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# Modeling Grassland Ecosystem Responses to Coupled Climate and Socioeconomic Influences in Multi-Spatial-And-Temporal Scales

Y. Xie[1,2] *, D. Crary[3], Y. Bai[4], X. Cui[5], and A. Zhang[2]

[1]*Institute for Geospatial Research & Education, Eastern Michigan University, Ypsilanti, Michigan 48197, USA*
[2]*School of Hydropower, Hebei University of Engineering, Handan 056021, China*
[3]*Department of Economics, Eastern Michigan University, Ypsilanti, Michigan 48197, USA*
[4]*Institute of Botany, Chinese Academy of Sciences, Beijing 100093, China*
[5]*International School of Software, Wuhan University, Wuhan 430079, China*

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**ABSTRACT.** Assessment of ecosystem responses to coupled human and environmental impacts is increasingly acknowledged as an important research of environmental informatics. However, current ecological and environmental models are not effective for capturing the coupled influences due to prevalent approaches of separating human interferences from environmental changes, common uses of time-averaged or cumulative data, and the lack of efficient methods integrating environmental observations with socioeconomic statistics that are tabulated over different spatial units. In this paper, we presented an integrated modeling framework to tackle these limitations. We developed data-assimilation techniques to integrate ecological and climate data with socioeconomic statistics into a coherent dataset on the basis of conforming spatial units. These data were used in panel regressions to estimate responses of grassland productivity to coupled climate factors (seven) and socioeconomic indicators (ten) across 37 counties for nine 16-day growing periods each year from 2000 to 2010. We also advanced the analysis of climate impacts by allowing for quadratic rather than linear impacts and by incorporating lagged time effects for the dependent variable. The case study was conducted in Inner Mongolia Autonomous Region of China. Our findings provided strong evidence that the grassland productivity responded significantly to variations in both climate factors and socioeconomic variables; displayed significant seasonal, annual, and regional variation; and revealed cumulative influences from prior climate conditions and extreme climate fluctuations. The assimilation of climatic, ecological and socioeconomic data into a big-data set and the application of multi-spatial-and-temporal panel regression model were much more comprehensive than prior studies.

*Keywords:* climate change, data assimilation, grasslands, multi-dimensional panel data model, socioeconomic transformation, spatiotemporal analysis

## 1. Introduction

Given the vast geographical scale and diversity of grasslands and their sensitivity to climate change, analysis of grassland productivity provides a vital channel for study of climate change and its ecological impacts at regional and local scales, and of interactions among species, communities, and ecosystems, and between ecological responses and human adaptations to these changes (Hagerman et al., 2010). Grasslands occupy about 40% of the Earth's land surface, support the livelihoods of nearly a third of humanity (Gibson, 2009), and are progressively being degraded (Li and Xie, 2013). Disturbances to grasslands caused by grazing, farming, and mining, compounded with climate change, create challenges for ecosystem recovery and sustainable economic development (Brown et al., 2013). Global climate change has been widely recognized as a new natural threat to biodiversity and human welfare in the 21st century. Climate change has been manifested in increased global temperatures, but also in increasing frequency of extreme weather events such as floods and droughts, severe winds, and increased temperature extremes of both hot and cold. Pronounced phenological or seasonal life-cycle shifts for flora and fauna, geographic shifts in growing ranges, and shifts in socioeconomic activity are important observed responses of ecosystems to global climate change (Walther et al., 2002; NRC, 2008).

Despite its potential benefits, analysis of interactions among coupled climate and human systems has been challenged by the complexity of diverse factors that are multi-scaled in space and time (Swain and Thomas, 2010). Studies of variations of ecological phenomena at multiple scales in space are well-informed traditions in ecological and geographical sciences (NRC, 2010). Empirical studies have demonstrated that spatial heterogeneity has a significant impact on diversity and

* Corresponding author. Tel.: +01 734 4877588; fax: +01 734 4875394.
*E-mail address:* yxie@emich.edu (Y. Xie).

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resilience of ecosystems (Virah-Sawmy et al., 2009; Parrott and Meyer, 2012). Factors significantly affecting the richness and density of species at one scale may not have similar impact at other scales (Stiles and Scheiner, 2010). Since the processes affecting plant species are operating at local, regional and global scales, it is critical to adopt a multi-scale perspective to examine their distribution patterns (Seipel et al., 2012). Conclusions on plant diversity patterns and underlying processes can be reversed with choices of different scales (Münkemüller et al., 2014). Moreover, some ecological factors and processes interact across scales and the investigation of the cross-scale interactions (CSIs) can shed insights on a wide range of multi-scaled problems such as climate change, ecosystem evolution, and land-use and land-cover change (Soranno et al., 2014).

