A Dissertation

entitled

The Effects of Land Cover/Land Use Change on Ecosystem Functions in Semi-arid Inner Mongolia

by

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Submitted to the Graduate Faculty as partial fulfillment of the requirements for the Doctor of Philosophy Degree in Biology

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May, 2011
An Abstract of

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Land cover change in semi-arid areas, in the context of climate change, can significantly affect the carbon sequestration potential in these fragile ecosystems. Semi-arid Inner Mongolia, P.R.C, is experiencing climate change with associated land cover/use change that includes an increase in irrigated agriculture and population growth. Land cover change was monitored at the regional level through the use of MODIS derived remote sensing products along with meteorological and carbon exchange data obtained from five EC flux towers across a variety of ecosystem types that include natural and disturbed grassland, shrublands as well as land use types such as croplands and dune stabilizing poplar stands. Firstly, I quantified the land cover/use change at the regional and biome levels in the context of landscape fragmentation and the possible consequences. Secondly, I used flux data to validate intra-annual dynamics of satellite derived GPP in different ecosystem types using existing GPP models. In addition I developed and validated a new model, the modified vegetation photosynthesis model.
Finally, I derived predictive models of plant species diversity, developed specifically for semi-arid grasslands which used improved vegetation and water indices.

The major finding of this study were: (1) increasing portions of dominant grassland shrubland and barren cover within the decade points toward a water stressed landscape that is becoming more homogenous and is corroborated by a decrease in proportions of rare cover types. The rapid increase in socio-economic growth leading to a growing population base is described by increasing cohesion and aggregation of urban/built-up patches as well as an increasing number of patches and interspersion of cropland land use. (2) variance in GPP and water content indices were the two most important variables for predicting species richness in Inner Mongolia, while MODIS-derived vegetation and water content indices were selected as significant independent variables for specific biome type. The predictive power of models improved greatly when the region was stratified by biome and life-form type and especially when the anthropogenically modified cover types such as croplands were excluded from the model. (3) The intrannual dynamics of satellite derived GPP vegetation photosynthesis model (VPM) and modified VPM (MVPM) models were validated by flux towers at five ecosystem types across semi-arid Inner Mongolia. Though not as computationally intensive like most process-based models, MVPM offers an advantage over VPM by being independent of any ground measured meteorological data. MVPM provides a cost effective method of predicting GPP, especially at remote study sites which lack the required infrastructure to set up EC flux towers. While there was reasonable agreement between the observed $GPP_{\text{tower}}$ and predicted $GPP_{\text{VPM}}$ and $GPP_{\text{MVPM}}$ indicating the potential of these models for modeling of GPP in semi-arid ecosystems, there was some
uncertainty in the predictive ability of these models, attributed to different sources of error.
Acknowledgements

This research was conducted as part of the Northern Eurasia Earth Science program (NEESPI) and supported by the National Aeronautics and Space Administration (NASA) Land Cover Land Use Change (LCLUC) Program, Institute of Botany, Chinese Academy of Sciences (IBCAS) and the US-China Carbon consortium (USCCC).

I would like to thank my advisor for his continued support and guidance towards improving my professional skills in ecosystem science and landscape ecology. I also wish to thank the rest of my advisory committee, Dr. Scott Heckathorn, Dr. Xiangming Xiao, Dr. Jiaguo Qi and Dr. Jonathan Bossenbroek for their help and advice during my dissertation research.

I wish to thank my present and former lab mates, especially Jianye Xu for his intensive field work campaign in the summers of ’06 and 07 as well as developing manuscript figures. I would also like to thank Dr. Nan Lu for her help these past years. I especially would like to thank former post docs, Dr. Asko Noormets who helped with gap filling and processing EC tower GPP and Dr. Burkhard Wilske for extensive editing of manuscripts and presentations.

Finally, I wish to thank my grandparents and parents for bringing me up, with many a great sacrifice. I would not have been able to get to this point without their love and support.
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List of Abbreviations

AVHRR...............................Advanced Very High Resolution Radiometer

BRDF ..................................Bidirectional Reflectance Distribution Function
Biome BGC.........................Biome Bio Geo-chemical Cycles
BP-LUT................................Biome Properties Look-up Table

EVI..................................Enhanced Vegetation Index (0-1)
ET..........................Evapotranspiration

f/PAR..............................Fraction of Photosynthetically Active Radiation

GPP ...................................Gross Primary Production (g C m⁻²)

IGGBP ........................International Geosphere Biosphere Program

LCLUC ..............................Land Cover/Land Use Change
LST ................................Land Surface Temperature
LSWI.................................Land Surface water Index (-1 to 1)
LUE..................................Light Use Intensity

MOD09A1 ..........................MODIS derived Surface reflectance product
MOD11A2 ..........................MODIS derived land surface temperature product
MOD15A2 ..........................MODIS derived leaf area index/fpar product
MOD17A2 ..........................MODIS derived GPP product
MODIS..............................MODe rate resolution Imaging Spectroradiometer
MVPM ................................Modified Vegetation Photosynthesis Model

NEESPI...........................Northern Eurasian Earth Science Partnership Initiative
NDVI..................................Normalized Difference Vegetation Index (0-1)
NDSVI.................................Normalized Difference Senescent Vegetation Index
NPV..................................Non-Photosynthetic Vegetation

PAR..................................Photosynthetically Active Radiation
PPT..........................Precipitation

T_{opt}.................................Optimal temperature
$T_{\text{max}}$.................................Maximum Temperature
$T_{\text{mean}}$.................................Mean Temperature
$T_{\text{min}}$.................................Minimum Temperature

SD ...........................................Standard Deviation
SE ...........................................Standard Error

VPM ...........................................Vegetation Photosynthesis Model

WUE ...........................................Water Use Efficiency
Chapter 1

1. Introduction

Rapid changes in the global climate have resulted in an increase of the global mean temperature by 0.7°C (IPCC, 2007). In the recent past, governments across the world have recognized that climate change and its effects are the biggest challenges for humankind in the 21st century. Many negotiations such as the recent meeting in Copenhagen, addressed the phenomenon of climate change and the urgent need to reduce global temperatures. Owing to the multiple interactions between vegetation, land surface processes and anthropogenic modification of the earth’s surface, a myriad of scientific techniques and analyses need to be employed to provide decision makers with the requisite scientific support. Though historical meteorological records and data archives provide the foundation for studying climate change, recent advances in technology such as increased computational power enable ecosystem scientists to study the land cover changes in context of climate change and the possible feedbacks at scales and resolutions that were not possible before. Though climate change is a global phenomenon, rates of climate change owing to variability in land surface properties and their feedback to climate.

The Northern Eurasian Earth Science partnership initiative (NEESPI, http://neespi.org) was initiated by the NASA Land Cover Land Use Change program
(LCLUC) in order to understand the nature of global climate feedback to land surface processes and anthropogenic activities in Eurasia at latitudes > 40’ N (Groisman et al., 2009). Within the broader purview of the NEESPI domain, the Landscape Ecology and Ecosystem Science laboratory (LEES lab) based it research efforts on “The Effects of Land Use Change on the Energy and Water Balance of the Semi-arid region of Inner Mongolia”. Thus the contribution of the LEESLAB to NEESPI was to fill some of the gaps within the NEESPI domain (Figure 1-1).

Inner Mongolia, the third largest province in China (1.18 mill. km$^2$) is characterized by a semi-arid to arid climate and represents the south eastern edge of the NEESPI domain and the Eurasian steppe, which includes the worlds largest extratropical semiarid and arid land area. A large proportion of the Eurasian steppe is under increasing stress owing to climate change, changes in the local hydrological cycle and energy balance and rapid socio-economic development in the recent past. These changes have resulted frequent extreme weather events, severe soil erosion owing to intensified grazing and finally frequent sandstorms that have a regional reach as far as Beijing. The semi-arid grasslands in IM, make up 41% of the land area, are prone to degradation owing to warming trends in northeast Asia over the last 50 years (Chase et al., 2000), and intensification of anthropogenic land use practices (Kang et al., 2007). The primary productivity of Inner Mongolia varies from 100 g$^{-2}$ yr$^{-1}$ in desert regions in the west to about 4000 g$^{-2}$ yr$^{-1}$ in the northeast forests (Brogaard et al., 2005) and is very sensitive to interannual climatic variation and anthropogenic disturbance (Bai et al., 2004). Though there is rapid population growth in this region in both rural and agricultural areas, the ability of this fragile landscape to support the growing population base is not sustainable
and beyond the present capacity of the ecosystems. The fourth assessment report of the Intergovernmental panel on Climate change (IPCC, 2007) suggest that rainfed crops in Northern China could face water shortages owing to projections of decreasing precipitation combined with increasing water and soil moisture deficit. Degradation of the steppe and an increasingly dry projected dry climate has lead to an increase in the proportion of invasive shrub cover and offers further evidence of gradual desertification eastward along the desert –grassland ecotone (Cheng et al., 2007). Rapid development over the last five decades has lead to over 60% of the grasslands turning into highly disturbed shrub land (Zhang, 1992). Previous studies (Parizek et al., 2002, Schlesinger et al., 1996) have related the relative abundance of grasses vs. shrubs in native and disturbed grasslands to significant changes in ecosystem properties, for e.g., the loss of soil nutrients, primary productivity, spatial heterogeneity, shoot/root density and soil nutrient pool (N and P).

Grassland degradation can be defined as the deterioration and reduction in the structure and function of grasslands leading to a persistent decline in its ability to provide ecosystem services through primary production and energy /water balance. The reduction in ground cover leads to decrease in radiant energy absorbed, which in turn, leads to increase in land surface temperature and a subsequent reduction in moisture content. The increased albedo from bare/sparsely vegetated areas leads to a greater proportion of energy dissipated to the atmosphere as sensible heat rather than latent heat. This in turn leads to a warmer drier atmosphere with less precipitation, favoring the persistence of arid to semi-arid rangelands instead of the typical steppe.

Intensive land use practices such as cultivation and grazing combined with changes in mean and extreme climatic conditions have lead to decline in native ecosystems. However, the changes in the carbon and water cycles have not been studied
extensively in the framework of climate and land cover change. It is therefore important to monitor this fragile region at multiple scales to study vegetation dynamics through a synergistic use of EC flux towers in conjunction with satellite derived GPP models. In addition, it would be necessary to explain land cover changes, fragmentation and its consequences. Finally, predictive models of plant species diversity will be derived to help monitor changes in community assemblages that might affect the integrity of the steppes.

1.1. Objectives

In this study, I will:

1) Quantify land cover/use change and explain fragmentation in semi-arid Inner Mongolia between 1996 and 2004.

2) Model gross primary production in semi-arid Inner Mongolia using MODIS imagery and eddy covariance data among different land cover/use types in typical and desert steppe across climate gradients and account for the spatio-temporal variability.

3) Build predictive models of species diversity based on remote sensing products for semi-arid Inner Mongolia.

1.2. Dissertation Chapters

My dissertation is composed of three chapters (Figure 1-1):


The first chapter quantifies land cover/use changes in semi-arid Inner Mongolia and seeks to explain landscape fragmentation and its consequences (John et al., 2009). The study
conducted at the regional and biome sales found fragmentation in the dominant cover
types like grassland, barren and shrubland. At the same time the decrease in rare cover
types suggests that the landscape is becoming homogenous. Land cover/use change is
driven by an increase in economic growth characterized by increase in urban/cropland
land use. This chapter will provide an indispensable background for the last two chapters.

2. Modeling gross primary production in semi-arid Inner Mongolia using MODIS
imagery and eddy covariance data.

The second chapter describes a ‘bottom-up’ scaling exercise, where GPP derived
from a network of five EC towers across various land cover/use and ecosystem types, are
scaled up to a MODIS driven VPM GPP estimates. The EC towers sites include typical
steppe, cropland, irrigated poplar plantation and desert steppe/shrubland. In addition to
obtaining GPP_VPM, I modified the VPM model to create the Modified VPM or MPVM
which was found to reasonably improve GPP_VPM estimates in some land cover types. A
major advantage of MPVM is that it is entirely independent of EC tower measurements.

3. Predicting plant diversity based on remote sensing products in the semiarid region of
Inner Mongolia.

The third chapter covers the development of predictive models of species
diversity based on remote sensing derived semi-arid grasslands in Inner Mongolia (John
et al., 2008). Previously, remote sensing based species diversity models were based on a
linear function of NDVI and were carried out in various types of forest ecosystems. My
study is unique in that it covers the vast province of Inner Mongolia, dominated by semi-
arid grasslands, and that it uses a suite of improved vegetation and water indices, which are surrogates of productivity and leaf water availability.
Figure 1-1: Conceptual flowchart of activities to quantify land cover/use change and ecosystem functions in semi-arid Inner Mongolia using a combination of MODIS derived remote sensing products, species diversity database and flux tower measurements.
Chapter 2

2. Land cover/land use change in semi-arid Inner Mongolia: 1992-2004


Abstract:

The semi-arid grasslands in Inner Mongolia (IM) are under increasing stress owing to climate change and rapid socio-economic development in the recent past. We investigated changes in land cover/land use and landscape structure between 1992 and 2004 through the analysis of AVHRR and MODIS derived land cover data. The scale of analysis included the regional level (i.e., the entire IM) as well as the level of the dominant biomes (i.e., the grassland and desert). We quantified proportional change, rate of change and the changes in class-level landscape metrics using the landscape structure analysis program, FRAGSTATS. The dominant land cover, grassland and barren, 0.47 and 0.27 million km$^2$ respectively, have increased proportionally. Cropland and urban land use also increased to 0.15 million km$^2$ and 2197 km$^2$ respectively. However, the results further indicated in both the homogeneity and fragmentation of the landscape. Increasing homogeneity was mainly related with the reduction in minority cover types
such as savanna, forests and permanent wetlands and increasing cohesion, aggregation index and clumpy indices. Conversely, increased fragmentation of the landscape was based on the increase in patch density and the interspersion/juxtaposition index (IJI). It is important to note the socio-economic growth in this fragile ecosystem, manifested by an increasing proportion of agricultural and urban land use not just at the regional level but also at the biome level in the context of regional climate change and increasing water stress.

