vegetation water content (LSWI, NDSVI) and species diversity may have potential applications in other similar regions. Future research is needed to develop more attributes of individual species in the region, including their roles in communities, to improve the models predictability for relevant basic and applied research (e.g., conservation of species in the region).

Acknowledgments

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