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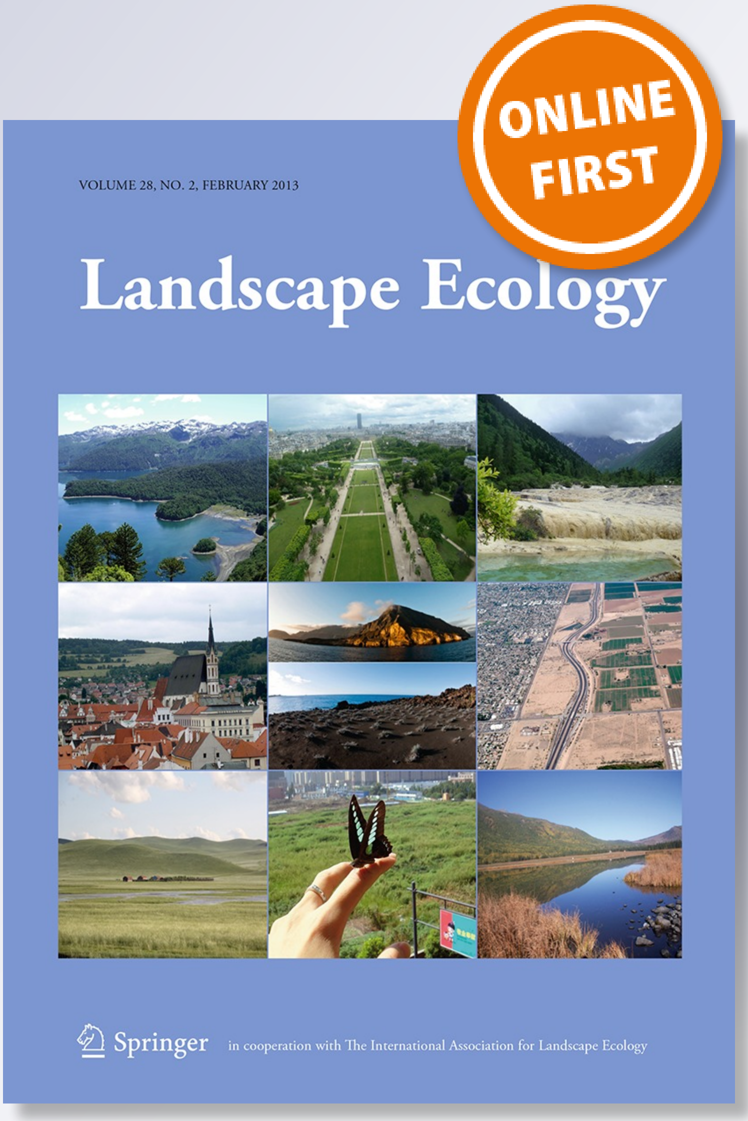
Landscape Ecology

ISSN 0921-2973

Landscape Ecol
DOI 10.1007/s10980-013-9865-1



Springer

Landscape Ecol
DOI 10.1007/s10980-013-9865-1

RESEARCH ARTICLE

Drivers of the dynamics in net primary productivity across ecological zones on the Mongolian Plateau

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Received: 28 September 2012 / Accepted: 27 February 2013

Abstract Understanding the drivers and mechanisms of the dynamics in grassland productivity is prerequisite for studying effective resource institutions and policies that can be used to govern grassland resources sustainably. We present a diagnostic analysis of the major drivers of the dynamics in grassland net primary productivity (NPP) across ecological zones on the Mongolian Plateau. We estimated a spatial panel data model for NPP (1986–2009) as a function of climatic and socioeconomic variables. Static and dynamic spatial panel models were estimated in each of the sub-regions, which were classified based on rural livelihoods and ecological models of grassland dynamics, to identify the major drivers of NPP dynamics. The statistical modeling results indicated that the major drivers of NPP dynamics vary across the six sub-regions. Grain output was the major predictor of NPP dynamics in the farming and farming-grazing zones of Inner Mongolia. Precipitation and livestock populations both had significantly positive relationships with NPP in the two grazing zones of Inner Mongolia. However, in Mongolia, livestock populations was the only significant predictor of NPP in the grazing zone with relatively stable climate, and precipitation was the only significant predictor of NPP in the grazing zone with highly variable climate. Human land-use activities and livestock management behaviors and the bidirectional causal relationships between livestock populations and NPP could explain the positive relationships between livestock population and grassland NPP. The heterogeneous drivers of NPP dynamics across space indicated the necessity of diverse resource polices and institutions for sustainable governance of grassland resources.

Keywords Grassland ecosystem · Net primary productivity · Drivers · Spatial panel data models · Ecological zones · Mongolian Plateau

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Introduction

Grassland degradation on the Mongolian Plateau, including the country of Mongolia and the Inner Mongolia Autonomous Region (IMAR), China, has undermined ecosystem functions, including carbon sequestration (Lu et al. 2009), and endangered the livelihoods of local herders (Li et al. 2007; Wang et al. 2012) since the early 1960s, especially following the political-economic transitions in IMAR and Mongolia in the mid-1980s and the early 1990s, respectively. Empirical studies have shown that grassland degradation

Published online: 12 March 2013

has increased the cost of livestock grazing, and poverty has become prevalent in the grazing communities of Mongolia and IMAR, China (Zhang 2007; Olonbayar 2010). Understanding the drivers and mechanisms of grassland productivity dynamics over the past decades on the Mongolian Plateau is prerequisite for developing effective resource policies and institutions that can govern grassland resources sustainably. Previous studies have identified that climate change, increasing populations of humans and livestock, inefficient resource institutions, distorted market incentives, and reclamation of grasslands for grain production are the major causes for grassland degradation on the Mongolian Plateau (Fernandez-Gimenez 1997; Sneath 1998; Neupert 1999; Wang et al. 2012). However, most of these studies just focused on one or several of these drivers at regional scales, and a systematic analysis of the major drivers across heterogeneous landscapes of the Mongolian grasslands is still missing.