Likewise, many natural factors and processes are operating at a wide variety of time scales. For instance, short-term change of precipitation in semi-arid areas affects vegetation through adjustments in plant physiology and leaf phenology, while long-term variation influences vegetation through responses in plant establishment and mortality, community composition and disturbance regimes (Jin and Goulden, 2014). From the perspective of longitudinal dimension, time scales include commonly used terms of hourly, daily, monthly, seasonally, yearly, decadal, and abrupt changes (Propastin et al., 2008). Among them seasonal, yearly, decadal and abrupt changes are most important events that need to be addressed in the context of studying ecosystem changes (Baker et al., 2014). Four quantities, frequency, magnitude, sequence and span are often used to describe temporal changes (Watson et al., 2013). Furthermore, the term of sequence is a complicated temporal concept in ecological studies. The original meaning of sequence indicates an order through which different plant communities have evolved in a specific location over a given time period. The term of sequence also implies a correlation or causal relationship between a series of events (or phases or states) of a research object in a time-series. Statistically this relationship is called as time-autocorrelation, which has been a hot research topic in data mining (Filho et al., 2014). However, the time-autocorrelation is less examined in macroecological studies.

Additionally, quantifying the coupled relationship between natural and human systems has been challenged by manifold difficulties. Analytically, it involves the selection of a conceptual paradigm. Pragmatically it requires large volumes of comprehensive data sets and a good software package to implement the selected paradigm. A wide array of paradigms has been experimented to depict coupled nature-human interactions, including indicator identification (Dale et al., 2013; Nazari et al., 2015), multivariate regression-based techniques, cellular automata (White and Engelen, 1997), agent-based models (Xie and Fan, 2014), and stochastic system dynamics (Crépin et al., 2011). In many cases several different methods are integrated to describe and predict the coupled natural-

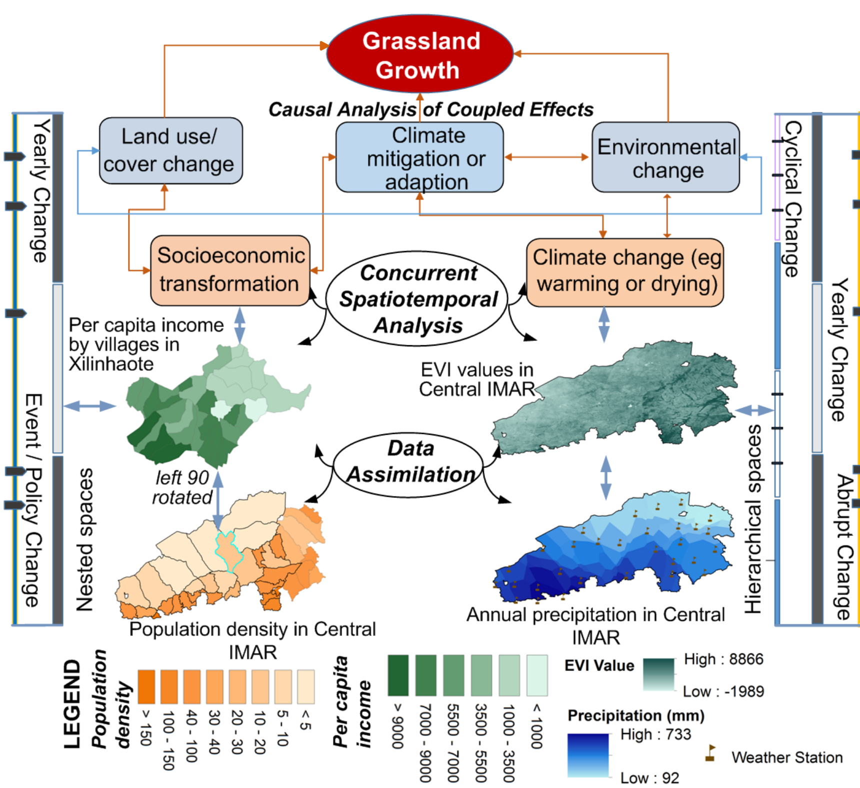


**Figure 1**. A framework of multi-scale spatiotemporal analysis of causal relations between grassland growth and coupled climate and socioeconomic changes.

human interactions.

Another big hurdle to instigate coupled nature-human analysis is the data inconsistency between the natural and socioeconomic data. For instance, the areal and temporal units over which ecological and environmental data are collected are usually different from those units in which socioeconomic data are numerated. The inconsistency between the natural and socioeconomic datasets prevents researchers from applying most commonly used analytical methods. This paper will present a computational framework for exploring grassland ecosystem responses to coupled climate and socioeconomic influences at multi-spatial-and-temporal scales. Among the aforementioned challenges, this paper will address the following three major issues: (1) data assimilation techniques for matching inconsistencies of areal units over which natural and socioeconomic datasets are collected; (2) autoregressive panel data analysis to investigate causal relationship between coupled natural and human interactions; and (3) the examination of the coupled interactions at multi-temporal scales from seasonal to yearly, decadal, sequential and extreme changes.