**Keywords:** Inner Mongolia, LCLU, MODIS, AVHRR, IGBP, FRAGSTATS

### 2.1. Introduction

Semi-arid and arid regions have been undergoing severe stresses due to the combined effects of growing population and climate change (Ojima et al. 1998). The degradation of grasslands will significantly impact ecosystem service (e.g., its carbon sequestration) and local economy as well as the regional climate (Angell and Maclaran 2001). For example, carbon sequestration in Inner Mongolia (IM), varies spatially from a mean annual gross primary production (GPP) of about 100 gm$^{-2}$ yr$^{-1}$ in desert regions in the west to about 4000 gm$^{-2}$ yr$^{-1}$ in the northeast which are mostly under forest cover (Brogaard et al. 2005). The grasslands in northern China, a greater portion of which are in IM, make up 41% of the land area, are prone to degradation owing to warming trends in northeast Asia over the last 50 years (Chase et al. 2000), and intensification of anthropogenic land use practices (Kang et al. 2007). The climatic changes (Zhai et al. 1999, Hu et al. 2003, Zhai and Pan 2003) have influenced not only the ecosystem dynamics, productivity, and stability of the Eurasian steppes, but are also coupled with the accelerated impacts of land
use associated with the rapid socio-economic growth. This growth is characterized by increasing pressure of population combined with grazing pressure resulting in increased degradation (Jiang et al 2006, Kang et al 2007). Consequently, these degraded arid/semi-arid ecosystems have become prone to wind erosion and are considered to be the cause of frequent sandstorms with a subsequent loss of biodiversity (Ye et al 2000, John et al 2008). For example, intensive land use of semi-arid grasslands has resulted in the replacement of dominant herbaceous grass communities by invasive shrubs, which are less efficient in water use but more tolerant to heat stress (Cheng et al 2006, Cheng et al 2007).

A practical and cost-effective method to successfully map and monitor Land cover/land use (LCLU) change within a large region like IM is to use land cover datasets derived from remotely sensed Earth Observation (EO) data that provide regional coverage with moderate (~1km) spatial resolution (Loveland et al 2000, Freidl et al 2002). LCLU change studies often employ landscape metrics that measure spatial attributes such as landscape pattern and structure, to determine effects of fragmentation.

Landscape patterns produced as a result of the fragmentation and loss of natural habitat might affect the sustainability of diverse flora and fauna (Turner et al 2001). Aware of the link between ecological pattern and processes at varying scales, land managers have long sought out measures of landscape change in order to monitor changes, e.g., in forest cover and beyond, to aid their decisions (Noss 1999, Lindenmayer et al 2002). Landscape metrics are therefore important tools through which management plans can be framed (Baskent and Jordan, 1996; Herzog et al 2001), especially if they are
able to track meaningful changes in the ecological, or socio-economic variables of interest (McAlpine and Eyre 2002).

In the recent past, multiple scale forest fragmentation studies using landscape metrics such as patch size have been conducted for the continental United States between 1992 and 2001 using the National land cover dataset (Riitter et al 2002, Wickam et al 2004). The use of metrics to track LCLU change on the Tibetan plateau found a 20% increase in croplands driven by socio-economic changes with a subsequent decrease in cover types with high ecological value such as montane grasslands (Wang et al 2008). Landscape metrics have also been used track LCLU change trajectories in the Tarim basin, Northwest China (Zhou et al 2008). The 1973 to 2000 study showed that anthropogenic modification was responsible for altering water resources as indicated by interspersion and juxtaposition index (IJI) indicating greater aggregation and increased homogeneity with simpler, larger patches (Zhou et al 2008).

Recent landscape metrics studies in IM include quantification of landscape structure in the Heihe river basin (Li et al 2001) and the increasing road density between 1990 and 2002 (Li et al 2005). However, these studies were made at the basin or watershed scales and failed to capture landscape structure and LCLU at the regional scale. The objective of this study is to quantify changes in land cover/land use as well as landscape structure in semi-arid IM through the use of AVHRR and MODIS derived IGBP classification, between 1992 and 2001/2004 at the regional and biome scales. We confine our study area to semi-arid IM and exclude the forested North East in IM as it is not representative of the dominant steppe vegetation. Based on the theory in landscape ecology that LCLU changes are scale-dependent, and that management plans differ by
cover type, our study is organized by two hierarchical levels, the region and biome. Thereby the study combines analysis of fragmentation and LCLU change trajectories with two specific hypotheses: (1) whereas land use practices across the entire region have intensified in recent decades, there exist significant differences in LCLU change across the region and among biomes. (2) We expect an increase in homogeneity synonymous with increasing dominance of the main natural land cover types, (i.e., grassland, barren) despite the increase in agricultural and urban land use.

2.2. Methods

2.2.1. Study Area

The Inner Mongolia Autonomous Region is the third-largest province in China, lies between 37°01’-3°02’N, 95°02’-123°37’ E (figure 2-1), and has a mean elevation of 1014 m. IM lies along the southeastern fringes of the Northern Eurasian Earth Science Partnership Initiative (NEESPI, http://neespi.org) study area. The NEESPI domain of approximately 28.6 x 106 km² accounts for 60% of Eurasia north of 40°N, was formed to understand the nature of global climate feedbacks (both biogeophysical and biogeochemical) to land processes and anthropogenic activities in the region (Groisman et al 2009). The ecosystems within this vast region include tundra in the North to semi-arid grassland and deserts in the South. The NEESPI region is undergoing rapid changes resulting both from a warming climate and socio economic changes (Groisman et al 2009).

Inner Mongolia has a semi-arid to arid continental climate (Yu et al 2003) with a significant proportion of cropland and urban land use (figure 2-1). This region includes
three biomes: the arid deserts in the west, grasslands in the center and forests in the northeastern region (Olson et al 2001, http://www.worldwildlife.org/science/data/item6373.html) (figure 2-1). The major mountain ranges are the Greater Hingaan in the east and the Yinshan and Langshan in the center. The arid regions include the Gobi desert in the northwest, the Mu Us and Hobq deserts south of the Yellow River, and the Tengger and Badain Jarian desert in the west, which, in total, cover 40.03% of the province (figure 2-1). The climate is characterized by a decrease in precipitation (400 to 100 mm) and an increase in temperature as one moves from east to west (Ellis 1992, Kang et al 2007). The precipitation in the northeast section of IM exceeds 400 mm (Ellis 1992, Yu et al 2003) to support deciduous forest (0.23 million km², 19.7% of the region) and irrigated agriculture (Yu et al 2003). The north central region of IM borders the Gobi desert and is dominated by the semi-arid steppe with annual rainfall <100 mm.

2.2.2. Data

MODIS derived land cover/land use (LCLU) data for 2001 and 2004 with 1 km resolution (MOD12Q1) was downloaded from the EOS data gateway (https://wist.echo.nasa.gov/api/), while 1 km AVHRR derived IGBP DISCover LCLU data for 1992 was obtained from the global land cover characteristics Database (http://eros.usgs.gov/products/landcover/glcc.php). These data were projected to the Albers equal area projection with datum WGS 84, allowing an easy overlay of the two datasets for intercomparison. Both land cover datasets were classified according to the standard definitions of the International Geosphere Biosphere Program.
(IGBP) which makes them comparable (Loveland et al 2000, Freidl et al 2002). The IGBP classification has 17 land-cover/land-use classes, out of which only a few were dominant in IM, suggesting a need for map generalization. For example, out of the five forest cover types in the IGBP classification scheme, only mixed forests cover was significant in areal extent. Some of the land cover classes, especially those in minority needed to be recoded (i.e. aggregated) to forest, shrubland and savanna so that the final classifications included 10 of the 17 IGBP classes (table 2.1). Evergreen needleleaf, Deciduous needleleaf, Deciduous broadleaf, and Mixed forests were recoded to Forest; Closed and open shrublands were recoded to shrublands, whereas woody savannas and savannas were recoded to savannas. In addition, the recoded IGBP datasets were overlaid (figure 2-1) with desert, grassland, and forest biomes derived from WWF terrestrial eco-region boundaries (http://www.worldwildlife.org/science/data/terreco.cfm).

2.2.3. Accuracy estimates of land cover data

The IGBP DISCover is a second generation land cover dataset and was derived from 1-km AVHRR 10-day composites for April 1992 through March 1993 and had 17 classes based on the IGBP standard (Loveland and Belward 1997, Loveland et al 2000). IGBP DISCover original accuracy estimates range from sample point accuracy of 59.4% and area weighted accuracy 66.9% (Scepan 1999): These accuracy figures were based on random sample stratified sampling by land cover type (Belward et al 1999). Higher resolution Landsat/SPOT images were independently interpreted for validation, with the majority of the three agreeing on the land cover type (Scepan 1999). The revised
accuracy figures based on majority rule ranged from 73.5% to 78.7%, the area weighed estimate (Scepan 1999).

A parallel validation approach investigated the accuracy of the dataset in climate modeling (Defries and Los 1999). The IGBP classes were aggregated into two groups corresponding to key variables in climate modeling, leaf area index (LAI) and surface roughness. The accuracy figures were reported to be 84.5% and 82.4% for LAI and surface roughness respectively. The area weighed accuracy of the two variables was higher at 90.2% and 87.8% respectively (Defries and Los 1999).

The MODIS global land cover product was derived from MODIS 1km resolution data using state of the art, supervised classification system using decision tree classifier and is representative of the third generation land cover product technology (Freidl et al 2002). The MODIS dataset is equivalent to the IGBP-DISCover global 1 km land cover dataset and distinguishes the same 17 classes (Wu et al 2008). Globally, an area weighed accuracy of 71.6 (± 0.25) % has been reported (Freidl 2002, Wu et al 2008). Accuracy estimates for continental regions vary with Eurasia reported to have 67.8 (± 0.40) % overall accuracy. Global accuracy estimates for the dominant IGBP classes in IM were grasslands – 66%, cropland – 58%, open shrubland – 85%, mixed forests – 65% and barren – 74.5%.

2.2.4. Quantifying landscape structure

The FRAGSTATS program was used to compute quantitative metrics for describing landscape structure (McGarigal et al 2002). We chose the metrics most appropriate to our research based on previous large scale, multi temporal landscape
fragmentation/LCLU change trajectory studies conducted on the Tibetan plateau (Wang et al. 2008), in the Tarim Basin, Northwest China (Zhou et al. 2008) and in the Heihe river basin (Lu et al. 2003).

The metrics chosen for this study were 1) area metrics (e.g., the number of patches, patch density), 2) contagion/interspersion metrics such as the aggregation index (AI), the interspersion and juxtaposition index (IJI), and the clumpy index, and 3) cohesion to represent connectivity metrics. FRAGSTATS was run using signed 8-bit IGBP classification in ERDAS format. In addition, Shannon and Simpson’s diversity indices were calculated to measure heterogeneity in the landscape (McGarigal et al. 2002, Lu et al. 2003).

2.3. Results

2.3.1. Regional Scale

The changes in IM’s LCLU between 1992 and 2001/2004 are most obvious in the dominant cover types (i.e., grassland, shrubland, agriculture, and barren cover types) (figure 2-1). Grasslands, the most dominant cover, increased from 0.38 to 0.47 million km$^2$ (33.25% in 1992 to 41.21% in 2004 of the total area) (table 2.1). Croplands, the major land-use class, increased from 0.08 to 0.15 million km$^2$ (7.36% in 1992 to 13.10% in 2004). The largest increase in LCLU for all types was for the barren cover, from 0.12 to 0.27 million km$^2$ (10.49% in 1992 to 23.58% in 2004). A decreasing trend was found in shrublands, from 0.23 in 1992 to 0.11 million km$^2$ in 2004 (20.46% to 9.92%). The proportion of forests and savanna also decreased from 0.11 to 0.08 million km$^2$ and 0.08 to 0.03 million km$^2$ (by 3%) between 1992 and 2004. An increasing trend was found in
urban/built–up land from 620 km² in 1992 to 2197 km² in 2004 (from 0.05% and 0.19% in 2004) (table 2.1).

The number of patches between 1992 and 2001/2004 increased for all cover types, with the single exception of natural vegetation mosaic class (i.e., regrowth or crop rotation) (figure 2-2). The increase was the greatest for shrublands, followed by grasslands, savannas, croplands, forest and barren (figure 2-2). The barren cover, however, showed a maximum increase in patch density between the two time periods, followed by forests. We also detected decreasing cohesion, especially in the minority classes (e.g., savanna, permanent wetland, and natural vegetation mosaic classes).

However, the increase in urban land was coupled with no changes for cohesion in the dominant cover types between 1992 and 2001/2004. We found a significant decrease in the AI for shrubland, savanna, permanent wetland, and natural vegetation mosaic types, but an increase in the AI for the barren class type and, to a lesser extent, the urban type (figure 2-2).