Since the early 1960s, climate on the Mongolian Plateau has been getting warmer and drier (Wang et al. 2012). The number of droughts and winter snowstorms has increased apparently in Mongolia over the last 50 years, particularly in the last decade (NCRMSAP, Mongolia 2009). The increased climatic variability likely affects grassland productivity and leads to grassland degradation. Studies have also shown that in some areas of Mongolia where grazing is not allowed grassland productivity has declined by 20–30 % over the past 40 years (Angerer et al. 2008). IMAR and Mongolia have been transforming from centrally planned to market economies since the mid-1980s and the early 1990s, respectively. Grasslands in IMAR have been allocated to individuals through contracts and fenced. Nomadic herding has been replaced by farming and livestock grazing activities. As a result, seasonal and interannual migrations have become less feasible. In Mongolia, due to lack of effective resource institutions, conflicts among herders over grassland use have increased since the early 1990s (Upton 2009). Moreover, livestock privatization and market factors have given herders strong incentive to keep more animals and therefore stimulated the growth of livestock populations. For example, based on annual census data, from 1985 to 2009, livestock populations in IMAR increased from around 40 to 100 million; from 1990 to 1998, livestock populations in Mongolian increased from 26 to 33 million (ACBIMAR 2008; ACBM 2010). Livestock populations in Mongolia crashed in the 1999–2002 Dzud (heavy snowstorms), although they rebuilt by 2009 and then crashed (though less extremely) in the 2009–2010 Dzud. The rapid increase of livestock populations following economic transitions caused disastrous impacts on grassland quality. Livestock privatization and grazing sedentarization have been identified as the major reasons for the degradation of the Mongolian grasslands, especially in IMAR (Humphrey and Sneath 1999; Jiang et al. 2006; Li et al. 2007). Studies based on large-scale field samplings showed that from the early 1980s to 2010, the average grassland dry biomass productivity in IMAR and Mongolia decreased from 1069 to 900 kg/ha and from 610 to 369 kg/ha, respectively, (IMIGSD 2011; IOB, Mongolia 2011). However, the extent of grassland degradation in Mongolia is still controversial (Addison et al. 2012).

Our understandings of the dynamics in grassland productivity and sustainable governance of grassland resources rests on contributions from both ecologists and institutional economists. Grassland ecologists developed two conceptual explanations of the dynamics in grassland productivity, referred to as the equilibrium and non-equilibrium grassland models, although there are still some controversies about these models (Ellis and Swift 1988; Fernandez-Gimenez and Allen-Diaz 1999; Oba et al. 2000; Briske et al. 2003; Zemmrich et al. 2010; Wehrden et al. 2012). In grazing zones with relatively stable climate, vegetation can have stable seasonal growth rhythms across the years. Livestock grazing intensity has a direct impact on grassland quality, and over-grazing leads to the deterioration of grassland quality. However, in grazing zones with highly variable climate, climate has a more important effect on grassland quality than livestock grazing intensity (Ellis and Swift 1988; Oba et al. 2000). Predictions from the non-equilibrium ecosystem model have been tested in grassland areas of Mongolia and China and shown to better explain grassland productivity dynamics in the semi-arid and arid portions of the region (Fernandez-Gimenez and Allen-Diaz 1999; Ho 2001; Zhang 2007).

Institutional economists interested in studying sustainable governance of natural resources focus on analyzing the social-ecological performance of resource institutions. Three institutional solutions studied for solving common-pool natural resources problems include privatization, state-control, and community-based natural resource management (Hardin 1968;

Ostrom 1990, 2005, 2010; Agrawal 2001). In the semiarid and arid grasslands, cooperative use of grasslands, which makes seasonal and interannual migrations possible, can reduce uncertainties caused by the highly variable precipitation and grassland productivity and avoid pasture over-grazing in the years with droughts (Wilson and Thompson 1993; Agrawal 2001). Studies have shown that clear differences in levels of grassland degradation were achieved under mobile grazing in Mongolia versus forced grazing sedentarization in China and Russia (Sneath 1998; Humphrey and Sneath 1999).

The primary objective of this work is to identify the major drivers of the dynamics in grassland net primary productivity (NPP) across ecological zones and between IMAR and Mongolia after economic transitions in the two political regions. Statistical models have commonly been estimated to diagnose the major drivers of land-use and land-cover change (Seto and Kaufmann 2003; Brown et al. 2004), and we used static and dynamic spatial panel data models (Elhorst 2010a; Lee and Yu 2010) to evaluate the major drivers of dynamics in grassland productivity across ecological zones and two political regions of the Mongolian grasslands. To the best of our knowledge, this is the first introduction of using spatial panel data models for modeling land use/cover change. Satellite images provide a strong basis for measuring grassland productivity at a regional scale, as the dependent variable in the spatial panel data models. Time-series satellite images offer the opportunity for studying grassland productivity over time and space. Specifically, we estimated annual grassland NPP using a remote sensing based light-use efficiency (LUE) approach. The independent variables are the biophysical and/or socioeconomic factors that we hypothesized to drive the dynamics of grassland productivity, such as demographic and climatic variables. Because we are concerned with a large area, socioeconomic census data are virtually the only source of region-wide data on the socioeconomic factors, like livestock populations.

Most parts of the Mongolian grasslands locate in the semiarid and arid regions with high interannual variations of precipitation and grassland productivity. For thousands of years, pastoralists have adapted to the highly variable and vulnerable physical environment by migrating seasonally and inter-annually, and nomadism also preserved the grassland ecosystems. Over the past half century, a large amount of the Mongolian grasslands have been reclaimed for grain and fodder production, especially in IMAR, China. In addition, cropland productivity was also included in the analyses of grassland productivity dynamics because we were not able to mask cropland out of the study area. We hypothesized that the major drivers of the dynamics in grassland NPP vary across ecological zones and two political regions. Specifically, we hypothesized that: grain output is the major determinant of NPP dynamics in the farming and farming-grazing zones; livestock grazing intensity is the major driver of NPP dynamics in the grazing zone with relatively stable climate; precipitation is the major driver of NPP dynamics in the grazing zone with highly variable climate; and the major drivers of NPP dynamics vary between IMAR and Mongolia, given grazing systems in IMAR are likely also affected by external forces, e.g., market incentives and fodder import from farming areas.

To test these hypotheses, we first divided the Mongolian grasslands into several sub-regions, based on the livelihood sources of rural households and amounts and the interannual variability of precipitation, stated in the non-equilibrium grassland models (Ellis and Swift 1988). Then, we diagnosed the major drivers of NPP dynamics in each of these sub-regions by estimating spatial panel data models. Finally, we interpret the results in light of scholarship on efficient resource institutions and policies that can govern grassland resources sustainably in the context of the causal factors identified by statistical models. The reminder of this paper is organized as follows. In "Study area and data" section, we describe the study area and the datasets used. "Methods" section introduces the methodology for classifying the sub-regions of the Mongolian grasslands and the structures of the static and dynamic spatial panel data models used in this work. In "Results" section, we present the modeling results and interpretations. In "Discussion" section, we summarize the findings and discuss model limitations and policy and institutional implications.