## 2. Data and Methods

### 2.1. Computational Framework of Multiple Spatial and Temporal Analysis

A conceptual framework for analyzing the impact of climate and socioeconomic factors on grassland productivity across different spatial and temporal scales is shown in Figure 1. Variation in the time dimension includes explicit "Seasonal Change", "Yearly Change" and "Abrupt Change" for natural phenomena, but only "Yearly Change" and "Event/Policy Change" along the socioeconomic periphery. It is worth pointing out that the sequential change or autoregressive phenomenon is embedded in both natural and socioeconomic data. Analysis of temporal changes pertaining to natural or socioeconomic phenomena is constrained by how these datasets are collected. For instance, socioeconomic data are often enumerated annually over an administrative areal unit or deliberately gathered for special events like county economics surveys.

Hierarchical spatial structures are also apparent. The four maps shown within Figure 1 illustrate the significantly different spatial scales at which different data are available. Enhanced vegetative index or EVI, the variable to be explained, is available at a very fine spatial scale with roughly 2,600 observations within the study area. In contrast, socioeconomic variables for this region are available for only 37 counties and cities as shown in the population density map. As can be seen by comparing these two maps, variation in EVI does not neatly overlap county borders. Similarly, per capita income shows dramatic variation across villages within Xilinhaote. Finally, climate variables are measured at 30 observation stations in the region and were interpolated to the same level of detail as the EVI data (Li et al., 2013). Here again, variation shown in the precipitation map does not neatly correspond to the county borders for which socioeconomic data are available.

This spatial mismatch between ecosystem borders and county borders is not surprising. Natural regions like the boundaries of vegetation zones or plant communities are influenced by precipitation and temperature gradients at macro scales and by topographical compositions at local scales. However, nation, state, and county enumeration areas for economic, demographic, and social statistics are determined by a separate set of historic and political considerations. For example, a river valley may form the core of an ecological system, but serve as the border between two political regions that each extends well beyond the ecological region of the river valley. Thus, the attributes of a vegetation zone such as temperature, precipitation, and species related parameters, cannot easily be assembled with the attributes of a county, including, population, demographics, GDP, and other socioeconomic indices. Even within a political space, such as a county that serves as an enumeration area, distribution of socioeconomic activity will not be homogeneous. A substantial share of population and economic activity in a county might be heavily concentrated in a single urban area with sparse concentration in the rest of the county, as shown for per capita income at the village level in Figure 1. Given this spatial mismatch between different data sources and between natural and socioeconomic areas, an integrating computational framework is needed in order to assimilating datasets of inconsistent scales, enabling concurrent spatiotemporal analysis and including multi-temporal-scales.

### 2.2. Data Assimilation of Integrated "Big Data" across Physical and Socioeconomic Spaces

There is a critical need for matching ecological data collected over natural regions with socioeconomic data tabulated by administrative areas when investigating coupled human and natural interactions. From the perspective of data mining, data assimilation (DA) techniques have to be utilized in order to provide reliable data overlaps across ecological and socioeconomic spaces (Ibáñez et al., 2014; Yang et al., 2015). DA is an emerging tool to distribute data from different sources and spatial scales into consistent spatial units in order to yield results that approximate reality as closely as possible (Luo et al., 2011). One approach is to aggregate data up from a detailed spatial scale to a less detailed scale for which other variables are available; for example, averaging EVI data from the 2,600 plot level to the 37 county level, but this eliminates much useful data. Another approach is to use areal interpolation (AI) to disaggregate available data at a large spatial scale to a finer spatial scale; for example, reallocating published data at the county level to the finer detailed village level. AI is a geographical data preprocessing technique, which transfers available attribute data from one spatial unit system such as a county (source layer in the terminology of GIS) to a finer set of spatial units such as a township (target layer) over which attribute data are not existing but are required to feed spatial analysis (Xie, 1995; Sridharan and Qiu, 2013). The critical process of AI is how to find or extract ancillary information, design a transfer procedure, and validate the transfer accuracy.