The IJI increased for barren (maximum increase) and natural cover types (e.g., shrublands and forests), but remained constant for other dominant cover types such as grassland and cropland. At the same time, there was a decrease in the IJI for the urban/built-up class. The clumpy index, akin to the AI, showed a decreasing trend in the natural vegetation mosaic, followed by forests, shrublands, savanna, permanent wetlands, and also to a small extent in grassland cover. However, the barren cover and urban/built-up land use indicated an increase in clumpiness. Decreasing landscape heterogeneity was measured by Shannon’s and Simpson’s diversity and evenness indices (table 2.3).
2.3.2. Grassland Biome

Within the grassland biome, grassland cover increased from 0.25 to 0.32 million km$^2$ (54.76% to 69.89%) between 1992 and 2004, followed by the shrubland cover, which increased from 9975 km$^2$ to 25973 km$^2$ (from 2.14% to 5.59%) (table 2.2). The savanna decreased from 44620 km$^2$ to 12809 km$^2$ (9.6% to 2.7%), while croplands increased from 49105 km$^2$ to 75816 km$^2$ (10.57% to 16.32 %) between 1992 and 2004 (table 2.2). Urban land use increased from 384 to 1363 km$^2$ (0.08% to 0.28%) while barren cover increased from 129 km$^2$ to 2796 km$^2$ (0.02% to 0.60%).

The number of patches increased between 1992 and 2001/2004, with maximum increase in the shrubland class, followed by the grassland, savanna, and forest. There was also an increase in the croplands and barren cover type. The patch density index showed a maximum increase in barren cover between 1992 and 2001/2004, followed by forest and savanna cover types. The patch density of the cropland for the same period decreased, while that of other cover types showed no obvious change.

The cohesion index decreased in the savanna, permanent wetland, and natural vegetation mosaic classes but increased in the urban land-use class. There were no changes for cohesion in the dominant cover types between 1992 and 2001/2004. However, there was a decrease of bare cover class within the grassland biome. There was a significant decrease in the AI for shrubland, savanna, permanent wetland, and barren and natural vegetation mosaic types. On the other hand, there was an increase in the AI for the urban land use class (figure 2-2).

The IJI increased for barren cover type and, to a lesser extent, natural cover types (e.g., shrublands and forests), but did not change for grasslands. There was a slight
decrease in the IJI for croplands and urban/built-up cover. There was a decrease in the clumpy index, especially with the natural vegetation mosaic (maximum decrease), followed by forests, shrublands, savanna, and permanent wetlands. However, the barren cover and urban/built-up land use showed an increase in clumpiness. There was a decrease in landscape heterogeneity in the grassland biome, indicated by decreasing Shannon’s and Simpson’s diversity and evenness indices (table 2.3).

2.3.3. Desert Biome

The desert biome had an increase in barren cover from 0.11 to 0.26 million km² (25.82% to 56.61%) and urban land use from 51 to 451 km² (0.01% to 0.09%) between 1992 and 2004 (table 2.2), while the proportion of grassland cover remained unchanged (table 2.2). On the other hand, there was a significant decrease in shrubland cover from 0.21 to 0.07 million km² (46.02% in 1992 to 15.35% in 2004) (table 2.2).

The number of patches in the desert biome showed a maximum increase in the shrubland class between 1992 and 2001/2004, followed by the grassland and the barren cover. There was an increase between 1992 and 2001/2004 in the shrubland cover type while other covers showed little or no change.

Cohesion decreased in the savanna and natural vegetation mosaic cover types while there were no changes in grassland, cropland, and shrubland types between 1992 and 2001/2004. However, there was an increase in cohesion in the urban land use class. The AI decreased for the shrubland, savanna, croplands, and natural vegetation mosaic types but increased for forest, barren, and urban land use types (figure 2-2). The IJI increased for the barren, savanna, and, to a small extent, urban cover, between the two
decades. There was a marked decrease in the clumpiness for the shrubland, savanna, and cropland classes with little or no change in the grassland cover type. The clumpy index increased in the barren cover, forest, and urban/built-up cover types. There was a decrease in Shannon’s diversity index between 1992 and 2001/04 indicating increasing homogeneity in the desert landscape (table 2.3).

2.4. Discussion
The dominant grassland cover had increased in proportion from 1992 to 2004; however, it was more fragmented as indicated by the increasing number of patches at the regional and biome scales. At the same time, the increase in proportion of barren cover along with increasing patch density at both the regional and biome scales between 1992 and 2001/2004 is evidence for the growing desertification caused by overgrazing (Wu and Ci 2002). The shrublands, which occupy a transitional belt between the grassland and the desert, have decreased in proportion, with a subsequent increase in patchiness at the regional scale and patch density in the desert biome. However, in the grassland biome, the proportion of shrubland cover increased, offering further evidence of gradual desertification eastward, along the desert-grassland ecotone (Cheng et al 2007). Within the desert-grassland ecotone, shrubland species such as Artemisia halodendron are sand dune stabilizing plants which play a key role preventing sand blowout (Zhang et al 2004), whereas Artemisia ordosica is an indicator species for mid-level desertification (Cheng et al 2007). Studies conducted in the Heihe Basin, suggest that increasing homogeneity within the grassland/desert biomes might be a manifestation of the intensive anthropogenic modification of landscape as evidenced by the increase in irrigated
farmland in an area with limited water resources (Lu et al. 2003). Landscape homogeneity potentially threatens the loss of biodiversity and native patch types that have evolved to resist desertification (Li et al. 2001) and facilitates the ingress of invasive shrub species (Cheng et al. 2007).

We found an increase in the cropland cover proportion and number of patches at the regional level – a possible consequence of a growing population and economy (Wang et al. 2008). A nationwide study carried out at the 30m Landsat scale suggested a per capita increase of croplands in the Northeast and Northwest provinces, including IM (Liu et al. 2005). However, these regions (e.g., the Hetao irrigation basin in IM) are also under severe water stress, with depleting groundwater levels leading to nitrate leaching and increased soil salinity due to the increased irrigation demands of the growing population (Feng et al. 2004). The Hetao irrigation basin is one of the three largest irrigation districts in China (Feng et al. 2004) and the primary cereal crop is wheat, which has high water use and evapotranspiration (He et al. 2007) in an increasingly drier climate (Zhai and Pan 2003).

Some of the minority cover types such as savannas, permanent wetlands, and natural vegetation mosaic showed a decrease in the cohesion index with no change in the dominant cover types. This could be attributed to the landscape becoming more homogenous, characterized by the dominant land cover types (Zhou et al. 2008). The increased cohesion for the urban/built-up cover at the regional scale and in both the grassland and desert biome offers evidence for a growing population driven by a growing economy and subsequent urban sprawl (Qi and Chopping 2007). Studies using nighttime light data derived from the defense meteorological satellite program (DMSP) operational
linescan system (OLS) have also found increases in the extent of urban areas in the
Yellow River watershed and confirms our findings (Qi and Chopping 2007).

The general decrease in the AI for the vegetated cover classes such as shrubland,
savanna, wetlands, and natural vegetation mosaic from 1992 to 2001/2004 is consistent
with the fragmented minority classes within the dominant landscape matrix (grassland
and desert cover types). On the other hand, the increase in the AI for the barren cover
offers further proof that the desert matrix is more homogenous than in the past. The
increase in the AI for urban cover corroborates with increasing cohesion and suggests
expanding urban settlements (Zhou et al 2008). This increase in urban areas has led to an
increasing non-agricultural water demand and transfer from agricultural use to municipal
and industrial needs, further adding to regional water stress and compounding the
problems of efficient water management (Cai 2008).

It is important to note the increase in the AI for forest cover in the desert. In the
recent past, attempts have been made by authorities to stem the tide of advancing
desertification through the use of poplar plantations serving as shelter belts (Chang et al
2006, Hu et al 2008). Such large-scale plantations may significantly alter the water
budget in this fragile semi-arid region, with higher evapotranspiration than the native
species and, therefore, has limited utility as regional climate predictions suggest a drier
climate with lower water availability (Wilske et al 2009). An experimental study in dune
stabilization, conducted in 1997 in the Horqin Sandy Land to evaluate different methods,
found that the most successful combination was of planting *Artemisia halodendron* as
well as corn and wheat straw fencing (Zhang et al 2004).
The increase in the IJI between the two time periods for natural cover types such as shrublands, forests, and savannas (desert biome) is consistent with the results for cohesion and the AI and offers proof for the interspersion of minor classes leading to a homogenous matrix (Zhou et al 2008). At the same time, greater interspersion of the barren cover in the grassland biome as compared to the region and desert biome corroborates with increasing proportion of shrublands and suggests desertification (Cheng et al 2007).

The segregation in natural cover classes such as forests, shrublands, savanna, permanent wetlands, natural vegetation mosaic and, to a small extent, in grassland cover is characteristic of a fragmented landscape brought about through a combination of intensive land use practices and climate change in a semi-arid region (Wang et al 2008, Zhou et al 2008). The increased aggregation of the urban and built-up LCLU type offers proof that urban sprawl has occurred in the last decade. Further proof of desertification is obtained from the increase in the clumpy index for barren cover both at the regional scale and in the desert biome.

Our findings need to be viewed in context of the accuracy of the two land cover datasets. Some of the uncertainty in the 1km AVHRR derived IGBP DISCover data set, is owing to the resolution of the 1km data set, which is also a first generation product. The dataset has artifacts owing to a variety of factors which include cloud cover, gaps in data acquisition, and misregistration. Unlike the MODIS land cover, the data set does not have a QA/QC flag layer (Hansen and Reed 2000).

Recently, Wu and others (2008) carried out a comparative validation of four land cover datasets of 1 km resolution across China. This study compared the IGBP-DISCover
and MODIS land cover, with the higher resolution, Landsat derived National Land Cover Dataset 2000 produced by the Chinese Academy of Sciences (Wu et al 2008). The analysis found discrepancies in area total estimates as well as spatial disagreement in cropland cover.

The MODIS land cover dataset was most representative of cropland cover in China with a bias of 2.9% from the NLCD (Wu et al 2008). On the other hand, IGBP-DISCover overestimated cropland cover by 26% and had the highest bias (37.4%). At the provincial level, cropland estimates for IM by IGBP-DISCover and MODIS land cover differed from the NLCD with a bias of 67% and 18.2%. However, it must be noted that the IGBP DISCover dataset is based on AVHRR data acquired between April 1992 through March 1993 and the MODIS data represents 2004 acquisition. Therefore any discrepancy might indicate change in LCLU over time rather than misclassification error.

The study also reported higher accuracies in cropland cover estimates for all land cover datasets in north and north eastern China (including IM) which were largely homogenous and had large contiguous areas under cultivation as compared to the northwest and south east regions which were more heterogeneous and had smaller land holding (Wu et al 2008).

Our study is limited by the non-availability of IGBP level classification at a resolution of < 1 km in the AVHRR era before the advent of MODIS. A comparison of the currently available 500m resolution IGBP data with a similar dataset in the 1990s would have greatly improved and validated our understanding of changes in LCLU and landscape structure. In order to evaluate the LCLU change trajectories over the past decade, we propose to continue monitoring them in the present to see if they are
consistent. The MODIS 500m LCLU dataset can be used to monitor LCLU change trajectories in IM in the present decade (2000-2010) and monitor structural changes in critical cover types such as shrubland that indicate water stress. The higher resolution will allow better characterization of ecotone shifts, e.g., as at the desert-grassland transition as well as increasing cropland and agricultural land use in the context of climate change. In addition to categorical change, we are also monitoring continuous changes in biophysical variables such as GPP, evapotranspiration, vegetation water content and stress in response to climate drivers. Presently, we have extended the domain of our study across the International border in to neighboring Outer Mongolia to compare LCLU trajectories. Preliminary results suggest significant differences in LCLU and GPP as Outer and Inner Mongolia, although part of the Mongolian grasslands ecoregion, differ in ethnicity (Mongolian and Han Chinese), economic policy, land management, population growth and density which have implications for policy makers.

2.5. Conclusions

Our analysis at the regional and biome scales offers proof of a fragmented landscape characterized by the increase in the number of patches, especially in the dominant land cover types such as grassland, shrubland, and barren. Furthermore, the increase in portions of dominant grassland and barren cover within the decade suggests that the landscape is becoming more homogenous and water stressed. The decrease in proportions of rare cover types corroborates this finding. The effects of increasing socio-economic growth are manifested in increasing cohesion and aggregation of urban/built-up patches.
as well as an increasing number of patches and interspersion of cropland cover in this
fragile semi-arid region.