Study area and data

Study area

The Mongolian Plateau is part of the larger central Asian Plateau and has an area of approximately 2.6 million km^2. It is occupied by Mongolia in the northwest and IMAR, China, in the southeast. The study area exhibits gradients of topography, climate, soil, and vegetation (Fig. 1). Climate on the Mongolian Plateau is continental with extremely cold winters and warm summers. The multi-year mean annual precipitation varies from less than 50 mm in the western desert to around 650 mm in the northeastern forests. Grasslands are the dominant ecosystem types, covering about 66 % (0.78 million km^2) and 84 % (1.26 million km^2) of the total territories in IMAR and Mongolia, respectively (Zhang 1992; Angerer et al. 2008). Over the past 50 years, some of the grasslands in IMAR and Mongolia have been reclaimed for grain and fodder production, especially in IMAR. During 1985–2005, 20.3 % (23.9 million hectares) of the total land in IMAR was reclaimed for grain production, fodder production, and other uses (IMIGSD 2008). Since the year 2000, the national government of China has implemented a range of policies for grassland restoration in IMAR, including cropland abandonment (Waldron et al. 2010). In Mongolia, 1.34 million hectares of grasslands were converted to cropland from the late 1950s to the early 1990s (Olonbayar 2010). The total area of cropland in Mongolia decreased 24.3 % from 1995 to 2009 (ACBM 2010). The decreasing trend was mainly driven by the abandonment of state-farms following the economic transition in Mongolia (Olonbayar 2010).

The time-series of annual NPP

Regional-scale annual NPP (1986–2009) was estimated using a LUE approach based on remotely sensed data. Vegetation NPP (g C m^{-2} day^{-1}) represents the total amount of solar energy converted into dry plant matters through photosynthesis, and it is calculated as the total energy used in plant photosynthesis (referred to as gross primary productivity; GPP) subtracted by the energy used for plant respiration for maintenance and growth. In the LUE approach, GPP is assumed to be proportional to the amount of absorbed photosynthetically active radiation (APAR). APAR is the product of incident photosynthetically active radiation (PAR) and the reflectance properties expressed through a vegetation index (Running et al. 1999). Annual NPP is accumulated in the growing season of grasslands. In the Mongolian grasslands, the growing season is roughly from late April to September. Detailed descriptions about the NPP estimation and validation procedures for the annual grassland NPP time-series on the Mongolian Plateau are provided in Wang et al. (2013). The spatial resolution of the annual NPP time-series was 8 $\times$ 8 km.

Climatic and socioeconomic data

We compiled climate data from national standard meteorological stations in Mongolia (17 stations) and IMAR (47 stations) (CIMAR 2010; CM 2010). We spatially interpolated monthly total precipitation and monthly mean temperature (1986–2009) using universal Kriging. Previous studies using long-term field measurements of aboveground biomass have shown that grassland productivity in IMAR was sensitive to mean temperature and total precipitation between January and July (Bai et al. 2008). The climate variables accumulated between January and July were used as independent variables in the spatial panel data models. County-level annual livestock populations (the year-end value), grain output, and human populations of IMAR (1986–2007) and the province-level annual populations of people and livestock of Mongolia (1995–2009) were compiled from annual census books of IMAR and Mongolia (ACBIMAR 2008; ACBM 2010). Based on census data, cropland occupies only a very small portion (i.e., less than 0.5 %) of Mongolia (ACBM 2010). Therefore, data on grain output of Mongolia were not used here. In order to accommodate socioeconomic data, climate and NPP datasets were spatially aggregated to county and province levels in IMAR and Mongolia, respectively.

Methods

Mapping ecological zones of the Mongolian grasslands

Ecological conditions, including climate and vegetation, vary greatly across the Mongolian grasslands (Fig. 1). In order to identify the major drivers of the dynamics in grassland NPP over space, we assigned the counties and provinces of IMAR and Mongolia to different ecological zones based on information about sources of rural household income and precipitation criteria stated in the non-equilibrium grassland model (Ellis and Swift 1988). Based on census data (ACBIMAR 2008; ACBM 2010), if more than 80 % of agricultural income of rural households in a jurisdictional unit is from farming or grazing, we assigned the unit as farming or grazing zone, respectively. If farming and grazing income were equally important in

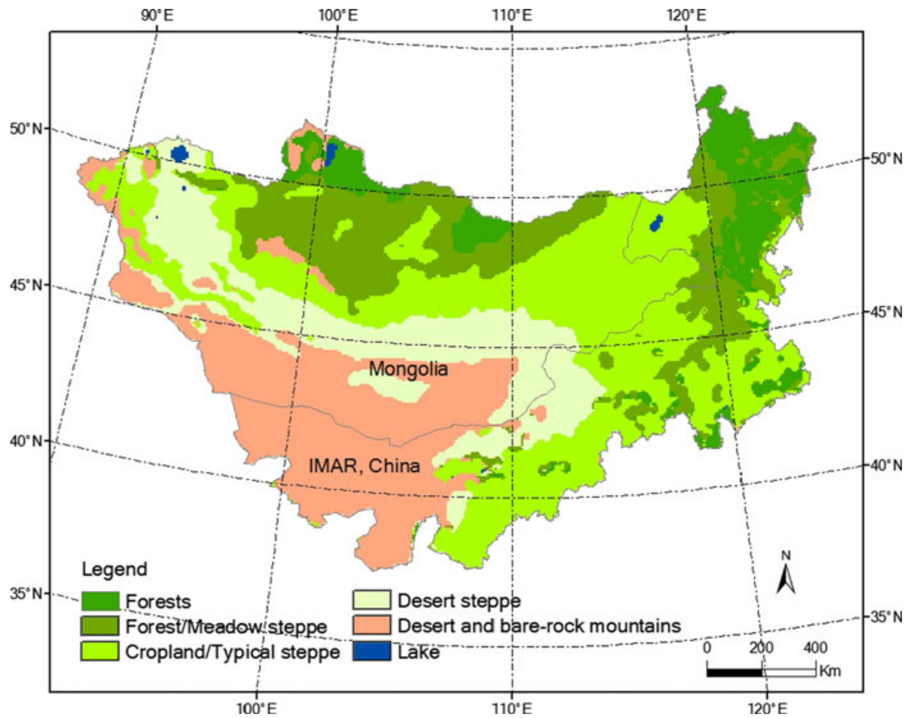


Fig. 1 Major land-cover types on the Mongolian Plateau from the vegetation maps produced by the Institute of Botany, China (1990s), and the Institute of Botany, Mongolia (1980s). The original scale of the two vegetation maps was 1:1,000,000