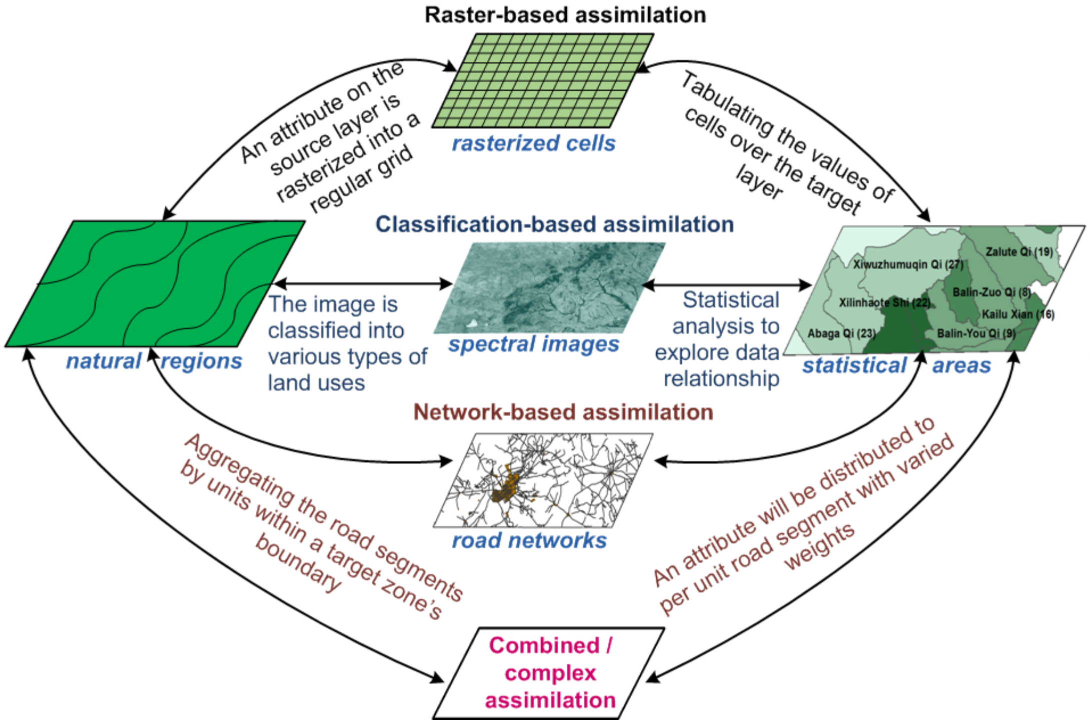


**Figure 2**. Flowchart of assimilating data between natural regions and statistical areas.

Based on current developments of AI and common needs for interpolating data over natural regions and statistical areas, a generic framework of data assimilations between statistical areas (for socioeconomic datasets) and natural regions (for ecological and environmental datasets) is proposed in Figure 2. Four approaches shown in Figure 2 are 1) raster-based, 2) classification-based, 3) network-based, and 4) combined/complex. The first approach of data assimilation is the raster-based. A data item (or an attribute) on the source layer in either natural regions or statistical areas will be rasterized into a regular grid through a GIS software. Each natural region or statistical area will comprise a set of cells and each cell within the cell-set will carry the original value of the attribute. The assimilation will be done through tabulating the sum, or the average, or the majority of the cells that fall within a region or area on the target layer (Harris and Longley, 2000; Zhang and Qiu, 2011).

The second approach is called image classification based assimilation. This technique applies remote sensing techniques to provide large quantities of physio-geographic data that have statistical relationship with the attribute that needs to be assimilated (Yuan et al., 1997). In other word, it employs land covers or land uses derived from classified satellite imagery as the ancillary data input and uses a statistical analysis to explore the relationship between the land covers (or uses) and the attribute for interpolation (Langford, 2013).

The third approach is called the network-weighting algorithm (Xie, 1995). This approach is to distribute an attribute in a source zone to road segments, for example, lying within its boundary to get enumerated road segments. Then these linear features will be intersected with a target zone. The attribute assimilation is executed by aggregating the total number of road segment units within a target zone's boundary. Three weighting methods (the average, the hierarchical and the building counts along road segments) can be used for more accurate fitting.

The last approach is an integrated method of combing the above three approaches, called the networked hierarchical land-patch based assimilation (Kohl et al., 2006; Xie and Ma, 2015). This approach is proposed to deal with complex data assimilations between natural regions and statistical enumeration areas. This new algorithm constructs a hierarchical structure of networked (connected) county land parcels to transform socioeconomic data to ecological patches or environmental zones. When transferring an attribute (taking population as an example) from a statistical area to a natural region, a set of differentiated weights will be calibrated for county land parcels according to the parcels' positions on the hierarchical road network structure. The calibration is an iterative process to sum to the total value of population. Afterwards, the disaggregated population counts over all urban parcels can be rasterized as values over a set of pixels, which can be easily resampled or summarized over a different spatial unit system as a new attribute. This algorithm can also be used to interpolate ecological and environmental data over the statistical areas as was done for data used in the precipitation map in Figure 1.

### 2.3. Modeling Ecological Responses to Coupled Climate Change and Socioeconomic Transformation across Seasonal, Yearly, Decadal, Sequential and Extreme Temporal Changes

Multiple regression and related statistical analysis have long been used by ecologists, environmental scientists and geographers in various forms to examine relationships between ecological status (as a response variable) and a set of human and natural factors (explanatory variables). Until recently, most of this analysis has either focused on analysis across space at a point in time, or analysis across time for a single spatial unit. Recent advancements of cross-section quantitative analysis have included path analysis, structured equation modeling, and Bayesian structured equation modeling. Path analysis places a heavier focus on interpretive structure than regression analysis does (Grace, 2006). Structural equation modeling (SEM) has been developed for understandding coupled human and natural systems and enhancing the interpretation of results (Brown et al., 2013). SEM is a general analytic framework that encompasses more traditional analysis, such as multiple regression and analysis of variance, but it has substantial advantages over traditional methods because it allows for simultaneous testing of variables and hypotheses that results from the complex social-ecological systems (Grace, 2006; Kline, 2011). Lastly, Bayesian structured equation modeling (BSEM) has the advantage over SEM of enabling fitting a wider variety of substantive models based on *a priori* researcher hypotheses that are not identifiable in the tradetional frequentist framework (Muthén and Asparouhov, 2012).

