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Article

Assessing Ecological Compensation Policy Effectiveness: A Case Study in Inner Mongolia, China

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Abstract: As a vital component of the terrestrial ecosystem, grassland accounts for one-third of the global vegetation system. Grassland degradation has been exacerbated due to extreme overgrazing in China's Inner Mongolia Autonomous Region (IMAR). While conservation was carried out as the Ecological Subsidy and Award Program (ESAP) to mitigate grassland degradation, little is known about its effectiveness in improving the biophysical conditions of grassland. This paper integrates the conceptual frameworks of total socio-environmental systems (TSES) to assess how ecological systems respond to ESAP, investigate spatial heterogeneity of ESAP, and explore the mediating effects of socio-environmental interactions on ESAP. We integrate ecological, climate, and socioeconomic data and developed several hierarchical linear mixed models (HLMM) to investigate how these factors interact with ESAP in IMAR. Our findings prove that the above-ground biomass between 2011 and 2015 responds significantly to variations in socioeconomic conditions and ecological communities. Available land resources, hospital and medical facilities, and net farmer and herdsman income are the most critical factors contributing to grassland productivity. Primary industries like mining, total consumer retail value, farming, forestry, animal husbandry, fishery productions, and GDP are the most damaging factors affecting biomass. Our study recommends a regionally or locally tailored ecological recovery policy, instead of a generalized one, in the future effort to conserve grassland.

Keywords: Inner Mongolia Autonomous Region (IMAR); Grassland degradation; Total Socio-environmental systems (TSES); Hierarchical linear mixed model; Ecological subsidy and award program

1. Introduction

Grassland constitutes a vital part of the terrestrial ecosystem, occupying approximately one-third of the world's terrestrial vegetative cover [1]. Essential ecosystem service functions, including vital habitats and food production for organisms, are provided by it [2,3]. The semi-arid, arid, and semi-humid regions constitute the primary habitats for the majority of grasslands, which have long been utilized by humans and are particularly susceptible to the effects of global climate changes [4]. Due to their extensive geographical distributions and their susceptibility to both climate change and human exploitation, grassland productivity and degradation have long remained a focal point of ecological and environmental studies [5]. For example, in the Inner Mongolia Autonomous Region of China (IMAR), the population increased 8.97 percent from 23.18 million in 2001 to 25.26 million in 2017; the GDP increased 907.36 percent from 18.48 billion in 2001 to 186.16 billion Chinese Yuan in 2017; the livestock increased 140.65 percent from 46.75 million heads in 2001 to 112.50 million heads (in sheep units - SUs) in 2017 [6]. A field study on poverty alleviation and grassland degradation in IMAR estimated that the current amount of sheep units (SUs) in IMAR was about 140 million. Still, the livestock carrying capacity was 44 million and 31 million SUs in normal rainfall and during drought years, respectively [7]. The stocking rate exceeded the estimated carrying capacity by 3.2

times in one case, and by 4.5 times in another. This means that extreme overgrazing was happening on the grassland in IMAR to seek maximum GDP at the price of accelerated grassland degradation.

The gravity of grassland degradation in IMAR has long been recognized by research communities and governmental institutions in China. The Chinese central and regional governments have carried out three nationwide major grassland conservation programs in this specified region since the year 2000: the Beijing–Tianjin Wind/Sand Source Control Program in 2001, the Grazing Withdrawal Program in 2003, and the Ecological Subsidy and Award Program (hereafter ESAP) since 2011. A good description of these programs can be found in the paper by Chen and his colleagues [8].

Increasing pieces of literature have been published in recent years to assess and evaluate the effectiveness and outcome of these grassland conservation or recovery programs. Many of them are focusing on improvements of grassland biophysical conditions. One study examined three management regimes, full-year continuous livestock grazing (FG), 2 years excluded grazing (2EX), and 6 years excluded grazing (6EX), to assess how different grazing intensities affected soil properties and vegetation changes in IMA [9]. The plant cover was found to be $6EX > 2EX > FG$, with the highest 46 percent over 6EX grasslands and the lowest 31 percent in FG grasslands. The same findings were valid for plant above-ground biomass and vegetation diversity. The results suggested that implementing protection practices significantly increased soil fertility, vegetation diversity, coverage, and biomass. A second field-based research confirmed a similar finding [10]. After a six-year grazing exclusion, significant gains in ecosystem biomass and substantial elevations in soil carbon (C) and nitrogen (N) contents were observed, resulting in a marked restoration of ecosystem C and N storage. Notably, the accrual of C and N in the soil accounted for over 87.6% and 98.2% of the respective increases in ecosystem C and N, thereby suggesting that the primary driver of ecosystem C and N restoration was the augmentation of soil C and N content following grazing cessation. Another study monitored the grassland communities in 11 research sites characterized by temperate steppe ecosystems in IMAR over 8 years (2004–2011) [11]. The selection of these sites not only took into account varying precipitation levels across the arid, semi-arid, and humid climatic zones of the Mongolian Plateau but also considered the diverse landscapes. Research has shown that, following grazing exclusion, the community structures of degraded grasslands were able to rapidly recover to a healthy state. Specifically, grasslands in the humid zone recovered the fastest and most favorably, followed by the semi-arid zone and then the arid zone.