the total agricultural income, we assigned the unit into farming-grazing zone. The annual mean precipitation and the interannual variability of precipitation (1986–2009) were used to distinguish grazing zones with different climate conditions (Ellis and Swift 1988; Fernandez-Gimenez 1997). The grazing zone with relatively stable climate was defined as having a mean annual precipitation of more than 250 mm and the interannual variability of precipitation, represented by the coefficient of variation of annual precipitation, of less than 33 %. The grazing zone with highly variable climate was defined as having a mean annual precipitation of less than 250 mm and the coefficient of variation of annual precipitation of more than 33 %. The classified grazing zones, farming zone, and farming-grazing zone are shown in Fig. 2 and Table 1. Compared to the vegetation map (Fig. 1), we can find that most of meadow steppes of IMAR and Mongolia are in the grazing zones with relatively stable climate; and typical and desert steppes are mostly in the grazing zones with highly variable climate.

Modeling the drivers of NPP dynamics with spatial panel data models

We began with exploratory analysis of the correlations between annual NPP and explanatory variables across time in each county or province, and we assigned each correlation to one of the four types: significantly positive, positive but not significant, negative but not significant, and significantly negative. We defined significant correlation coefficients as those with $p < 0.05$, and we labeled them as significantly positive or negative based on their p values. We used the false discovery rate (FDR) control procedure to exclude the polygons that may be falsely labeled due to spatial autocorrelations of these variables (Benjamini and Hochber 1995). The threshold value of FDR was set equal to the p value. Next, we built regression models between the time-series of NPP and explanatory variables. A simple cross-sectional regression model that links NPP and socioeconomic and biophysical variables does not allow sufficient degrees of freedom to estimate statistically reliable models (Hsiao 1986; Frees 2004). To increase the reliability of modeling results, we used panel data analysis to take advantage of the increased variation and reduced collinearity in data that we collected at the smallest possible administrative unit over time. Panel data models can be used to relax the common assumptions in traditional cross-sectional or time-series data analyses that regression parameters are identical for all individuals or at all time points. Incorporating heterogeneity into panel data models is often motivated by the concern

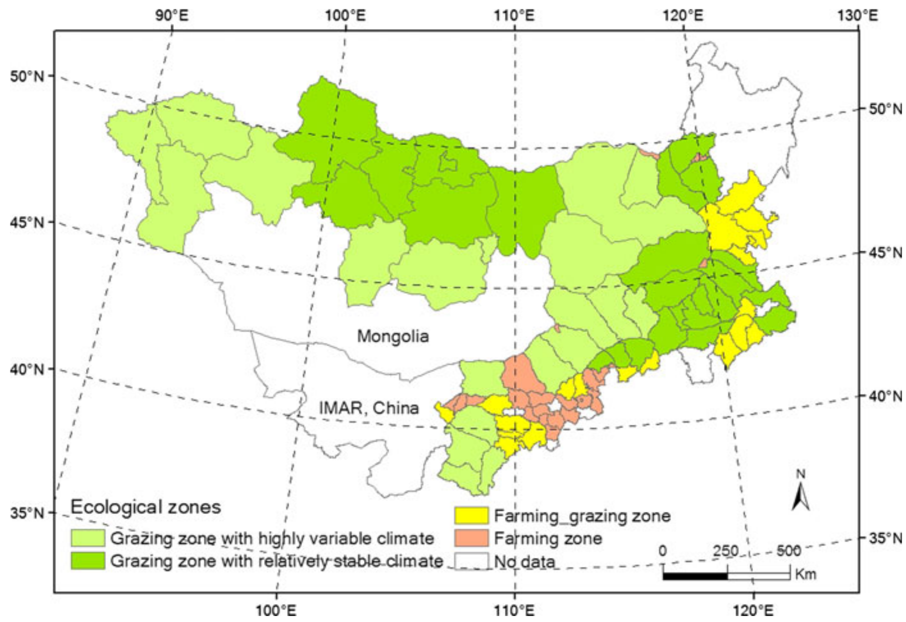


Fig. 2 Classified ecological zones in Mongolia and IMAR, China

Table 1 The number of counties and provinces and their areas in each ecological zone

Ecological zone	Number of counties/ provinces	Area (km^2)	
		Mean	Standard deviation
IMAR, China			
Farming zone	24	3,146	2,412
Farming-grazing zone	18	7,422	4,679
Grazing zone_H	18	14,052	7,558
Grazing zone_S	10	20,612	5,798
Mongolia			
Grazing zone_H	8	50,633	36,501
Grazing zone_S	9	81,233	24,286

Grazing zone_H means the grazing zone with highly variable climate; and grazing zone_S means the grazing zone with relatively stable climate

that important explanatory variables have been omitted from panel data models (Frees 2004). The obvious generalization of the constant-intercept-and-slope model for panel data is to introduce dummy variables to account for the effects of those omitted variables that are specific to individual cross-sectional units but stay constant over-time, and the effects that are specific to each time point but are the same for all cross-sectional units (Hsiao 1986; Elhorst 2003, 2010a). Panel data models can be assigned into four types in representing the heterogeneity among individual units: fixed effects, random effects, fixed coefficients, and random coefficients models (Elhorst 2010a).

Panel data models are promising options for modeling land use/cover change. They allow relationships between the independent variable (i.e., drivers of land use/cover change) and the dependent variable (i.e., measures of land use/cover) to vary across space and time (Seto and Kaufmann 2003; Brown et al. 2004). Because we only model NPP dynamics after economic transitions in Mongolian and IMAR, we assumed no time-specific effects and focused only on individual (i.e., spatial location) specific effects. The spatial panel data models, used in this work, have heterogeneous intercepts and homogeneous slope. Spatial specific effects may be treated as fixed effects or as random effects. In the fixed effects models, a dummy variable is introduced for each spatial unit; while in random effects models, the effects that are specific to spatial units are treated as a standard Gaussian random variable. When the random effect model is implemented, the units of observation should be representative of a large population, and the number of units should potentially be able to go to infinity (Elhorst 2010a). In this work, we have a limited number of observational units in Mongolia and IMAR. Therefore, we chose the spatial fixed effect models.