However, regression-based models have not adequately dealt with the reality that relationships among spatial phenomena vary across a landscape at multiple scales, with this failure resulting in regression coefficients being either over-estimated or under-estimated (Anselin and Arribas-Bel, 2013). Three groups of spatial regression models, spatial autoregressive models (Anselin, 1988), spatial filtering models (Getis and Griffith, 2002), and geographically weighted regression models (Fotheringham et al., 2002), have been developed by geographers to overcome this problem. A unique case of varying spatial scales is the “nested spaces.” For instance, investigation of grassland sustainability in the Mongolian Plateau involves measuring ecological variables at unique sites, land-cover changes over remote sensing scenes, surveys at selected households, grassland productivity and landscape pattern change over remote sensing scenes, and socio-economic characterristics by counties and provinces. The natural and socioeconomic data are hierarchical with correlated structures at multi-scales. With nested data, hierarchical linear modeling (HLM) or multi-leveled models (MLM) is an appropriate method to use because it supports exploration of variances in explanatory variables at multiple hierarchical levels (Gelman and Hill, 2007; Qian et al., 2010; Garson, 2013).

Models discussed so far focus on analysis across different spatial dimensions, but grassland productivity and climate variables demonstrate pronounced seasonal or intra-year variations in addition to yearly changes (Figure 1). Temporal dynamics embedded in socioeconomic variables are different from ecological and environmental factors. Socioeconomic statistics are numerated annually. Seasonal variations are hardly captured in socioeconomic data, which makes much more complicated to examine the associations between the coupled natural and socioeconomic systems longitudinally. In addition, noises (or abrupt or extreme changes) are usually found in time-series changes to both natural and human systems although the causes are different (Figure 1). Extreme changes or disasters often happen in natural systems, while unexpected changes are direct outcomes of policy changes or man-made incidents. Furthermore, earlier conditions of ecosystems may have an explicit influence on the later status of the systems, which is called sequential change or effect.

Panel data analysis (PDA), to be used in the results section below, provides a flexible mechanism to address all of the above concerns. PDA is a regression technique that can examine multi-scaled spatiotemporal causal relationships betweeen ecological functions and coupled natural and human systems. PDA, explicitly considers both time and space simultaneously and has been widely applied in econometrics (Baltagi et al., 2007; Elhorst, 2010; Parent and LeSage, 2011) and has started to emerge in recent ecological (Scrieciu, 2007; Miller-Rushin et al., 2008; Demeke et al., 2011; Li et al., 2013) and geographical studies (Oud et al., 2012; Liu and Xie, 2013a). PDA has the advantage of capturing complex data trends in multiple dimensions of cross-sections and time series concurrently. Moreover, PDA can be asymmetrically adjusted to examine how the variables in time-series respond to the deviations from the equilibrium through an integration of threshold vector error correction model (TVECM) (Esso, 2010; Liu and Xie, 2013b). The asymmetric adjusted PDA can account for structural breaks in the time-series caused by disastrous natural disturbances or abrupt policy change. Moreover, pass-through variables can be added into PDA to examine sequential (lagged) effects, whereas dummy variables can be included to investigate unexpected (extreme) events (Petrie et al., 2012).

## 3. Results

We adopt the raster-based data assimilation method to assimilate the 250 meter pixel-based EVI and climate data items over 37 counties with their average values from the middle zone of Inner Mongolian Autonomous Region (IMAR) of China. As a result, we create an integrated EVI, climate and socioeconomic dataset on the geography of counties. PDA will be then carried out across 37 counties for nine 16-day periods for each of the years 2000 to 2010. This area is a northern, temperate zone composed of twelve types of plant communities and, among them, arid and semi-arid stepped grasslands are predominant**.** EVI is used as a proxy of grassland growth condition (Glenn et al., 2008) and serves as the dependent variable. Seven climate variables BAR (barometric pressure), PREC (precipitation), VAP (vapor), HUM (humidity), SUN (sunshine hour), TEMP (temperature), and WIND (wind speed) come from the same sources used by Li et al.