Acknowledgments

This study was supported by the National Aeronautics and Space Administration (NASA
Grant NEWS 2004 NRA: NN-H-04-Z-YS-005-N) as part of the Energy and Water Cycle
Study. Partial support was received from the Institute of Botany, Chinese Academy of
Sciences.
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Table 2.1: Change in IGBP LULC at regional level between 1992 to 2001 & 2004 in km² (%). Δ denotes rate of change

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Table 2.2: Change in IGBP LULC at biome level between 1992 to 2001 & 2004 in km² (%). Δ denotes rate of change

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</tr>
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Table 2.3: Measure of landscape diversity for IM between 1992 and 2001/2004.
SHDI-Shannon’s Diversity Index; SIDI-Simpson’s Diversity Index; SHEI- Shannon’s
Evenness Index; SIEI- Simpson’s Evenness Index

<table>
<thead>
<tr>
<th>Biome</th>
<th>SHDI</th>
<th>SIDI</th>
<th>SHEI</th>
<th>SIEI</th>
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Figure 2-2. Changes in landscape metrics for regional scale (grey), grassland biome (red), and desert biome (blue) for 1992 AVHRR derived and 2001/2004 MODIS derived IGBP classification.
Chapter 3

3. Modeling gross primary production in semi-arid Inner Mongolia using MODIS imagery and eddy covariance data

Abstract
Semi-arid Inner Mongolia, P.R.C, is experiencing climate change with associated land cover/use change that includes an increase in irrigated agriculture and population growth. Temporal scaling up of carbon fluxes from eddy covariance (EC) tower observations is evaluated in different water-limited land cover/use and biome types. The Vegetation Photosynthesis model (VPM) and modified VPM (MVPM), driven by Enhanced Vegetation Index (EVI) and Land Surface Water Index (LSWI) for 2006-2007 that were derived from the MODerate resolution Imaging Spectroradiometer (MODIS) surface reflectance product (MOD09A1) was used to scale up and validate temporal changes in GPP from the EC towers during 2006 & 2007 growing seasons. The VPM model predicted the annual GPP (GPP\textsubscript{VPM}) reasonably well in 2006-2007 at the Duolun cropland ($R^2 = 0.67$ & 0.71) and Xilinhaote typical steppe ($R^2 = 0.80$ & 0.73). The predictive power of VPM varied in the desert steppe, at an irrigated poplar stand ($R^2 = 0.74$ & 0.68) and nearby shrubland in Kubuqi ($R^2 = 0.31$ & 0.49). The comparison between GPP\textsubscript{tower} and GPP\textsubscript{MVPM} predicted GPP showed good agreement for the Xilinhaote typical steppe
(\(R^2 = 0.84 \& 0.70\) in 2006-2007, Duolun typical steppe \((R^2 = 0.63)\), and cropland \((R^2 = 0.63)\) in 2007. The predictive power of MVPM decreased slightly in the desert steppe, at the irrigated poplar stand \((R^2 = 0.55 \& .47)\) and the shrubland \((R^2 = 0.20 \& 0.41)\). The results of this study demonstrate the feasibility of scaling up GPP from EC towers to the regional scale.

Keywords: Carbon flux, scaling, MODIS, eddy covariance, VPM, semi-arid, Inner Mongolia

3.1. Introduction
Grasslands, which account for 32% of global vegetation (Parton, 2005), are under serious pressure in Asia from the effects of climate change and a growing population (Ojima, 1998). Semi-arid grasslands in Northern China, most of which are in Inner Mongolia, make up 41% of the country’s land area, are especially prone to degradation on account of the consistent warming trends in Northeast Asia for the past 50 years (Chase et al., 2000; Lu et al., 2009) and with an increase in grazing related economic activities (Kang et al., 2007). These climatic changes (Zhai et al., 1999; Hu et al., 2003; Zhai and Pan, 2003) have affected the productivity and stability of these semi-arid grasslands, which are under increasing pressure from an intensification of over grazing and irrigated agriculture leading to their degradation and desertification (Christensen et al., 2004; Zhou et al., 2002). Such degradation has lead to a dramatic modification of biophysical properties, which include albedo, leaf area index (LAI), surface roughness, soil water holding
capacity and soil moisture content, which has the potential to bring significant changes in
the regional and global climate (Li et al., 2005). Though grasslands play an important
role in carbon sequestration, there have been very few attempts to scale up carbon and
water fluxes in arid and semi-arid regions (Baldocchi et al., 2001).

The eddy covariance (EC) method, used for continuous, automated, on site
observations of carbon, water and energy fluxes, has helped obtain timely net ecosystem
exchange (NEE) data which in turn provides gross primary production (GPP) and
ecosystem respiration (Re) estimates (Falge et al., 2002). Though the EC technique is
meant to represent various types of terrestrial ecosystems, a major limiting factor is that
the sampling footprint is limited to a kilometer or less (Osmond et al., 2004). In addition,
these measurements are limited to homogenous, flat terrain and equipment cannot be
easily installed over the world, owing to logistic issues (Running et al., 1999). Satellite
remote sensing data provides a practical, objective method to obtain synoptic coverage of
the spatio-temporal dynamics of ecosystems. In the recent past, many studies have
attempted to effectively scale up estimates of primary production from EC towers using
remote sensing data to estimate the regional carbon budget (Aalto et al., 2004; Turner,
2003; Xiao et al., 2011). Remote sensing based studies (TURC, MODIS-PSN and GLO-
PEM) have used ecosystem production efficiency to estimate GPP at regional scales
(Goetz et al., 1999, Ruimy et al., 1999; Running et al., 2004). While satellite remote
sensing can estimate GPP or NPP, it cannot validate ecosystem respiration or NEE
(Running et al., 1999). Production efficiency models (PEMs) usually estimate GPP as a
product of photosynthetically active radiation (PAR), canopy fPAR (fraction of PAR
absorbed by the canopy) and light use efficiency (εg). These models usually consider
fPAR as a linear function of the normalized difference vegetation index (NDVI) (Tucker, 1979). However, the traditional use of NDVI to model GPP is constrained by its sensitivity to soil background signature in semi-arid regions with 50% fractional cover (Huete et al., 2002). A satellite remote sensing based vegetation photosynthesis model (VPM) was developed and tested for GPP modeling in different ecosystems that include evergreen conifers, temperate deciduous forest, seasonal tropical forests, and alpine meadows (Li et al., 2007; Xiao et al., 2004a, b; Xiao et al., 2005). VPM is an improvement over legacy NDVI driven PEMs in that it uses enhanced vegetation index (EVI) as a function of fPAR. VPM also uses land surface water index (LSWI) along with in situ measurements of air temperature (Ta) and PAR from EC towers.

In addition to validating GPP estimates of the VPM model, I also tested the scalability of our modified VPM (MVPM) that runs solely on MODIS derived biophysical variables independent of EC tower measurements to the region. This model offers a cost effective method of obtaining an estimate of GPP when an EC tower or climate station is not readily available at the site of interest. Since the scaling up of carbon fluxes has not been extensively evaluated and applied in arid-and semi-arid grassland ecosystems, I chose a network of EC tower sites across the temperate semi-arid steppe in Inner Mongolia as our field study area. The objectives of this research are to: 1) evaluate the response of vegetation indices (EVI and NDVI) to the seasonal dynamics of carbon exchange in semi-arid grassland ecosystems, 2) further evaluate the temporal scaling ability of the VPM model for estimating the primary productivity of semi-arid grassland ecosystems, and 3) test and validate a modified VPM independent of EC tower
measurements. This study provides validation of two broadly used GPP models in semi-arid region in both natural and agricultural ecosystems.

3.2. Methods

3.2.1. Study sites

This study was conducted in Inner Mongolia, China, characterized by the continental, semi-arid monsoon climate of eastern Eurasia, with a growing season that starts in April and ends in early October. Our study sites consist of a network of five EC towers in: 1) a typical steppe-cropland tower pair at Duolun, 2) heavily grazed steppe at Xilinhaote, and 3) a pair of EC towers in the desert steppe at Kubuqi with one tower in an irrigated poplar plantation and the other in the surrounding shrubland (Figure 3-1).

The Duolun sites are located within the Duolun Restoration Ecology Research Station. The Duolun EC towers are located in agro-pastoral typical steppe with long term climatic data indicating annual mean temperature of 8.4°C with mean monthly temperatures ranging from -15.9°C in January to 19.9°C in the growing season peak. The mean annual precipitation is 399 mm with maximum precipitation in July or August. The typical steppe is dominated by *Stipa krylovii*, *Artemisia frigida*, *Cleistogenes squarrosa* and *Leymus chinensis* and characterized by annual precipitation of 350 mm or less (*Kang et al.*, 2007). The cropland site was previously typical steppe until it was converted to agricultural fields in which *Triticum aestivum L.*, *Avena nuda L.*, and *Fagopyrum esculentum Moench* were planted in mid-May and harvested in the mid-September. The EC tower in Xilinhaote is also located in the typical steppe, where livestock grazing is the primary land use with heavy degradation of the steppes due to overgrazing. The mean
annual temperature here is 7.2°C, with January and July being the coldest and hottest months respectively (-22.3 and 18.8°C, respectively). The EC towers are in a fenced area of the Inner Mongolia Grassland Ecosystem Research Station (IMGERS), Chinese Academy of Sciences, and have an annual precipitation of 400 mm.

The two Kubuqi towers were erected in a 3 year-old poplar plantation and the surrounding shrubland. This region is around 400 km long and 50 km wide, between the southern bank of the Yellow River and the northern portion of the Ordos plateau (~1000 m a.s.l). The desert steppe is characterized by the continental type of climate with annual precipitation at 150-200 mm. Mean monthly temperatures range between -11 °C to 24°C in January and July, respectively, based on data from nearby meteorological stations from 1957 to 2000; No. 53336, 53446, 53513, 53529, 53543; China Meteorological Data Sharing Service System (http://cdc.cma.gov.cn, China Meteorological Administration, 2006). As a dune stabilization measure, ~200 km² were planted with poplar since 1998 (Wilske et al., 2009). These young poplars have a mean height of 1.5-2.0 m, with an intercrop of *Glycyrrhiza uralensis Fisch*. The plantation near the EC tower covered an area of 3.73 km². Tree height and LAI varied greatly as some trees had grown to a height of 4 m while others exhibited stunted growth. The water table varied between 1 and 4 m deep, depending on the height of the sand dunes. The poplar plantation is provided with drip irrigation during droughts with irrigation periods lasting for about 11 h. Water equal to precipitation of 1.46 mm was supplied during each period, nine times from April through September 2005. Drip irrigation in 2006 was provided twice in April and once in May and June.
The second EC tower at Kubuqi is located 20 km to the south of the poplar plantation tower in a native shrubland. The shrubland matrix in Kubuqi is dominated by shrub species *Artemisia ordosica* Krasch and *Hedysarum mongolicum* Turcz. The *Artemisia ordosica* found here is deciduous shrub with a height of 0.6-1 m (Wilske et al., 2009) with fractional cover of 15-23%. It is important to note that soil moisture at the Kubuqi shrubland tower site was twice as high as the irrigated poplar site (Wilske et al., 2009).

The EC flux towers at the aforementioned sites measured fluxes of CO$_2$, latent heat and sensible heat at 4 m height (Chen et al., 2009). The flux data was processed using EC_Processor (Noormets et al., 2007) using planar fit coordinate rotation (Wilczak et al., 2001), included temperature and pressure corrections for sonic temperature (Schotanus et al., 1983), air density (Webb et al., 1980) and additional heat flux (Burba et al., 2008) corrections for turbulent fluxes. Daily totals of NEE, ER and GEP were calculated from quality-checked (Foken and Wichura, 1996) and gapfilled data using non-linear functional regression models (Moffat et al., 2007). Different parameterizations of the light- and temperature-response functions were used for the active and dormant seasons, which were delineated according to soil temperature at 5 cm with a threshold of 3°C. Additional meteorological data measured at each site included net radiation, photosynthetically active radiation, temperature and relative humidity at 30 minute intervals.

3.2.2. Satellite Data
I analyzed time series of imagery from the MODIS sensor aboard the morning overpass, Terra satellite (crossing the equator at 10:30 AM) through acquisition of 8-day composites of MODIS derived surface reflectance (MOD09A1) from the NASA Warehouse Inventory Search Tool data gateway (https://wist.echo.nasa.gov/api/). Of the seven spectral bands in MOD09A1 used to study vegetation and land surface properties, I used blue (459–479 nm), green (545–565 nm), red (620–670 nm), NIR (841–875 nm), and SWIR (1628–1652 nm) to derive the spectral indices (EVI, NDVI, LSWI) for VPM and MVPM. In addition, I also acquired 8-day composites of MODIS derived biophysical variables such as GPP (MOD17A2), fraction of photosynthetically active-radiation (fPAR, MOD15A2), land surface temperature (LST, MOD11A2). The MODIS GPP (GPP\text{MODIS}) is calculated based on a LUE model (Running et al., 2004);

\[
GPP_{\text{MODIS}} = \epsilon_{\text{max}} \times m(T_{\text{min}}) \times m(VPD) \times f\text{PAR} \times SW\text{rad} \times 0.45
\]  

(1)

where \(\epsilon_{\text{max}}\) is the max LUE, \(m(T_{\text{min}})\) and \(m(VPD)\) are scalars which lower \(\epsilon_{\text{max}}\) under stressful condition of low temperature and high vapor pressure deficit (VPD). SWrad is the shortwave radiation component and \(f\text{PAR}\) is the fraction of PAR. While \(\epsilon_{\text{max}}\) is derived from a lookup table, \(T_{\text{min}}, VPD, SW\text{rad}\) are obtained from coarse resolution NASA Data Assimilation Office.