A simple panel data model with spatial fixed effects is (Frees 2004)

$$y_{it} = x_{it}\beta + \mu_i + \varepsilon_{it} \tag{1}$$

where y_{it} is the dependent variable value at measurement of unit i $(i = 1, 2, \ldots, N)$ and time point t $(t = 1, 2, \ldots, T)$; x_{it} is vectors of observations for m independent variables $([N \times T] \times m)$; β is a matching vector of fixed but unknown model parameters $(m \times [N \times T])$; ε_{it} is an independently and identically distributed error term with zero mean and variance of σ^2; μ_i denotes a spatial specific effect. The standard reasoning behind spatial specific effects is that they control for all space-specific and time-invariant variables whose omissions could bias the parameter estimates in a typical cross-sectional model (Elhorst 2010a). In the case of our modeling of grassland NPP dynamics, we may omit some space-specific variables that affect annual NPP dynamics, for example soil fertility. The random variables μ_i and ε_{it} are assumed as independent of each other. For many panel datasets, the number of units is large relative to the number of observations per unit, and these are useful to reveal the relationships among variables and to account for subject-level heterogeneity (Frees 2004).

Grassland annual NPP tends to have spatial and/or spatio-temporal autocorrelations. In order to account for the spatial and/or temporal interactions, we used both static and dynamic spatial panel data models to diagnose the drivers of NPP dynamics across ecological gradients and between IMAR and Mongolia. When the interactions between spatial units of observation are taken into consideration, the panel data model will contain a spatially lagged dependent variable or a spatial autoregressive process in the error term, known as the spatial lag model and the spatial error model, respectively (Elhorst 2010a). In this study, we chose spatial-lag models to account for the spatial autocorrelations of grassland annual NPP on the Mongolian Plateau. Grassland productivity in one study unit tended to be affected by the productivities of neighboring units. For example, if one study unit was surrounded by neighboring units with high productivities, this unit tended to have better ground water supply and be less affected by wind erosions. In addition, the spatial fixed effects included in the panel model could also account for the missing variables (e.g., soil types) which could explain the dynamics of grassland annual NPP. The spatial lag model posits that the dependent variable value is affected by the value of the dependent variable in neighboring units.

$$y_{it} = \delta \sum_{j=1}^{N} w_{ij} y_{jt} + x_{it}\beta + \mu_i + \varepsilon_{it} \tag{2}$$

where $i = 1, 2, \ldots, N$, $j = 1, 2, \ldots, N$, $t = 1, 2, \ldots, T$, δ is called the spatial autoregressive coefficient, representing the influence from neighboring units. w_{ij} is an element of the spatial weights matrix, and it describes the proximity of two observational units. It is assumed that the spatial weights matrix is a pre-specified non-negative matrix. We assumed a constant spatial weight matrix over time, based on the inverse distance method to calculate spatial weights between spatial units in the software package ArcGIS (ESRI, Redlands, CA, USA).

An important advantage of panel data is the opportunity to model the dynamic patterns in the data. Incorporating the correlation structure of the data over time is important for achieving efficient parameter estimates, especially for datasets with many observations over time Frees 2004; (Elhorst 2010a). If temporal autocorrelation of the dependent variable is taken into consideration, the spatial panel data model becomes a dynamic spatial panel data model.

$$\begin{aligned} y_{it} = {} & \delta \sum_{j=1}^{N} w_{ij} y_{jt} + \gamma y_{i,t-1} \\ & + \rho \sum_{j=1}^{N} w_{ij} y_{j,t-1} + x_{it}\beta + \mu_i + \varepsilon_{it} \end{aligned} \tag{3}$$

where $i = 1, 2, \ldots, N$, $j = 1, 2, \ldots, N$, $t = 2, 3, \ldots, T$. The parameters γ and ρ are measures of the relationship between $y_{i,t-1}$ and $y_{i,t}$, which are called the temporal and spatio-temporal autoregressive parameters, respectively. In this study, grassland annual NPP tended to be temporally auto-correlated. Grassland NPP in one specific year was affected by productivities in the previous years (e.g., livestock overgrazing tends to cause the degradation in grassland productivity). Therefore, in addition to static spatial panel data models, we also ran the dynamic spatial panel data models in this study.

Given space limitations, the parameter estimation procedures for static and dynamic spatial panel data models are not detailed here. Readers are referred to Elhorst (2010b), Yu et al. (2008), and Lee and Yu (2010) for detailed discussions about using the maximum likelihood method to estimate the parameters of the spatial panel data models. *T* test was used to analyze whether the estimated regression coefficients were significantly different from zero. We calculated the goodness of fit (pseudo-R^2) to measure the explanatory power of the spatial panel data models. In order to test the contribution of each of the independent variables to both static and dynamic spatial panel data models, we iteratively removed the independent variables and ran the spatial panel data models to calculate the values of pseudo-R^2. The static and dynamic spatial panel data models used in this study were coded by the authors in MATLAB (Mathworks Inc., Natick, Massachusetts, USA), based on the sample MATLAB codes provided in Elhorst (2010b) and Lee and Yu (2010). The biophysical and socioeconomic data used for fitting the static and dynamic spatial panel data models (Table 2) were normalized to 0–1.

Results

Correlations between NPP and explanatory variables

Temperature was positively correlated with NPP in most parts of Mongolia and IMAR, but most of the correlations were not statistically significant (Fig. 3a, e). The relationships between NPP and precipitation were only significant in two provinces of Mongolia (Fig. 3b); both of which are in the grazing zone with highly variable climate (Fig. 2). In most semiarid and arid counties of IMAR, precipitation was significantly correlated with annual NPP (Fig. 3f). In Mongolia, livestock populations were positively correlated with NPP in the grazing zone with relatively stable climate, although the correlation relationships were not statistically significant for most provinces. In Mongolia, the correlations between livestock populations and NPP were not significant for most provinces in the grazing zone with high variable climate (Fig. 3c). The correlations between NPP and human populations were not significant all provinces. The correlations were positive for most provinces of the grazing zone with highly variable climate and negative in most provinces of the grazing zone with relatively stable climate (Fig. 3d). Livestock populations were positively correlated with NPP in most of the grazing counties of IMAR (Fig. 3g). Annual grain output was significantly correlated with NPP in most of the farming and farming-grazing counties of IMAR (Fig. 3h). Human populations were significantly correlated with NPP in some of the farming counties of IMAR (Fig. 3i).