**Table 1.** Panel Regression Results for EVI, with County, Year and Period Fixed-effects

| Variable | Coef. | t-stat | p\|t\| | Variable | Coef. | t-stat | p\|t\| |
|---|---|---|---|---|---|---|---|
| $S_{k=1}$*EVI(-1) | 0.338 | 9.66 | 0.000 | Socio-economic Variables | | | |
| $S_{k=2,9}$*EVI(-1) | 0.627 | 50.80 | 0.000 | RGDPpc | 0.038 | 1.86 | 0.063 |
| Climate Variables and Their Squared Values | | | | SFARM | 0.034 | 2.57 | 0.010 |
| BAR | 0.711 | 6.32 | 0.000 | DAA | -0.028 | -1.71 | 0.087 |
| $BAR^2$ | -0.476 | -6.91 | 0.000 | DGR | 0.054 | 2.55 | 0.011 |
| PREC | 0.227 | 9.59 | 0.000 | **DLS** | **0.014** | **0.83** | **0.406** |
| $PREC^2$ | -0.150 | -4.55 | 0.000 | DHW | -0.025 | -2.00 | 0.046 |
| **VAP** | **0.048** | **0.77** | **0.441** | **DPOP** | **0.051** | **0.66** | **0.508** |
| $VAP^2$ | 0.090 | 1.95 | 0.051 | SRURAL | -0.041 | -1.73 | 0.085 |
| HUM | 0.257 | 4.97 | 0.000 | SLGOV | 0.017 | 2.17 | 0.030 |
| $HUM^2$ | -0.208 | -4.39 | 0.000 | **SINV** | **0.013** | **1.13** | **0.257** |
| SUN | 0.164 | 4.64 | 0.000 | Special Adjustments for 2002 period 7 and 2008 period 4 | | | |
| $SUN^2$ | -0.102 | -3.30 | 0.001 | | | | |
| TEMP | 0.207 | 5.25 | 0.000 | DS027 | 0.143 | 17.89 | 0.000 |
| $TEMP^2$ | -0.187 | -6.11 | 0.000 | DS027(-1) | -0.129 | -18.09 | 0.000 |
| WIND | 0.041 | 1.69 | 0.091 | DS084 | 0.255 | 21.70 | 0.000 |
| $WIND^2$ | -0.064 | -2.04 | 0.042 | DS084(-1) | -0.157 | -19.93 | 0.000 |
| Equation Summary Statistics | | | | | | | |
| $AdjR^2$ = 0.932 | | RMSE = 0.044 | | F-stat (85,3541) = 600 | | DW Stat = 1.94 | |
| F statistics for Fixed-Effects (1% critical values shown in parentheses) | | | | | | | |
| Counties = 12.83 (1.62) | | Years = 10.20 (2.32) | | Seasonal growing periods = 162.17 (2.51) | | | |

*(1) Each variable is normalized over its range to equal 0 at its minimum value and equal 1 at its maximum value. (2) p|t| column indicates the significance level of each coefficient, with t stat and p|t| values based upon White (diagonal) robust standard errors. (3) Shaded coefficients indicate that they are insignificant. (4) Estimation was conducted using the Eviews 6 econometric software package. (5) See Figure 3 for fixed-effects coefficients for each county.

(2013), but were recalibrated to match county boundaries through the raster-based assimilation as aforementioned. Wind and air pressure affect evaporation, transpiration and moisture, which influence vegetation growth (Whitehead, 1957; Daunicht and Brinkjans, 1996; Smith and Ennos, 2003; Hoffmann et al., 2008). EVI is based upon satellite imaging that became available in 2000 and the climate variables are derived from 30 meteorological stations in IMAR. EVI and climate variables cover the normal growing season in IMAR, roughly from May through September of each year.

Ten socioeconomic variables for each county during the period of 2000–2010 were derived from data collected from Chinese Statistical Yearbooks (IMAR Statistical Bureau, 2001–2011). The resulting variables are *RGDPpc* (real GDP per capita), *SFARM*, (farm income as share of county GDP), *DAA* (arable area density), *DGR* (grain density per unit of area), *DLS* (livestock density), *DHW* (highway density), *DPOP* (population density), *SRURAL* (rural population share), *SLGOV* (local government revenue as share of GDP), and *SINV* (investment spending as share of GDP). For the five density variables, raw data for each variable were divided by total area in the county.

The seven climate variables, their squared values, and ten socioeconomic explanatory variables are fitted into a fixed-effects, PDA model to explain variation in EVI across-counties ($C_i$), years ($Y_j$), and intra-year growing seasons ($S_k$). It is worth pointing out that two sets of pass-through variables [ $S_{k=1}$*EVI(-1) : the EVI pass-through values from the final period in the prior-year to the first growing season, and $S_{k=2,9}$*EVI(-1) : the within-year pass-through for each seasonal period to the next period] are added to examine the lagged EVI effects. Two dummy variables (DS027, seventh growing period in 2002 and DS084, the fourth growing period in 2008) are included to analyze two extreme disturbances identified in the datasets.

$$EVI = \boldsymbol{f}\,(C_i, Y_j, S_k, S_{k=1}{*}EVI(-1), S_{k=2,9}{*}EVI(-1), BAR, BAR^2, HUM, HUM^2, PREC, PREC^2, VAP, VAP^2, SUN, SUN^2, TEMP, TEMP^2, WIND, WIND^2, RGDPpc, SFARM, DAA, DGR, DLS, DHW, DPOP, SRURAL, SLGOV, SINV, DS027, DS084).$$

This model performs remarkably well, explaining 93% of the variation in EVI across counties, years and seasons as indicated by the adjusted $R^2$ and having an F-stat of 600 which is far above the 1% critical value of 1.40 (Table 1). Given that the dependent variable is natural log of EVI normalized to equal 0 at its minimum value and 1 at its maximum value, the root mean squared error of 0.0442 equals 4.42% of the range in values for log of EVI. Finally, the panel Durbin Watson (DW) statistic of 1.94 is very close to the ideal value of 2.0 so shows very low probability of serially-correlated errors.