3.2.3. VPM Model

3.2.3.1. Vegetation photosynthesis model

The fraction of light absorbed by the canopy (\(f\text{PAR}_{\text{canopy}}\)) is partitioned in to the fraction of light absorption by chlorophyll (\(f\text{PAR}_{\text{chl}}\)) and NPV (\(f\text{PAR}_{\text{NPV}}\)). Based on this Xiao et al., (2004) developed the VPM model which differs slightly from the MODIS GPP.
equation. Instead of the BPLUT look up table, which in turn was derived from BIOME-BGC, \( \varepsilon_g \) is obtained from remote sensing inputs and meteorological inputs as follows:

\[
GPP = \varepsilon_g \times f_{\text{PARchl}} \times \text{PAR} 
\]

\[
\varepsilon_g = \varepsilon_0 \times T_{\text{scalar}} \times W_{\text{scalar}} \times P_{\text{scalar}}
\]

where PAR is the photosynthetically active radiation (\( \mu\text{mol m}^{-2} \text{s}^{-1} \)), \( f_{\text{PARchl}} \) is the fraction of PAR absorbed by chlorophyll, \( \varepsilon_g \) is the light use efficiency, LUE (\( \mu\text{mol CO}_2 \text{ PAR}^{-1} \)). The parameter \( \varepsilon_0 \) is the maximum light use efficiency (\( \mu\text{mol CO}_2 \text{ PAR}^{-1} \)), and \( T_{\text{scalar}}, W_{\text{scalar}}, \text{ and } P_{\text{scalar}} \) are the regulation scalars for the effects of temperature, water and leaf phenology on the light use efficiency of vegetation.

The input data for simulation of the VPM model are remote sensing data (from MODIS and SPOT vegetation), air temperature, PAR and vegetation type (deciduous & evergreen, \( \text{C}_3 \) & \( \text{C}_4 \) plants). It was proposed that \( f_{\text{PARchl}} \) can be estimated as a linear function of the enhanced vegetation index (EVI) that uses surface reflectance values (where \( \rho_{\text{nir}}, \rho_{\text{red}}, \text{ and } \rho_{\text{blue}} \) are near infrared, red and blue bands):

\[
f_{\text{PARchl}} = a \times \text{EVI}
\]

\[
EVI = \frac{\rho_{\text{nir}} - \rho_{\text{red}}}{\rho_{\text{nir}} + 6 \times \rho_{\text{blue}} - 7.5 \times \rho_{\text{red}} + 1}
\]

Because the short infrared (SWIR) spectral band is sensitive to vegetation water content and soil moisture, a combination of NIR and SWIR bands have been used to derive water-sensitive vegetation indices, including the Land Surface Water Index. LSWI values vary from -1 to +1 with a range of 2.

\[
LSWI = \frac{\rho_{\text{nir}} - \rho_{\text{swir}}}{\rho_{\text{nir}} + \rho_{\text{swir}}}
\]
As leaf liquid water content increases or soil moisture increases, SWIR absorption increases and SWIR reflectance decreases, resulting in an increase in LSWI. Recent work in evergreen needleleaf as well as temperate broadleaf forests has shown that LSWI is sensitive to changes in leaf water content (equivalent water thickness) over time (Xiao et al., 2004a, b).

$W_{\text{scalar}}$, $T_{\text{scalar}}$, and $P_{\text{scalar}}$ are down regulation scalars that describe the effects of water, temperature, and leaf phenology on the light use efficiency of vegetation, respectively.

The seasonal dynamics of $W_{\text{scalar}}$ is obtained as:

$$W_{\text{scalar}} = \frac{1 + LSWI}{1 + LSWI_{\text{max}}}$$  \hspace{1cm} (7)

$T_{\text{scalar}}$ is a measure of the sensitivity of photosynthesis to temperature, calculated at each time step using the equation developed for the Terrestrial Ecosystem Model (Raich et al. 1991).

$$T_{\text{scalar}} = \frac{(T - T_{\text{min}})(T - T_{\text{max}})}{[(T - T_{\text{min}})(T - T_{\text{max}})] - (T - T_{\text{opt}})^2}$$  \hspace{1cm} (8)

where $T_{\text{min}}$, $T_{\text{max}}$, and $T_{\text{opt}}$ are minimum, maximum, and optimal temperatures (0°C) for photosynthesis, respectively. If air temperature falls below $T_{\text{min}}$, $T_{\text{scalar}}$ is set to be zero.

$$P_{\text{scalar}} = \frac{1 + LSWI}{2}$$  \hspace{1cm} (9)

The $P_{\text{scalar}}$ accounts for the effects of leaf phenology on photosynthesis at the canopy level. The calculation of $P_{\text{scalar}}$ is dependent upon the longevity of leaves (deciduous as compared to evergreen). Since a grassland canopy has new leaves through the growing season, the $P_{\text{scalar}}$ is set to 1.
3.2.3.2. Model parameterization

The VPM model has four important parameters: 1) maximum light use efficiency, 2) the effect of temperature on vegetation photosynthesis \( T_{\text{scalar}} \) as governed by minimum, maximum and optimal temperature measurements, 3) the effect of water on photosynthesis \( W_{\text{scalar}} \), represented by the maximum LSWI of the growing season, and 4) the effect of phenology \( P_{\text{scalar}} \) on photosynthesis.

Light use efficiency \( \varepsilon_g \) varies by ecosystem type and can be obtained through metanalysis from published literature or can be estimated through a nonlinear regression of site specific NEE with PAR data within the growing season (Xiao et al., 2004b; Li et al., 2007). Maximum LUE \( \varepsilon_0 \) varies with vegetation type and can be obtained from NEE of CO\(_2\) flux and incident PAR. I derived \( \varepsilon_0 \) for the different ecosystem types, through nonlinear models with the best fit based on the Michaelis–Menten function between NEE and PAR during the peak period of the growing season.

\( T_{\text{scalar}} \) was obtained through analyzing the relationship between temperature and daily GPP. Temperature is an important control on GPP as sufficient but not extreme temperature is required for photosynthesis. Photosynthesis increases until optimal temperature range beyond which it begins to decrease. This optimal range is quite large and I established the limiting temperatures based on relationships between photosynthesis and air temperature measured at the tower sites. In 2006, I estimated a minimum of 1°C temperature and optimal temperature of 17°C with maximum temperature of 29.7°C in D01, 30.7°C in D02, 31.7°C in X03, 35.8°C in K04 and 37.7°C in K05. In 2007, I again estimated a minimum of 1°C temperature while optimal temperatures ranged between
18.5°C at D01 to 23.5°C at K05. The maximum temperatures in 2007 were 23.9°C in D01, 28.1°C in D02, 29.4°C in X03, 27°C in K04 and 27.4°C in K05.

\( W_{\text{scalar}} \) is obtained through selection of the site-specific maximum LSWI value in the active growing season. I did not use the annual \( LSWI_{\text{max}} \) as winter LSWI values are extremely high owing to snow cover and are therefore excluded. In 2006, \( LSWI_{\text{max}} \) varied among sites with peak values of 0.2 in Duolun steppe, 0.2 in Duolun cropland, and -0.01 in Xilinhaote grassland on 28 July, 2006. In the desert steppe, maximum LSWI values were -0.05 in K04 and 0.05 in K05 on 22 September and 29 August, respectively. \( LSWI_{\text{max}} \) in 2007 varied between sites with values of 0.04 in D01, 0.08 in D02, and -0.003 on 28 July, 21 August and 5 August, respectively. In the desert steppe, \( LSWI_{\text{max}} \) of 0.008 at K04 and -0.035 at K05, were reached on 20 July.

\( P_{\text{scalar}} \) accounts for the effects of phenology on photosynthesis at the canopy level. The calculation of \( P_{\text{scalar}} \) is dependent upon the longevity of leaves (deciduous as compared to evergreen). Since a grassland canopy has new leaves through the growing season, the \( P_{\text{scalar}} \) is set to 1 for D01, D02 and X03. However, for the irrigated poplar stand and shrubland sites, K04 and K05, I computed \( P_{\text{scalar}} \) as a linear function of LSWI from budburst to leaf expansion after which it is set to 1.

3.2.4. Modified Vegetation Photosynthesis Model (MVPM)

The model is based on the light use efficiency models where GPP is linearly related to the product of PAR and the efficiency with which the absorbed light is used to fix carbon (Running et al., 2004). Early LUE models (Monteith, 1972) assumed that LUE was constant; however, recent studies have shown that LUE varies considerably across
ecosystem types and environmental stochasticity such as drought and diffuse albedo
(Ruimy et al., 1995). GPP models generally estimate LUE through the use of look up
tables of LUE for a given biome type (Running et al., 2004). This can lead to errors
owing to the coarse resolution (1° x 1.25° pixel) in the meteorological data from the Data
Assimilation Office (DAO) and the spatial mismatch with the higher resolution (1 km) of
the MODIS GPP data (Zhao et al., 2005). It would be much simpler from a processing
point of view to create a GPP model entirely on remotely sensed data of similar
resolution.

Previous studies have suggested that independent measures of LUE were
unnecessary as they found good correlations between satellites derived spectral indices
with carbon fluxes as well as with LUE (Sims et al., 2006a). While most of the early
studies showing good correlations between spectral indices and primary productivity
were integrated over growing season composites (Goward et al., 1985), it remains
unclear as to what extent can short term variability in carbon fluxes be estimated through
spectral indices (Sims et al., 2006b). While some scaling up studies in semi-arid areas
using correlations between NDVI and carbon fluxes have been carried out (Wylie et al.,
2003), they have not been measured across different ecosystem types (Sims et al., 2006b).

An important limitation of the VPM is that it is not entirely independent of ground
based sensor measurements such as PAR and temperature. I studied the feasibility of
replacing these variables with MODIS derived GPP, fPAR and LST products. In the
following equation I obtained PAR by dividing GPP_{MODIS} with MODIS fPAR, which is
then multiplied with a suite of MODIS derived variables EVI, LSWI and LST that are
surrogates of productivity, water content and temperature respectively to obtain GPP. I included LSWI and LST as my study area is predominantly a water limited ecosystem.

\[
GPP = \alpha \left[ \ln \left( \text{GPP MODIS} \right) \times (\text{EVI} \times \text{LSWI} \times \text{LST}) \right] / \text{fPAR MODIS} \tag{10}
\]

I log-transferred GPP_{MODIS} in the regression analysis because tower GPP may reflect only a fraction, possibly a nonlinear relationship with GPP_{MODIS} which is an aggregate measure over the 8-day period.

3.3. Results

3.3.1. Seasonal dynamics of vegetation indices and tower GPP

The seasonal dynamics of GPP is driven by temperature and PAR in these temperate steppes with GPP_{tower} values near zero in the winter season with day of year (DOY) ranging from 1 to 113 and from 297 to 365 owing to the absence of photosynthetic activity (Figure 3-2). The GPP_{tower} time series for 2006-2007 had a seasonal cycle with distinct differences in phase and amplitude (Figure 3-3). There were temporary decreasing trends in the GPP_{tower} time series (Figure 3-3) owing to low temperature and low PAR during rainy days (Figure 3-2).

The growing season began on April 23 (DOY 113) with an increase in PAR and air temperature, leading to growth in vegetation and subsequent increase in the ecosystem’s photosynthetic capacity (Figure 3-2). EVI and NDVI follow the increase in GPP_{tower} closely until the growing season peak is reached in the late July (DOY 185-217) after which GPP_{tower} declines. There is a subsequent decrease in EVI and NDVI, as vegetation senesces with a decrease in temperature and PAR availability.
The photosynthetic capacity of the different land cover/use types vary between the two years. In 2006, D01 & D02 have peak values of 3.07 gC m\(^{-2}\) d\(^{-1}\) and 8.71 gC m\(^{-2}\) d\(^{-1}\) (Figure 3-3a, b) while their total GPP\(_{tower}\) was 40 gC m\(^{-2}\) d\(^{-1}\) and 77 gC m\(^{-2}\) d\(^{-1}\), respectively. X03 has a peak value of 3 gC m\(^{-2}\) d\(^{-1}\) (Figure 3-3c) and a total GPP\(_{tower}\) value of 49.62 gC m\(^{-2}\) d\(^{-1}\). K04 and K05 had peak GPP\(_{tower}\) values of 2.97 gC m\(^{-2}\) d\(^{-1}\) and 1.41 gC m\(^{-2}\) d\(^{-1}\) (Figure 3-3d, e) while their total GPP\(_{tower}\) values are 45.44 gC m\(^{-2}\) d\(^{-1}\) and 30.24 gC m\(^{-2}\) d\(^{-1}\) in the growing season, respectively (Table 3.2).

In contrast, GPP\(_{tower}\) in 2007 is slightly less compared to 2006. This difference is especially true for D01 & D02 with a peak value of 1.3 gC m\(^{-2}\) d\(^{-1}\) and 1.9 gC m\(^{-2}\) d\(^{-1}\) (Figure 3-3a, b) with total GPP\(_{tower}\) values of 33.2 gC m\(^{-2}\) d\(^{-1}\) and 69 gC m\(^{-2}\) d\(^{-1}\), respectively (Table 3.2). X03 differs from 2006 in that the peak season reaches later in the growing season with a peak value of 3.43 gC m\(^{-2}\) d\(^{-1}\) (Figure 3-3c) and a total value of 42.18 gC m\(^{-2}\) d\(^{-1}\) (Table 3.2). The lagged 2007 peak season seems evident in K04 & K05 sites with peak values of 1.8 gC m\(^{-2}\) d\(^{-1}\) and 1.15 gC m\(^{-2}\) d\(^{-1}\) (Figure 3-3d,e) and a total GPP\(_{tower}\) value of 30.24 gC m\(^{-2}\) d\(^{-1}\) gC m\(^{-2}\) d\(^{-1}\), respectively (Table 3.2).

The intra-annual seasonal dynamics of vegetation indices (i.e., EVI and NDVI derived from the MODIS 8-day reflectance product) follow seasonal changes in vegetation but differ in amplitude among the different land cover/use types (Figure 3-3). The maximum NDVI values in D01, D02 and X03 are in the range 0.7-0.8 while the EVI values range between 0.5 and 0.6. While EVI and NDVI closely follow the 2006 & 2007 seasonal changes in GPP\(_{tower}\) at D01 & D02, X03, and K04 with peak season in late July, the vegetation indices in the desert steppe, (K05) lag behind GPP\(_{tower}\) due to a delayed
peak season in response to rains in late August. The lag effect is especially obvious in 2007 for all five sites with the peak season at the end of August.