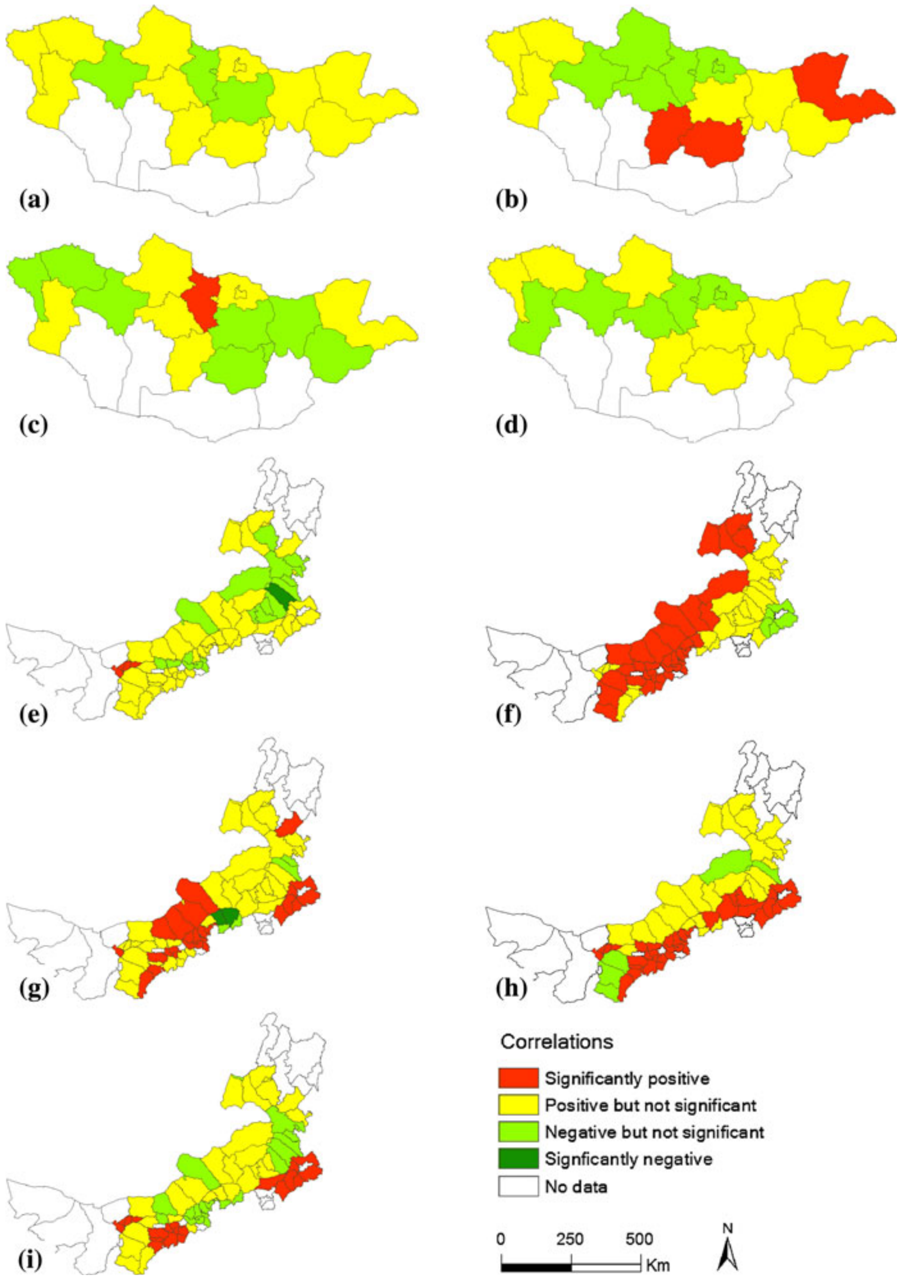
Drivers of NPP dynamics across ecological zones

In the farming and farming-grazing zones of IMAR, precipitation and grain output had significantly positive relationships with NPP, which was indicated by t-statistics of the regression coefficients at $p < 0.01$ (Table 3). In these two regions, grain production was the major human land-use activity, and grain output

Table 2 Variables for the static and dynamic spatial panel data models

Name	Description	Definition
NPP	Net primary productivity	Annual NPP accumulated in the growing season from late April to September
PRECIP	Precipitation	Total monthly precipitation from January to July
TEMP	Temperature	Mean monthly temperature from January to July
LIVE	Livestock populations	Year end livestock populations
GRAIN	Grain output	Annual grain output
POP	Human populations	Annual human populations
DELTA (δ)	Spatial autoregressive term	Spatially lagged dependent variable in Eqs. 2 and 3
RHO (ρ)	Spatio-temporal autoregressive term	Spatio-temporally lagged dependent variable in Eq. 3
GAMMA (γ)	Temporal autoregressive term	Temporally lagged dependent variable in Eq. 3

Fig. 3 Temporal correlations between NPP and explanatory variables in counties of IMAR (1986–2007) and provinces of Mongolia (1995–2009): **a** NPP—temperature in Mongolia; **b** NPP—precipitation in Mongolia; **c** NPP—livestock populations in Mongolia; **d** NPP—human populations in Mongolia; **e** NPP—temperature in IMAR; **f** NPP—precipitation in IMAR; **g** NPP—livestock populations in IMAR; **h** NPP—grain output in IMAR; **i** NPP—human populations in IMAR



played a dominant role in influencing NPP dynamics. In the two grazing zones of IMAR, precipitation and livestock populations had significantly positive relationships with NPP. In IMAR, precipitation played a dominant role in influencing NPP dynamics in the grazing zone with highly variable climate, and its influence relative to livestock populations declined in the grazing zone with relatively stable climate. In

Table 3 Static spatial panel data models for NPP dynamics using normalized variables

Variable	IMAR, China				Mongolia	
	Farming	Farming_grazing	Grazing zone_H	Grazing zone_S	Grazing zone_H	Grazing zone_S
PRECIP	0.1826***	0.0275**	0.2568***	0.1684***	0.0927**	−0.0304
TEMP	0.0054	−0.0264	−0.0157	−0.0909	−0.0149	0.0410
LIVE	0.0431	0.0084	0.1381**	0.1281**	−0.0353	0.1053**
GRAIN	0.2579***	0.0468**				
POP	0.1842*	0.0944	0.0962	0.4042*	0.0060	−0.3106
DELTA	0.1361**	0.6690***	0.1361**	0.1361**	0.3285***	0.5107***
Pseudo-R^2	0.8935	0.8709	0.8640	0.8082	0.8613	0.8894