Turning to the estimated coefficients on explanatory variables only those shown in shaded shells were not statistically significant. Lagged values of EVI play a highly significant role in determining current EVI. For the first period in the growing season, the coefficient on EVI from the final period in the prior-year growing season is 0.3381, and the within-year pass-through for each of the other periods is 0.6268 with this coefficient having the highest t-statistic of any of the explanatory variables in the model. Strong support is found for the climate variables included in the model and for use of a quadratic specification in capturing their influence on EVI. Six of the climate variables (BAR, PREC, HUM, SUN, TEMP, and WIND) show positive impacts for their levels and negative impacts for their squared values, indicating that EVI increases, reaches a maximum, and then decreases as each of these variables increases. Vapor (VAP) shows positive signs for both its level and squared value, so its impact on EVI increases at an increasing rate as vapor increases. Despite multi-collinearity which can renders coefficients insignificant, all of the climate variables are statistically significant at the 1% level or better; except for the level of VAP which is insignificant, $VAP^2$ and WIND which are significant at 10%, and $WIND^2$ which significant at 5%.

Turning to the socioeconomic variables, they do not exert as strong of an impact on EVI as the climate variables, but their effects may be under-estimated since common values had to be used within each of the 9 growing seasons for each year since only annual data are available. Seven of these ten variables are statistically significant at the 10% level or better. RGDPpc, SFARM, DGR, and SLGOV each exerts a positive impact on EVI. The positive impacts for per capita income and the share of GDP coming from farm income could result from reverse causality, but may indicate that higher income levels lead to more sophisticated approaches to grassland management. The positive impact for grain density may result from a higher vegetative index for grain than for grassland. SLGOV is used as a proxy for government financed grassland enhancement policies, and its positive sign is consistent with this interpretation. DAA, DHW and SRURAL each exert significant negative impacts indicating that increases in plowed croplands, highways and rural population all lower EVI. DLS is insignificant in our results, despite earlier studies (Li et al., 2013) that found that livestock density had a significant negative impact on grassland productivity in the 1980s and 1990s.

Fixed impacts by years, growing periods and counties all exert significant impacts (the measures of the significance of these fixed effects are shown at the bottom of Table 1, with F statistics well above the 1% critical values). Of the three groups, the effects for the growing periods are most signifycant (Table 1), followed by those for counties and then those for years. The effects by growing period indicate a pattern of EVI increasing about 3% of the total range of EVI for each period one through six with this total increment of 18% reversed in the next three periods. These seasonal effects seem quite logical as reflecting the normal growing pattern of grasslands over a typical year. The differentials by year are relatively small ranging from EVI about 1.4% of its range above average in 2003 and about 1.7% below average in 2009.

The geographic distribution of the fixed-effects coefficients by counties (cities) is shown in Figure 3. The map indicates a general pattern of EVI above levels predicted by climate and socioeconomic variables in the southern and western portions of IMAR, close-to-predicted EVI for the northern and central counties, and below-predicted EVI for the eastern counties. The clustering of the above-predicted, close-to-predic-