3.3.2. VPM model output and tower GPP

The VPM model is run on an 8-day time scale with EC tower inputs such as air temperature and summed PAR in conjunction with satellite derived vegetation indices. The intraannual dynamics of predicted GPP\textsubscript{VPM} were compared to the observed GPP\textsubscript{tower} in 2006 (Figure 3-4) and 2007 (Figure 3-6). However, the reduced amplitude in 2007 as compared to 2006 (Figure 3-3) might be attributed to lesser precipitation in 2007 (Table 3.1). Cumulative rainfall in 2006 was almost twice that of 2007 for D01 & D02 and ~40mm more in the K04 & K05 desert steppe sites (Table 3.1). I reasoned that the difference in precipitation between 2006 (wet year) and 2007 (dry year) affect the interannual dynamics of LSWI which is an important driver of the VPM and MVPM models.

A linear regression of the GPP\textsubscript{VPM} with GPP\textsubscript{tower} as the dependent variable shows reasonable agreement and explains a significant amount of the variation (Table 3.3). The results are significant ($\alpha =0.05$). Scaling up efficiency decreased from X03 site in the typical steppe to the K04 & K05 sites in the desert steppe (Table 3.2). The predicted GPP\textsubscript{VPM} at the Kubuqi tower sites overestimated the observed GPP\textsubscript{tower} in 2006 and underestimated GPP\textsubscript{tower} in 2007 (Table 3.2). At X03, integration of GPP\textsubscript{VPM} over the active growing season (May-October) and the entire year was slightly higher than GPP\textsubscript{tower} in 2006. However, the GPP\textsubscript{VPM} for both time periods were much higher than GPP\textsubscript{tower} in 2007. The simulated GPP\textsubscript{VPM} at the cropland site, D02, closely matched
GPP$_{\text{tower}}$ during the active growing season and the entire year in 2006 while the simulated GPP$_{\text{VPM}}$ overestimated the GPP$_{\text{tower}}$ in 2007. There was an overestimation of GPP$_{\text{VPM}}$ at the typical steppe site, D01 during the active growing season as well as the entire year in 2006, but GPP$_{\text{VPM}}$ reasonably matched GPP$_{\text{tower}}$ in 2007 (Table 3.2), partially because of missing/bad data in June & July 2006 (D0Y 153-209).

In 2006, at D02, X03 and K04, the GPP$_{\text{VPM}}$ tracks GPP$_{\text{tower}}$ closely, though the magnitudes are not always consistent (Figure 3-4 and Figure 3-6). This is especially true for cropland tower (D02) in the peak growing season, where GPP$_{\text{tower}}$ is higher than the GPP$_{\text{VPM}}$. The growing season curve for D02 has a sharp, narrow peak which is characteristic of agriculture with a short growing season. While the seasonal dynamics of GPP in a semi-arid steppe could be explained by temperature and PAR, the cropland land use type is not a natural ecosystem like the surrounding matrix of semi-arid grassland even though they both have similar climatic conditions. The seasonal dynamics of D02 can be explained by cultivation stages of seeding, fertilizer application and harvesting. With the onset of spring, the GPP$_{\text{VPM}}$ in the typical steppe increases gradually while the cropland site is in dormancy until a rapid increase of D02 GPP$_{\text{VPM}}$ in late April-Early May (Figure 3-4b).

3.3.3. MVPM model output and tower GPP

Observed GPP$_{\text{tower}}$ at EC towers was regressed with the simulated GPP$_{\text{MVPM}}$ estimate. The regression model showed a strong correlation between GPP$_{\text{tower}}$ and GPP$_{\text{MVPM}}$ in the typical steppe site (X03) and irrigated poplar stand (K04) in 2006 and 2007, where MVPM performed better than VPM (Table 3.2). The regression model also explained a
significant amount of variation in $GPP_{MVPM}$ for cropland (D02) and desert shrubland (K05) in 2006 & 2007, and typical steppe (D01) in 2007 (Table 3.4, Figure 3-8). The results were significant ($\alpha = 0.05$) except for D01 in 2006 owing to missing data in the months of June-July. This also explains the overestimated $GPP_{MVPM}$ at the typical steppe D01 site (Table 3.2). $GPP_{MVPM}$ integrated over the entire year in 2006 at D02 slightly underestimated $GPP_{tower}$ whereas it was overestimated in the active growing season (Table 3.2). The $GPP_{MVPM}$ at X03 is almost the same for integrated $GPP_{tower}$ over the entire year in 2006 and 2007 while $GPP_{MVPM}$ was overestimated in the active growing season. In the desert steppe, at the irrigated poplar stand (K04), $GPP_{MVPM}$ slightly underestimated $GPP_{tower}$ in 2006 and 2007 for both periods. However, the $GPP_{MVPM}$ overestimated $GPP_{tower}$ at the K05 shrubland site in the active growing season and the entire year (Figure 3-8).

3.4. Discussion

I evaluated the potential of the VPM model to estimate and scale up GPP from EC flux towers in different semi-arid land cover/use types. In addition, I developed and tested a modified version of VPM that was validated with tower-derived GPP. Both VPM and MVPM have simple structures with few parameters to be adjusted. For example, VPM needs just four parameters for each vegetation type along with vegetation indices (EVI & LSWI) from MODIS in a simple equation and is able to reproduce spatiotemporal changes in GPP.

When used with ancillary data such as maps of Biome & Terrestrial Ecoregions and land cover/land use (e.g., IGBP), meteorological data, satellite derived albedo and
shortwave radiation, the models provide a good understanding of carbon fluxes with high
temporal and spatial resolution which matches the 500 m -1 km IGBP LCLU MODIS
(MOD12Q1) product. Though there are many process-based biogeochemical models
(e.g., SiB3 and Biome-BGC) which simulate carbon and water fluxes with high temporal
resolution (e.g., hourly), they require multiple input parameters which are often difficult
to obtain. For example, some SiB2 regional simulation runs needed more than 40
spatially interpolated parameters (Wang et al., 2007). The input parameters of process-
based models often need frequent recalibration which is computationally intensive.

The MVPM offers an alternative to existing PEM based GPP models in that it is
independent of ground based measurements and entirely based on MODIS data with
consistent spatial resolution. The establishment of climate stations or EC flux towers is
both expensive and time consuming especially in a remote region like the Mongolian
Plateau. The MVPM model can help obtain an estimate of 8-day GPP from the previous
year before setting up an EC flux tower site in a semi-arid region.

Similar models based solely on MODIS EVI also exist (Sims et al., 2006b).
However, Sims et al. (2006b) found poor GPP estimates in the active season for sites
undergoing drought as their model lacked measures of drought stress and temperature
which are present in the MOD17 GPP model (Running et al., 2004). The MODIS land
surface temperature product (MOD11A2), which is a measure of ‘skin’ temperature as
compared to air temperature, normally measured by meteorological stations is also well
correlated with vapor pressure deficit (Wan et al., 2004). I optimized MVPM for GPP in
semi-arid regions by including LST and LSWI to account for variability in temperature
and vegetation water content as well as drought stress, which are the key regulators of
carbon fluxes in dryland regions. This may be an improvement over VPM, where the absence of a soil moisture component and its inability to measure water stress might be a source of error.

The advance of growing season, or phenological cycle (leaf flush/green up, maturity, senescence and dormancy), is characterized by biochemical changes in the vegetation canopy (e.g., chlorophyll, xanthophyll) which in turn affect the biophysical properties of the semi-arid land surface such as evapotranspiration, albedo, and surface roughness (Xiao et al., 2004b). Huete et al. (2002) described the biophysical/radiometric advantages and relative merits of EVI and NDVI especially in sparsely vegetated environments with pronounced soil background signature. This study evaluates the use of productivity and water indices such as EVI and LSWI to measure the growing season length and water stress that regulate carbon exchange in the ecosystem. Predicted $GPP_{VPM}$ agrees well with observed $GPP_{tower}$ in the semi-arid ecosystem types in Inner Mongolia. Our results suggest EVI can be linearly related to fPAR and chlorophyll, while LSWI seems a reasonable surrogate of leaf water content as was found in VPM studies in various forest ecosystems (Xiao et al., 2004a, Xiao et al., 2004b, Xiao et al., 2005). The VPM model provides an alternate to the MODIS GPP product (Running et al., 2004), which is based on the NDVI-fPAR-LAI relationship. $GPP_{MODIS}$ depends a great deal upon the availability and quality of daily meteorological observation data. Previous studies showed that VPD could capture interannual variability of the water stress in wet areas, where annual precipitation was $>400$ mm yr$^{-1}$. However, in arid regions where soil moisture is the limiting factor, MOD17 was found to underestimate water stress and overestimate GPP. It was found that MOD17 was better able to describe the inter and intra-
annual variability of GPP in the lower 48 states than in monsoon controlled China (Mu et al., 2007b).

Extensive validation of the MODIS GPP product was carried out by the BIGFOOT project that involved the use of traditional ecological measurements as well as process-based modeling through the use of Biome-BGC (Turner et al., 2005). The validation sites include a desert grassland site (SEVI) where the MODIS GPP product did not agree well with the tower GPP especially in the beginning and the end of the growing season. This suggests the need for GPP product validation in semi-arid grasslands as opposed to most validation studies which take place in various forest ecosystems.

The GPP_{VPM} and GPP_{MVPM} differ from the GPP_{tower} observations in some 8-day periods (Figures 2-4, 2-6, and 2-8) and these account for the differences between annual and growing season integration of predicted and observed GPP (Table 3.2). These differences can be attributed to the sensitivity of the model towards microclimatic variations in PAR and temperature, which vary among the five land use/cover types. Another source of error could stem from the overestimation or underestimation of GPP by the EC towers. In order to calculate GPP, ecosystem respiration has to be measured in addition to the gapfilling of net ecosystem exchange measured by the tower. These steps are subjective and potential sources of error leading to uncertainty (Falge et al., 2002). In spite of its limitations, the EC method has the potential to accurately measure light use efficiency across semi-arid ecosystems as the network of EC towers increase globally. A possible source of error leading to overestimation of GPP_{pre} is the use of 8-day surface reflectance (M0D09A1) which has no BRDF correction or normalization, resulting in the
derived spectral indices being affected by angular geometry and extreme look angles (Li et al., 2007).

Finally, GPP measurements might be higher than expected in arid and semi-arid regions owing to an increase in irrigated agriculture even though evapotranspiration exceeds precipitation (Mu et al., 2007a) which is ~150 mm annually (Kang et al., 2007). This is especially true in along the desert margin in Inner Mongolia where the typical steppe gives way to desert steppe, e.g. the Hetao irrigation district, along the Yellow River (John et al., 2009). Higher than expected evapotranspiration measurements in the desert steppe can also be attributed to subsurface flow and water infiltration within the Huang He basin (Feng et al., 2005; Wilske et al., 2009).

3.5. Conclusion

I used carbon flux data obtained from EC towers at five sites in semi-arid Inner Mongolia, to validate the intrannual dynamics of GPP using the VPM and MVPM models in conjunction with microclimatic variables such as PAR and air temperature. While VPM needs just four parameters obtained from flux towers for each of the five ecosystem/land cover/land use types, the MVPM is independent of any ground measured meteorological data. Both models are based on simple equations that are not computationally intensive like most process-based models. MVPM in particular, offers a cost effective solution in predicting GPP at remote study sites that lack infrastructure to set up ground based sensors. Our results indicate a reasonable agreement between the observed $\text{GPP}_{\text{tower}}$ and predicted $\text{GPP}_{\text{VPM}}$ and $\text{GPP}_{\text{MVPM}}$ indicating the potential of these satellite driven models for scaling up of GPP in semi-arid ecosystems. However, different
sources of error, either from the flux tower measurements or from MODIS derived indices/products, introduced uncertainties that lead to overestimation of GPP by VPM and MVPM. In addition, environmental factors such as precipitation and ground water flow as well as landscapes with a high degree of anthropogenic modification (e.g., croplands and irrigated poplar stands) play a role in a phase shift in predicted GPP as compared to GPP observed at EC towers. The ability to scale up in situ temporal measurements of carbon fluxes to the region are the first step to obtain a better understanding of the carbon cycle in semi-arid Inner Mongolia and might enable the estimation and scaling up of ET and water use efficiency in future studies.