Grazing zone_H means the grazing zone with highly variable climate; and grazing zone_S means the grazing zone with relatively stable climate

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

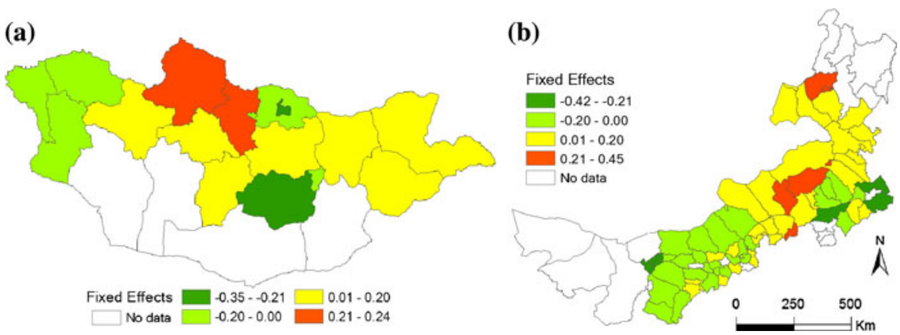


Fig. 4 Values of the spatial fixed effects for the static spatial panel data models of NPP dynamics: **a** Mongolia; **b** IMAR, China

Mongolia, precipitation was the only factor that had a significantly positive relationship with NPP in the grazing zone with highly variable climate. In this zone, livestock populations were negatively correlated with NPP, although the linear relationship was not significant. In Mongolia, livestock populations were the only factor that was significantly correlated with NPP in the grazing zone with relatively stable climate. This zone is mainly distributed in the northern mountainous regions with cold and wet climate (Fig. 2), and precipitation was less important in influencing NPP dynamics. For most of the sub-regions, human populations did not have a significant linear relationship with NPP. Temperature did not have significant linear relationships with NPP in any sub-region; and the observed relationships were negative for most sub-regions.

The relationships between NPP and explanatory variables identified by the spatial panel data model were consistent with results of the exploratory correlation analyses (Fig. 3). For all of the sub-regions, the spatially lagged NPP had significant linear relationships with NPP dynamics (Table 3). The values of the spatial fixed effects of the spatial panel data models for IMAR and Mongolia show clear spatial patterns (Fig. 4). This indicated that the spatial fixed effects in the models could account for some of the missing explanatory variables of NPP dynamics.

Adding the temporally lagged dependent variable and the spatio-temporally lagged dependent variable into the models did not change the relationships among the variables much. The relative importance of the causal factors in all of the sub-regions did not change in any of the models, although the temporally lagged dependent variable was significantly correlated with NPP in the farming-grazing zone and the grazing zone with relatively stable climate of IMAR (Table 4). This suggested that the models can provide the basis for constructing unbiased estimators when the dynamic aspects of the dependent variable are ignored.

Table 4 Dynamic spatial panel data models for NPP dynamics using normalized variables

Variable	IMAR, China				Mongolia	
	Farming	Farming_grazing	Grazing zone_H	Grazing zone_S	Grazing zone_H	Grazing zone_S
PRECIP	0.0963***	0.0294***	0.1302***	0.0873***	0.0925**	−0.0517
TEMP	−0.0244	−0.0324	−0.0153	−0.0367	−0.0142	0.0360
LIVE	0.0381	0.0070	0.0941**	0.0564*	−0.0370	0.1103**
GRAIN	0.1304***	0.0462**				
POP	0.0749*	0.0803	0.0780	0.1996*	0.0054	−0.2965
DELTA	0.1325***	0.6733***	0.1327***	0.1310***	0.3719***	0.5572***
RHO	0.0025	−0.1571	0.0182	−0.1991	−0.1355	−0.0744
GAMMA	0.0767	0.2077***	0.0231	0.1545*	0.1682	0.0913
Pseudo-R^2	0.9006	0.8825	0.8913	0.8104	0.8692	0.8996

Grazing zone_H means the grazing zone with highly variable climate; and grazing zone_S means the grazing zone with relatively stable climate

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

Table 5 Pseudo-R^2 values of static spatial panel data models for NPP dynamics: iteratively removing the independent variables to shown their explanatory power

Variable	IMAR, China				Mongolia	
	Farming	Farming_grazing	Grazing zone_H	Grazing zone_S	Grazing zone_H	Grazing zone_S
PRECIP	0.7784	0.7616	0.6343	0.6559	0.6024	0.7093
TEMP	0.8913	0.8657	0.8586	0.8062	0.8370	0.8125
LIVE	0.8394	0.8002	0.7049	0.6346	0.7992	0.6250
GRAIN	0.6123	0.6305				
POP	0.8288	0.7809	0.8086	0.7058	0.8026	0.7338
DELTA	0.4512	0.3086	0.4979	0.4713	0.4377	0.4107
Overall	0.8935	0.8709	0.8640	0.8082	0.8613	0.8894

Grazing zone_H means the grazing zone with highly variable climate; and grazing zone_S means the grazing zone with relatively stable climate

The values of the overall goodness of fit (psedudo-R^2) for the spatial panel data models show that all of the models have high explanatory power for the dynamics of NPP (pseudo-$R^2 > 0.8$). The results of testing the relative influence of each variable on the model's ability to predict NPP indicated that the spatially lagged NPP had the highest explanatory power for all panel data models. Grain output had high explanatory power in farming and farming-grazing zones of IMAR. Precipitation and livestock populations had high explanatory power in the two grazing zones of IMAR. In Mongolia, precipitation was the only variable that had high explanatory power in the grazing zone with highly variable climate, and livestock populations was the only variable that had high explanatory power in the grazing zone with relatively stable climate (Tables 5, 6).

Discussion

We have analyzed the drivers of NPP dynamics across the ecological zones in the Mongolian grasslands, using spatial panel data models. Most of the Mongolian grasslands are located in semi-arid and arid regions, and precipitation was significantly correlated with NPP, except the grazing zone with relatively stable climate in Mongolia. Annual grain production was the major reason for NPP dynamics in the farming and farming-grazing zones of IMAR.