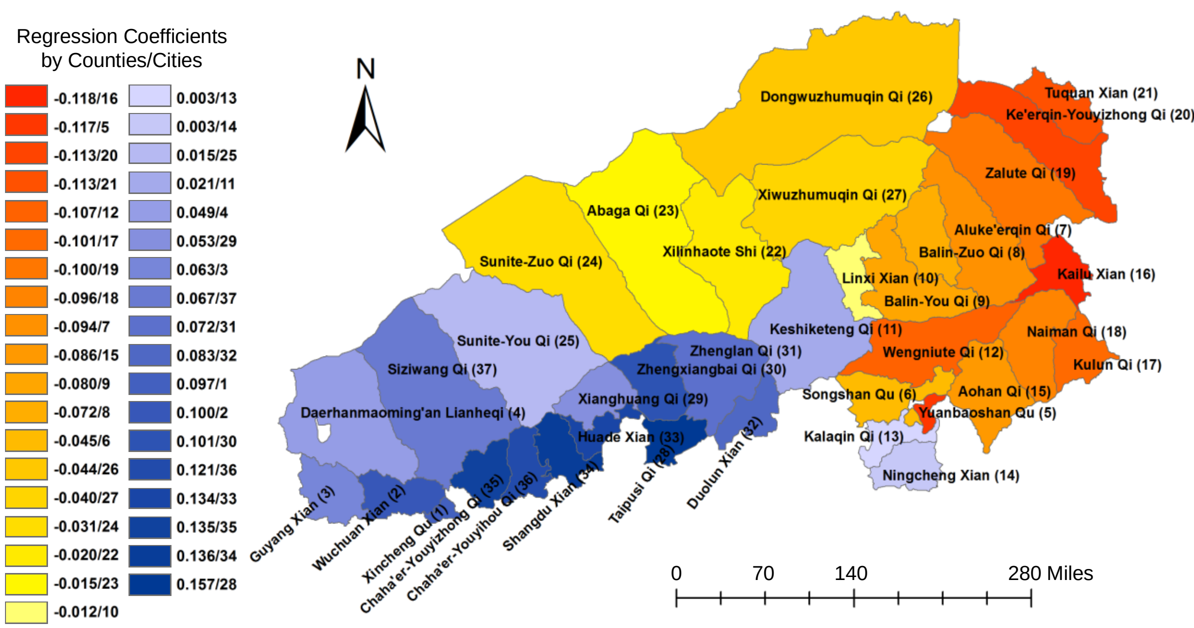


**Figure 3**. Spatial variations of coefficients by counties from panel regression shown in Table 1.

ted, and below-predicted EVI counties is fairly strong, but it does not neatly overlap with precipitation zones shown in Figure 1. Many of the counties with above-predicted EVI border the Yellow River, which suggests that water access may be an omitted explanatory factor that needs to be added to the model. Alternatively, the above predicted EVI in the primarily southern counties might be based upon higher average annual temperatures with local vegetation having evolved to respond positively to these higher normal temperatures. Similarly, some of the eastern counties tend to have higher elevations than other counties, so this is another variable that should be explored in the future.

Turning to the impacts by unique events, special treatment was executed for two periods within our sample: the seventh growing period in 2002 (DS027) and the fourth growing period in 2008 (DS084). Based upon initial regression results, it was discovered that these two periods generally had large unexplained increases in EVI across virtually all counties. This is visible in Figure 3, where these periods showed the two highest values for EVI. These extreme values might have resulted from region-wide, special combinations of climate variables the caused the surge in EVI, or they could even be due to measurement errors in these two periods. Dummy variables to capture the unusual behavior in these two periods and their lagged values, were included to avoid biasing results for the remaining variables, and each was highly significant.

## 4. Discussions and Conclusions

This paper discussed the challenges of analyzing coupled environmental and socioeconomic changes on dynamics of grassland productivity over annual, seasonal and special temporal scales, and over multiple spatial scales. Preliminary results were presented to demonstrate the power of panel data analysis as a useful tool in conducting large-scale applications of this type of integrated temporal and spatial analysis over 12 plant communities and 37 counties in the IMAR region of China. A significantly richer specification of the grassland productivity model was utilized here with EVI in each growing period determined partly by EVI in the prior growing period, with climate variables included in quadratic rather than linear form, and with socioeconomic variables added to the analysis. With these innovations, the model performs extremely well explaining over 93 percent of the variation in EVI over 37 counties, 11 years, 9 growing periods and 2 unique events. The climate variables have highly significant, non-linear impacts on EVI and seven of ten of the socioeconomic variables are significant. The combination of EVI pass-through from one period to the next and inverted U-shaped impacts of most climate variables indicate that the increasing weather extremes such as unusually high and low temperatures and rainfall tend to curtail grassland productivity.

The impact of socioeconomic variables on EVI is less pronounced than that of climate variables, but still significant. Real income levels and the share of income coming from farming both have a positive impact on EVI, but the mix of agricultural activity is important. A higher density of plow croplands lowers EVI but increased grain production increases EVI. Somewhat surprisingly, livestock density did not have a significant impact which may suggest better grazing-management practices over our sample. Increased highways and rural population have negative impacts on EVI, while increased local government revenue has a positive impact. These findings help assess potential adaptive management strategies in grassland areas in the face of climate change. Firstly, it would be a wrong assumption that grassland productivity was simply affected by climate changes. Secondly, the impacts of social and economic activities and policies on grassland productivity were very complicated. The responses of grassland productivity to policy interventions were sensitive and could fluctuate. Therefore, coordinated and balanced approaches of taking into consideration of climate changes, ecosystem responses and management strategies are strongly advocated. While much has been accomplished, much remains to be done. Results presented in this paper have made strong advances in explaining EVI changes over time, and particularly across different growing periods within each year that are driven primarily by intra-year changes in climate variables. However, only one spatial scale (the county level) was tested at present. Much remains to be explained in terms of the spatial differences in EVI productivity as illustrated by the substantial differences in EVI by county as shown in Figure 3. An agenda for addressing this challenge includes exploring additional socioeconomic and physical variables not included in the current analysis, nested spatial estimation in which sub-groups of counties with similar characteristics would be allowed to have different coefficients, and most importantly application of areal data interpolation of socioeconomic data to allow analysis at a more detailed spatial scale below that of the county level, such as intersected areas between counties and dominant plant communities, or between counties, plant communities and precipitation zones, or between villages, plant communities and precipitation zones.

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