Acknowledgements: This study was supported by the Natural Science Foundation of China (30928002), NASA-NEWS Program (NN-H-04-Z-YS-005-N), the Outstanding Overseas Scientists Team Project of CAS, and the State Key Basic Research Development Program of China (2007CB106800).
References


Table 3.1: Site location and characteristics of five flux towers in Inner Mongolia, China in 2006-2007

<table>
<thead>
<tr>
<th>Site</th>
<th>Vegetation</th>
<th>Location (decimal degrees)</th>
<th>Altitude (m)</th>
<th>Mean annual rainfall (mm)</th>
<th>Mean annual temperature (°C)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Latitude</td>
<td>longitude</td>
<td></td>
<td>2006</td>
</tr>
<tr>
<td>D01</td>
<td>Duolun steppe</td>
<td>42.046667</td>
<td>116.283610</td>
<td>1350</td>
<td>423</td>
</tr>
<tr>
<td>D02</td>
<td>Duolun cropland</td>
<td>42.045556</td>
<td>116.279722</td>
<td>1350</td>
<td>410</td>
</tr>
<tr>
<td>X03</td>
<td>Xilinhaote steppe</td>
<td>43.554444</td>
<td>116.671389</td>
<td>1250</td>
<td>152.9</td>
</tr>
<tr>
<td>K04</td>
<td>K Abuqi poplar stand</td>
<td>40.563333</td>
<td>108.745000</td>
<td>1020</td>
<td>227</td>
</tr>
<tr>
<td>K05</td>
<td>K Abuqi shrubland</td>
<td>40.451667</td>
<td>108.625000</td>
<td>1160</td>
<td>202.7</td>
</tr>
</tbody>
</table>
Table 3.2: Observed GPPTower as compared with predicted GPPVPM and GPPMVPM (gC m\(^{-2}\) d\(^{-1}\)) in five semiarid land cover/use types.

<table>
<thead>
<tr>
<th>Site</th>
<th>Flux tower</th>
<th>VPM Model</th>
<th>MVPM</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>GPP(_{\text{obs}}) (1-12)</td>
<td>GPP(_{\text{obs}}) (5-10)</td>
<td>GPP(_{\text{pre}}) (1-12)</td>
</tr>
<tr>
<td></td>
<td>40.00 24.00</td>
<td>33.20 21.41</td>
<td>69.42 29.43</td>
</tr>
<tr>
<td>D02</td>
<td>77.00 27.65</td>
<td>69.02 22.59</td>
<td>72.96 49.00</td>
</tr>
<tr>
<td>X03</td>
<td>49.62 50.14</td>
<td>42.18 43.67</td>
<td>59.36 70.20</td>
</tr>
<tr>
<td>K04</td>
<td>45.44 39.12</td>
<td>40.61 30.30</td>
<td>74.13 28.51</td>
</tr>
<tr>
<td>K05</td>
<td>30.24 25.40</td>
<td>21.43 21.50</td>
<td>86.28 19.31</td>
</tr>
</tbody>
</table>

Note: GPP\(_{\text{obs}}\) (1-12) and GPP\(_{\text{pre}}\) (1-12) are the observed and predicted annual integrated GPP. GPP\(_{\text{obs}}\) (5-10) and GPP\(_{\text{pre}}\) (5-10) are the observed and predicted integrated GPP within the active growing season.
Table 3.2: Comparison of Model $R^2$ from linear regression of observed GPP$_{tower}$ and predicted GPP$_{VPM}$ in five semiarid land cover/use types.

<table>
<thead>
<tr>
<th>Site</th>
<th>MODIS GPP $R^2$</th>
<th>VPM GPP $R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2006</td>
<td>2007</td>
</tr>
<tr>
<td>D01</td>
<td>0.44</td>
<td>0.61</td>
</tr>
<tr>
<td>D02</td>
<td>0.55</td>
<td>0.67</td>
</tr>
<tr>
<td>X03</td>
<td>0.82</td>
<td>0.79</td>
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<tr>
<td>K04</td>
<td>0.40</td>
<td>0.55</td>
</tr>
<tr>
<td>K05</td>
<td>0.41</td>
<td>0.63</td>
</tr>
</tbody>
</table>

* $p < 0.01$
Table 3.3: Comparison of Model $R^2$ from linear regression of GPP_{MVPM} in five semiarid land cover/use types.

<table>
<thead>
<tr>
<th>Site</th>
<th>year</th>
<th>slope</th>
<th>significance</th>
<th>SE</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>D01</td>
<td>2006*</td>
<td>0.049</td>
<td>0.642</td>
<td>0.105</td>
<td>.008*</td>
</tr>
<tr>
<td></td>
<td>2007</td>
<td>0.177</td>
<td>0.000</td>
<td>0.033</td>
<td>.527</td>
</tr>
<tr>
<td>D02</td>
<td>2006</td>
<td>0.582</td>
<td>0.014</td>
<td>0.222</td>
<td>.203</td>
</tr>
<tr>
<td></td>
<td>2007</td>
<td>0.241</td>
<td>0.000</td>
<td>0.035</td>
<td>.630</td>
</tr>
<tr>
<td>X03</td>
<td>2006</td>
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<td>0.000</td>
<td>0.540</td>
<td>.844</td>
</tr>
<tr>
<td></td>
<td>2007</td>
<td>0.437</td>
<td>0.000</td>
<td>0.056</td>
<td>.702</td>
</tr>
<tr>
<td>K04</td>
<td>2006</td>
<td>1.117</td>
<td>0.000</td>
<td>0.197</td>
<td>.553</td>
</tr>
<tr>
<td></td>
<td>2007</td>
<td>0.410</td>
<td>0.000</td>
<td>0.085</td>
<td>.471</td>
</tr>
<tr>
<td>K05</td>
<td>2006</td>
<td>0.200</td>
<td>0.013</td>
<td>0.076</td>
<td>.207</td>
</tr>
<tr>
<td></td>
<td>2007</td>
<td>0.218</td>
<td>0.000</td>
<td>0.050</td>
<td>.415</td>
</tr>
</tbody>
</table>

* missing data for June-July 2006 (summer/peak season)
Figure 3-1: Land Cover/Land use map of Inner Mongolia, P.R.C, overlaid with terrestrial ecoregion biome boundaries, Desert (D), Grassland (G), Forest (F), and flux towers sites in Duolun (D01 & D02), Xilinhaote (X03), and Kubuqi (K04 & K05).
Figure 3-2: Seasonal changes in tower PAR and Ta in: a) Duolun steppe, b) Duolun cropland, c) Xilinhaote steppe, d) Kubuqi poplar plantation, and e) Kubuqi shrubland
Figure 3-3: Seasonal changes in observed GPP\textsubscript{tower} and MODIS derived NDVI & EVI in: a) Duolun steppe, b) Duolun cropland, c) Xilinhaote steppe, d) Kubuqi poplar plantation, and e) Kubuqi shrubland.
Figure 3-4: A comparison of the seasonal changes in observed GPP$_{\text{tower}}$ with predicted GPP$_{\text{VPM}}$ and GPP$_{\text{MODIS}}$ at 5 flux sites in 2006: a) Duolun steppe, b) Duolun cropland, c) Xilinhaote steppe, d) Kubuqi poplar plantation, and e) Kubuqi shrubland. The Duolun steppe tower has missing data in June and July.
Figure 3-5: Linear regression of observed $\text{GPP}_{\text{tower}}$ with predicted $\text{GPP}_{\text{VPM}}$ and $\text{GPP}_{\text{MODIS}}$ at 5 flux sites in 2006: a) Duolun steppe, b) Duolun cropland, c) Xilinhaote steppe, d) Kubuqi poplar plantation, and e) Kubuqi shrubland. The solid line shows regression analysis between $\text{GPP}_{\text{tower}}$ and $\text{GPP}_{\text{VPM}}$ while the dashed line is the regression between $\text{GPP}_{\text{tower}}$ and $\text{GPP}_{\text{MODIS}}$ product.
Figure 3-6: Seasonal changes in observed GPP\textsubscript{tower} with predicted GPP\textsubscript{VPM} and GPP\textsubscript{MODIS} at 5 flux sites in 2007: a) Duolun steppe, b) Duolun cropland, c) Xilinhaote steppe, d) Kubuqi poplar plantation, and e) Kubuqi shrubland.
Figure 3-7: Linear regression of observed GPP\textsubscript{tower} with predicted GPP\textsubscript{VPM} and GPP\textsubscript{MODIS} at 5 flux sites in 2007: a) Duolun steppe, b) Duolun cropland, c) Xilinhaote steppe, d) Kubuqi poplar plantation, and e) Kubuqi shrubland. The solid line shows regression analysis between GPP\textsubscript{tower} and GPP\textsubscript{VPM} while the dashed line is the regression between GPP\textsubscript{tower} and GPP\textsubscript{MODIS} product.
Figure 3-8: A comparison of the seasonal changes in observed GPP\textsubscript{tower} with predicted GPP\textsubscript{VPM} and GPP\textsubscript{MVPM} at 5 flux sites in 2006 and 2007: a) Duolun steppe, b) Duolun cropland, c) Xilinhaote steppe, d) Kubuqi poplar plantation, and e) Kubuqi shrubland.
4. Predicting plant diversity based on remote sensing products in the semi-arid region of Inner Mongolia


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\textsubscript{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.

**Keywords:** Plant species richness, MODIS, semi-arid regions, GPP, LSWI, EVI, NDSVI, Inner Mongolia, China

### 4.1. 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 has 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 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) have 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. 4-1). 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 trends (~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 socioeconomic 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, Cheng et al. 2007; Zhang, 1994). These degraded arid and semi-arid 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 evapotranspiration (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.,...
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 et al., 1989-1998).

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.

4.2. Methods

4.2.1. Study Area

Inner Mongolia lies between 37°01'-3°02'N, 95°02'-123°37' E and is the third largest province in China (Fig. 4-1) with elevation 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. 4-1). 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 & Badain Jarian desert in the west, which cover 40.03% of the province (Table 4.2). 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 km², 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*, *Leymus 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 150-200 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., 2001a). Cropland and forest plantations occur along the riversides, but as isolated patches across the sandy steppe matrix (Zhang, 1994).

4.2.2. *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 et al., 1989-1998). 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 et al., 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 4.1.

4.2.3. 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, 1997 & 2002). The MODIS 16 day EVI is calculated as:
by the MODIS Data Processing System, or MODAPS at the NASA Goddard Space Flight Center, where, $\rho_{\text{NIR}}, \rho_{\text{Red}},$ and $\rho_{\text{Blue}}$ 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

$$EVI = G \cdot \frac{\rho_{\text{NIR}} - \rho_{\text{RED}}}{\rho_{\text{NIR}} - c_1 \cdot \rho_{\text{RED}} - c_2 \cdot \rho_{\text{BLUE}} + L} \quad [1]$$
obtained by calculating the annual maximum, mean and minimum EVI and then adding the annual mean to the minimum (Waring et al., 2006).

4.2.3.1 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 (GPPSD) and EVI (EVI 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 (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).

4.2.3.2 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 decrease 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 infra-red 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):

$$LSWI = \frac{(\rho_{\text{nir}} - \rho_{\text{swir}})}{\rho_{\text{nir}} + \rho_{\text{swir}}}$$  \[2\]

where $\rho_{\text{swir}}$ and $\rho_{\text{nir}}$ are atmospherically corrected surface reflectance in the infrared (841-876 nm) and 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
\[
\text{NDSVI} = \frac{(\rho_{\text{swir}} - \rho_{\text{red}})}{(\rho_{\text{swir}} + \rho_{\text{red}})} \tag{3}
\]

where \( \rho_{\text{swir}} \) and \( \rho_{\text{red}} \) 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 interannual variation (Table 4.2).

4.2.4. 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 4.2). The species richness was further studied as a function of life forms (Table 4.3). 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. 4-1) obtained from the World Wildlife Funds (WWF) terrestrial ecoregions 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.

4.3. 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 km², while the desert and grassland biome have 2.51 and 3.94 species for the same unit area, respectively (Table 4.2). 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 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 species increased (Fig. 4-2). 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 4.2). 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, EVImid 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 GPPSD and LSWI_{max} (Fig. 4-4a), 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. 4-5a; $R^2 = 0.28$, $p<0.001$) between species richness and GPP_{SD} (Table 4.3). The spatial CAR regression model fit for all counties returned the same results (Table 4.3).

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. 4-4b) 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. 4-4c) 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. 4-4d) 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. 4-4e, 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. 4-5b) 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. 4-5c) 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. 4-5d). The model for species richness of trees and
annual herbs did not improve (Table 4.3) 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 4.3).

Our predictions were further improved (Table 4.4) by stratifying the species richness by biome (Fig. 4-1). In the desert biome, species richness count was explained by a negative relationship (Fig. 4-6a) with $\text{LSWI}_{\text{avg}}$, and positive linear relationship with $GPP_{\text{max}}$ ($R^2 = 0.61$, $p<0.001$). The variation in species richness by life form in the desert biome was best explained by a negative relationship (Fig. 4-6b) with seasonal midpoint in shrub species and a positive relationship (Fig. 4-6d) with $\text{NDSVI}_{\text{max}}$ 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 $\text{EVI}_{\text{SD}}$ and $\text{EVI}_{\text{max}}$ (Fig. 4-6c). The spatial CAR model fit for the desert and grassland biome showed minimal change for all species as well as different life forms (Table 4.4).

In the grassland biome (Fig. 4-7a), species richness was explained by a positive linear relationship with $GPP_{\text{SD}}$ and negative relationship with $GPP_{\text{avg}}$ (Fig. 4-7a; $R^2 = 0.30$, $p<0.01$). When species richness was studied by life form, perennial herb species showed a positive relationship with $GPP_{\text{SD}}$ and negative relationship with $GPP_{\text{avg}}$ (Fig. 4-7c; $R^2 = 0.34$, $p<0.001$). The annual herb species richness showed a positive linear relationship, with $GPP_{\text{SD}}$ (Fig. 4-7d; $R^2 = 0.20$, $p<0.01$), while bulb species richness was explained by a positive linear relationship with $GPP_{\text{SD}}$ and a negative relationship with $\text{EVI}_{\text{mid}}$ (Fig. 4-7b; $R^2 = 0.40$, $p<0.01$). The species richness of shrubs was positively correlated with $GPP_{\text{SD}}$ ($R^2 = 0.27$ respectively, $p<0.01$, Fig. 4-7e). In the forest biome,
variation in species richness was explained by a positive linear relationship (Table 4.4) with NDSVI_{max} \left( R^2 = 0.26, p<0.01 \right). Species richness of trees and perennial herbs showed positive linear relationships with NDSVI_{max} \left( R^2 = 0.28 \text{ and } 0.31, \text{ respectively, } p<0.01 \right).