Table 6 Pseudo-R^2 values of dynamic spatial panel data models for NPP dynamics: iteratively removing the independent variables to show their explanatory power

Variable	IMAR, China				Mongolia	
	Farming	Farming_grazing	Grazing zone_H	Grazing zone_S	Grazing zone_H	Grazing zone_S
PRECIP	0.7812	0.7488	0.6130	0.6496	0.6003	0.7882
TEMP	0.8981	0.8711	0.8663	0.7993	0.8471	0.8207
LIVE	0.8431	0.8129	0.6992	0.6125	0.7960	0.6190
GRAIN	0.6036	0.6254				
POP	0.8259	0.8092	0.8160	0.6981	0.8015	0.7305
DELTA	0.4225	0.3119	0.4492	0.4637	0.4317	0.4139
RHO	0.8874	0.8794	0.8831	0.8059	0.8572	0.8701
GAMMA	0.8890	0.8633	0.8795	0.7937	0.8490	0.8693
Overall	0.9006	0.8825	0.8913	0.8104	0.8692	0.8996

Grazing zone_H means the grazing zone with highly variable climate; and grazing zone_S means the grazing zone with relatively stable climate

Livestock populations had significantly positive relationships with NPP in the two grazing zones of IMAR and the grazing zone with relatively stable climate in Mongolia. These relationships were counter to the hypotheses generated by the equilibrium grassland model, which postulates that increased grazing intensity results in decreased productivity and grassland degradation (Fernandez-Gimenez and Allen-Diaz 1999; Zhang 2007). Possible reasons for these counterintuitive results include imports of fodder and hay from other areas (e.g., farming and farming-grazing areas), human land-use (e.g., fertilization and irrigation) and livestock management activities, impacts of climate hazards on livestock populations, and low grazing intensity (i.e., not reaching the carrying capacity of pastures). In addition, there may be some endogeneity, in which herders move over time to areas with high productivity because they are high and abandon areas of low productivity. Such endogenous interactions cannot currently be represented in the spatial panel data models.

A number of challenges limit our ability to interpret causations based on the static and dynamic spatial panel data models of NPP dynamics. The results of the panel data models for IMAR and Mongolia may not be comparable because the data for fitting the spatial panel data models of the two regions were aggregated at different spatial and jurisdictional scales. In this case, we do not have fine resolution census data (i.e., at soum level) of Mongolia. One of the challenges in merging remotely sensed data and socioeconomic data is to identify the scale of analysis and modeling. Aggregating the values of remote sensing pixels to the scale of census polygons is a common way to match the two types of data. Because census data are collected at different jurisdictional levels with different sizes, analyzing and modeling the causes of land use/cover change often requires attention to the modifiable area unit problem (MAUP), i.e., the shape and size of data aggregation affects analysis. MAUP can produce analytical artifacts that result from the variations in the sizes and geographic arrangement of geographical units (Brown et al. 2004). The relationships inferred among the variables in the models may change as the sizes of spatial units change.

Inaccuracies and errors associated with data used in this study can be a problem. The estimated NPP included the productivity of cropland, and we were not able to exclude farming activities from the study area. Grassland biomass was not the only food source for livestock, especially in IMAR. Using imported fodder will definitely affect the model inferred relationships between annual NPP and livestock populations. Compared with Mongolia, the grazing systems in IMAR were more strongly affected by fodder imported from farming regions because of grassland degradation and incentives for keeping more animals, stimulated by market benefits (Li et al. 2007; Zhang 2007). Further, the data about the populations of people and livestock did not measure exactly the variables of interest. The data of human populations used here included both urban and rural populations, and we were not able to exclude urban population from total population due to lack of detailed data. The data of livestock populations used in the panel data models included both locally grazed and stall-fed livestock populations, and we did not have detailed census data about the proportions of livestock populations that were stall-fed. This data problem was less serious in Mongolia because most animals were locally and seasonally grazed.

Livestock management behaviors of herders also affected the statistical modeling results. Studies have shown that in IMAR, the number of livestock that herder households plan to manage is usually based on two factors: the ability to buy fodder when droughts happen and the anticipated amount of rainfall in the next year (Zhang 2007). Herders usually do not want to sell most of their livestock in the years with droughts when livestock prices were fairly low, and they usually want to buy fodder or migrate to greener places to keep their livestock alive and wait for the years with more rainfall. These livestock management behaviors of local herders should affect the inferred relationships among the variables. Moreover, empirical studies indicate that it usually takes 4 years to recover the livestock populations after severe droughts, due to the breeding cycles of livestock (Zhang 2007).

Other assumptions in the spatial panel data models, such as linear relationships among the variables, no correlations among independent variables, and no autocorrelations of independent variables, also affect the identification the major drivers of NPP dynamics accurately. The panel data models that account for both spatial and temporal autocorrelations of dependent and independent variables are still under development (Elhorst 2010a). In the static and dynamic spatial panel data models, the spatial autocorrelation term had significant relationships with NPP. This may be caused by other missing explanatory variables, such as soil fertility and ground water, which caused the spatial autocorrelation of NPP. In addition, we assumed unidirectional causal relationships for the spatial panel data models, i.e., the selected independent variables were the dominant causal factors for NPP dynamics. The endogeneity problem caused by the bidirectional causal relationships between livestock populations and NPP could affect parameter estimations and the interpretations of the modeling results, especially in the grazing zones with relatively stable climate in which livestock grazing intensity played a more important role in affecting NPP dynamics. Model misspecification can lead to spurious results. This is especially the case with panel data, where model coefficients can vary both temporally and spatially (Brown et al. 2004). The spatial panel data models that can account for the endogeneity problem are still underdevelopment. Finally, similar to any other statistical methods, spatial panel data models were insufficient to establish causal relationships among variables. However, they can be more useful than purely cross-sectional data models in establishing causality.

Understanding the drivers for NPP dynamics across heterogeneous landscapes is important for providing evidence-based policy recommendations for sustainable governance of grassland resources. The heterogeneous drivers of NPP dynamics indicated the necessity of diverse resource policies and institutions to accommodate the diversity of grassland social-ecological systems and to govern grassland resources sustainably (Ostrom 2005). In the farming and farming-grazing zones, farming can easily destroy the surface soil. Therefore, cropland abandonment is important for ecological conservation purposes in these zones. In the grazing zones with highly variable climate, cooperative use of grasslands is an effective way to minimize the loss caused by the high interannual variability of precipitation and forage. Studies have shown that in Mongolia, grassland productivity degraded the most in meadow steppe, and this was mainly driven by grazing sedentarization and overgrazing in these areas (Olonbayar 2010). In these grazing zones with relatively stable climate, controlling livestock grazing intensity is important for sustainable use of grasslands.

Acknowledgments The work was conducted with financial support from the NASA Land-Cover/Land-Use Change Program.

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