4.4. 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 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 -0.091 and -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 gm C m$^{-2}$ respectively, with annual maximum estimates being 8 and 19 gm 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 15-20, August 2004 in Duolun County, Inner Mongolia. The estimates of GPP ranged between 10-70 gm 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. 4-3). 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. 4-2), which decreases as one moves from the desert biome to the grassland and forest biomes.

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 4.2). 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. 4-3, Table 4.2). 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 (Table 4.2, 4.3) 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 4.4), but shrubs, trees, corms, and annuals differed in the moisture sensitivity (Fig. 4-6). In Inner Mongolia, xerophytic grass, herb and shrub species dominate and are characteristic of successional stages of desertified communities (Cheng et al. 2001a, Kang et al., 2007). Though species richness of shrubs (Fig. 4-2b) counts only 6.80% of all species (Table 4.2), the desert biome was dominated by open shrubland cover type (Fig. 4.1). 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. 4-6b,e, f). This can be attributed to local hydrological and landform influences such as river systems (e.g., Huang he near Baotou, Fig. 4-1) and oasis (e.g., the Ejina oasis). The bulb species were constrained by water availability (Fig. 4-6d) 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 (GPPSD and EVISD; Table 4.4, Fig. 4-3). This implies moisture limitation on SR, and corroborates with earlier studies that have suggested that interannual 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 in University of Inner Mongolia (Ma et al., 1989-1998). 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. 4-2). 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 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.

4.5. Conclusions

Based on the most comprehensive, regional species database and remote sensing products, we conclude that GPP_d 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

This study was conducted as part of the Northern Eurasia Earth Science Program (NEESPI) and supported by the National Aeronautics and Space Administration (NASA) Grant (NEWS 2004 NRA: NN-H-04-Z-YS-005-N) as part of the Energy and Water cycle
Study. Partial support was received from the Institute of Botany, Chinese Academy of Sciences (IBCAS) and the US-China Carbon Consortium (USCCC).
References


Table 4.1. List of variables and abbreviations used in this study.

<table>
<thead>
<tr>
<th>Full Name</th>
<th>Abbreviations</th>
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<tbody>
<tr>
<td>Enhanced Vegetation Index (0-1)</td>
<td>EVI</td>
</tr>
<tr>
<td>Seasonal Midpoint (0-1)</td>
<td>EVImid</td>
</tr>
<tr>
<td>Gross Primary Production (Kg C m^{-2})</td>
<td>GPP</td>
</tr>
<tr>
<td>Land Surface Water Index (-1 to 1)</td>
<td>LSWI</td>
</tr>
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<td>Normalized Difference Senescent Vegetation Index (0-1)</td>
<td>NDSVI</td>
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Table 4.2. Statistical summaries of MODIS derived metrics (independent variables) and species richness by life form (dependent variables).

*Perennial Herbs

<table>
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<tr>
<th>Region (N=88)</th>
<th>Independent variables</th>
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<tr>
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Of the total (%)

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<td>Of the total (%)</td>
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<td>Of the total (%)</td>
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<table>
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<td>Of the total (%)</td>
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Table 4.3. 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.

*p < 0.05, ** p < 0.01, *** p < 0.001, *SE standard error of spatial conditional autoregressive (CAR) model

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<tr>
<th>Inner Mongolia</th>
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<td>GPP$_{SD}$</td>
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<td>46</td>
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</table>
Table 4.4. Statistical evaluation of different biophysical indicators and their metrics to predict species richness by biome in Inner Mongolia.

*p < 0.05, ** p < 0.01, *** p < 0.001, *SE standard error of spatial conditional auto regressive (CAR) model

<table>
<thead>
<tr>
<th>Biome</th>
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<tbody>
<tr>
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<td>Shrubs</td>
</tr>
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<td>NDSVI$_{\max}$</td>
</tr>
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<td>(N=28)</td>
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<td>LSWI$_{\max}$</td>
<td>LSWI$_{\max}$</td>
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<td>EVI$_{\max}$</td>
<td>EVI$_{\max}$</td>
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<td>GPP$_{SD}$</td>
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Figure 4-1: 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 1km (MOD12Q1) IGBP classification, overlaid with biomes derived from WWF terrestrial eco-region boundaries (http://www.worldwildlife.org/science/data/terreco.cfm).
Figure 4-2: 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 et al., 1989-1998).
Figure 4-3: 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.
Figure 4-4: 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.
Figure 4-5: Species richness as a function of MODIS-based productivity (GPP\textsubscript{SD}, EVI\textsubscript{mid} and EVI\textsubscript{SD}) and surface water content (LSWI\textsubscript{SD} & LSWI\textsubscript{max}) metrics excluding counties with >50% land under agricultural use (a), and for functional groups, 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.
Figure 4-6: Species richness as a function of MODIS-based productivity (GPP$_{\text{max}}$, EVI$_{\text{mid}}$, EVI$_{\text{max}}$ and EVI$_{\text{SD}}$) and surface water content (LSWI$_{\text{avg}}$, LSWI$_{\text{max}}$, NDSVI$_{\text{max}}$ and NDSVI$_{\text{SD}}$) 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.
Figure 4-7: Species richness as a function of MODIS-based productivity (GPP_{SD}, GPP_{mean}, EVI_{mid}, and EVI_{SD}) and surface water content (NDSV{I_{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, & e) shrubs. The driving factors were identified with a stepwise linear regression, with α<0.05 entry requirement.
Chapter 5

5. Conclusion

5.1. Lessons learnt from this study

This study was conducted as part of a NASA-funded project which sought to understand the influence of climate and land cover/use change on water and energy balance in semi-arid Inner Mongolia. This study focused on the monitoring of land cover change at the regional level through the use of a wide range of MODIS derived remote sensing products in conjunction with meteorological and carbon exchange data obtained from a flux tower network. Firstly, the study quantified the land cover/use change at the regional and biome levels in context of landscape fragmentation and its consequences. Secondly, flux data was used to validate intra-annual dynamics of satellite derived GPP in different ecosystem types using existing and new GPP models. Finally, predictive models of plant species diversity were developed specifically for semi-arid grasslands which use improved vegetation and water indices. Overall, the study supported the conclusion that land cover/use change in semi arid Mongolia could be successfully monitored through the synergistic use of flux tower networks, ground truth measurements and synoptic, wide field remote sensing products such as MODIS.

Some of the major lessons learnt from the study were:
1. The intrannual dynamics of satellite derived GPP using the VPM and MVPM models were validated by flux towers at different land cover/use site types across semi-arid Inner Mongolia. While both models are not computationally intensive like most process-based models, MVPM offers a significant advantage over VPM in that it is independent of any ground measured meteorological data, while VPM needs PAR and air temperature. MVPM provides a cost effective method of predicting GPP, especially at remote study sites which lack the required infrastructure to set up EC flux towers. While there was reasonable agreement between the observed GPP\textsubscript{tower} and predicted GPP\textsubscript{VPM} and GPP\textsubscript{MVPM} indicating the potential of these models for modeling of GPP in semi-arid ecosystems, there were considerable uncertainty in the predictive ability of these models, especially at the Kebuqi shrubland and Duolun cropland sites in 2006. These uncertainties were attributed to different sources of error, from the flux tower measurements or from MODIS derived indices/products. It is also possible that environmental variability (e.g. precipitation and ground water flow) as well as anthropogenic modification (e.g., croplands and irrigated poplar stands) play a role in a phase shift in predicted GPP.

2. A landscape metrics analysis at the regional and biome scales describes semi-arid Inner Mongolia as fragmented landscape with an increase in the number of patches in the dominant land cover types such as grassland, shrubland, and barren. In addition, the increase in portions of dominant grassland and barren cover within the decade suggests that the landscape is becoming more homogenous and water stressed and is corroborated by a decrease in proportions of rare cover types. The increasing socio-economic growth
and a growing population base is described by increasing cohesion and aggregation of urban/built-up patches as well as an increase in the number of patches and interspersion of cropland cover in this fragile semi-arid region.

3. While developing predictive models of plant diversity, GPPSD and water content indices were the two most important variables for predicting species richness in Inner Mongolia, even though other MODIS-derived metrics were occasionally selected as significant independent variables. Initial models at the regional level, though significant, had low R² values. However, confidence levels were enhanced when models were based on biome and life form. The predictive power of the species richness models increased further when the counties with >50% croplands were excluded from the model. The meaningful relationships between the combinations of productivity (MODIS GPP, EVI) and vegetation water content (LSWI, NDSVI) and species diversity may have potential applications in other semiarid regions. Future research is needed to increase our knowledge of species attributes of in the region, and the roles they play in communities in order to improve the predictive power of models thus enabling the conservation of endangered species in the region.

5.2. Recommendation for future research

The GPP modeling and dynamics study is based on data collected in 2006-2007 in five sites. In addition to the carbon cycle, the measurement of ET at these flux towers will enable the estimation of water use efficiency in future studies. This study was based on ‘bottom-up’ temporal scaling at and around the ‘tower-pixel’ (i.e., the pixel in which the
EC flux tower is located). Future studies could employ the temporal tower pixel inputs as training data in data mining tools such as Rulequest’s Cubist/See5 to build rule based predictive models of satellite derived GPP. This would enable spatial scaling with wall to wall GPP maps.

In order to obtain a better understanding of the carbon cycle in semi-arid Inner Mongolia, there is a need to extend the flux network over a larger area and collect measurements for a longer time. Also, it would help greatly to study the Mongolian plateau of which semi-arid Inner Mongolia is a part. Though the Mongolian plateau has similar biogeographical attributes, Outer Mongolia (an independent republic) and Inner Mongolia (a province of P.R.C) have contrasting socio-economic and political systems. Since 1979, the regions have experienced divergence and socio-political changes with environmental changes taking place more rapidly in Inner Mongolia rather than Outer Mongolia. The Mongolian plateau will experience a warming trend above the global mean, longer and more intense summers, altered summer and winter precipitation and extreme precipitation events. In this context of climate change, it is important to note that the traditional nomadic and pastoral way of life is giving way to an increase in urban areas as people settle down owing to new economic growth and opportunities. The growing population base has lead to an increase in livestock resulting in overgrazing. These rapid changes will put stress on this already fragile ecosystem. It would be useful to forecast the effects of climate change on the Mongolian plateau using a regional climate mode such as the regional atmospheric modeling system (RAMS). The RAMS model would be parameterized with 50+ year climate data base from 50 stations in Inner Mongolia and others in Outer Mongolia. In addition, a suite of the latest (collection C5)
MODIS derived remote sensing products like Albedo, GPP, ET, will be used in the forecasting exercise.

Future research in the prediction of species richness using remote sensing should be made in context of functional groups. Species richness predictive models could be used to monitor the increasing spread of invasive shrubs with higher water use and toxic herbs and could be used to assist conservation efforts by identifying biodiversity hot spots that are not currently protected. The relationship between plant species richness and remote sensing products (including primary productivity) derived from new satellites such as the follow on to MODIS; the NPOESS Preparatory Project (NPP) can be explored to improve confidence in the predictive models. The availability of new sensors that operate at different resolutions will give the researcher flexibility to match the scale of the imagery with that of the species richness data collected on ground.

A worthwhile study would be to investigate changes in inter-annual trends of MODIS-derived biophysical variables across semiarid ecosystems of Inner Mongolia. Studies suggest a per capita increase in cropland cover in Northern China, including IM as a result of a growing economy with a subsequent increase in urban area and population growth. However, some cropland regions such as the Hetao irrigation basin are under severe water stress with depleting groundwater levels leading to leaching of fertilizers, leading to increased soil salinity and are attributed to increased irrigation demands of a growing population. The increase in irrigated croplands in the context of climate change is not sustainable. Wheat is the primary crop in Northern China and the 4th assessment of the IPCC have found that wheat crop in the mid latitudes was sensitive to changes in mean temperature change. Studies in IM have found that the combined
effects of 450 μmol mol⁻¹ CO₂ and 1.8°C temperature increase would result in 5.7% decrease in wheat yield. The study also suggests that supplementary irrigation must be provided, to make up for the loss in yield.

The objectives of this study would be to explain the interannual trends of MODIS derived biophysical land surface indicators in Inner Mongolia in the past decade as a function of climatic variables like temperature metrics and vapor pressure deficit (VPD), and to test for significant differences between irrigation intensive cropland counties and grassland dominated native steppe counties with conservative water use. I expect that interannual trends of biophysical indicators of productivity and water content in cropland counties would be significantly different from the native steppe. My research question is: What are the climate drivers that best explain interannual biophysical trends in semiarid Inner Mongolia?

Instead of using the traditional land surface biophysical indicator, NDVI, I intend to use MODIS derived GPP and EVI to account for productivity trends, while NDSVI, LSWI, and NTSG ET are used to account for as water stress & content. This study seeks to explain interannual changes in biophysical indicators, in cropland and native steppe dominated and examines the potential ramifications of their dynamics on ecosystems as well as land use.
References


terrestrial ecosystems by integrating eddy covariance flux measurements and satellite observations. *Agricultural and Forest Meteorology*, 151, 60–69.