However, it is controversial concerning how soon the effect of grazing exclusion on grassland biophysical characteristics becomes detectable. One study in IMAR argued that the ecological benefits of grazing exclusion were only noticeable over an extended period [12]. No improving effects could be detected five years after either reduced or excluded grazing. Severe grazing pressure significantly degraded the physical and chemical characteristics of steppe topsoil, but these attributes underwent remarkable recovery over a period of 25 years following grazing exclusion. This finding was confirmed by a comprehensive review of 145 sites published in 118 recent literature concerning IMAR ecological recovery policies [13]. When the recovery period is longer than 27 years as part of China's "Returning Grazing Land to Grassland" Project, grazing exclusion exhibited a significantly positive impact on vegetation coverage, above-ground biomass, and soil C stock at most sites.

Another school investigates the effectiveness of grassland recovery policies from the perspectives of herders' motivation, institutional engagement, market incentive, and economic and ecological benefits. Two obstacles are diminishing the effectiveness of current ecological compensation policies and allowing for a continued increase of livestock in recent years in IMAR [14]. At first, market existence enables herdsmen to buy forages to feed animals in the winter seasons, which breaks the natural dependency of grazing on the local grassland carrying capacity. Secondly, the top-down policy implementation, numerous policies, and short-term contracts cause herdsmen to have little confidence that their investments today in decreasing stocking rates will reap the rewards in the future. Herders are reluctant or less interested in giving up immediate profits to seek non-guaranteed long-term benefits, even if future profits could be much bigger than the current ones. The ecological compensation policy should be implemented as part of multifaceted collaborative efforts, increasing both net pastoral income and livestock production efficiency by marketing

outstanding quality animal products to China's burgeoning economy, all while mitigating the detrimental effects of livestock on grasslands [7]. To disrupt the detrimental loop between subsistence-based pastoralism and grassland degradation in Inner Mongolia, a novel strategy shall be devised and evaluated within a comprehensive social-ecological framework that effectively harmonizes the expansion of livestock product markets, modified pastoral perceptions of success, sustainable livestock carrying capacities, and motivations for preserving ecosystem services. A sole ecological compensation policy will not achieve a sustainable grassland ecosystem and improve residents' well-being.

In recent years integrated socioeconomic and ecological analysis-based studies on ecological compensation policies have increasingly been reported. Based on a household survey and a structural equation modeling, the outcomes of the statistical analysis suggest that the effect of the subsidy on live-stock numbers was mixed over different regions although the participation rates of grassland conservation were comparable [15]. For example, the ecological compensation implementation showed negative responses in Xilingol and Hulunbuir but positive responses in Ulanqab and Ordos. The biophysical conditions in the former areas occupied with predominant temperate steppe and meadow steppe on the east IMAR were better than in the latter regions with desert steppe on the west. Statistical evaluations of the income formula suggested that increased livestock inventories and higher education endowments were increasing income. However, the former was reluctant to respond to the compensation policy, but the latter was more receptive to the compensation policy. Furthermore, increased grazing intensity (stocking rate) would reduce income, when all other socioeconomic and ecological parameters were equal. The findings suggest that the effectiveness of ecological compensation was varying across geographical, socioeconomic, and ecological spectrums.

Another comprehensive and socio-ecological analysis, integrating multiple indicators across environmental, economic, and societal factors, was employed. For the environmental dimension, indicators such as water and food footprints were utilized; for the economic aspect, built-up area, GDP, household incomes, and energy consumption were utilized; while for the social dimension, the Human Development Index (DHI) and the Gini coefficient were chosen [16]. The study spanning from 1987 to 2015 uncovered that the energy consumption in IMAR surged approximately seven-fold, the utilization of water resources increased four-fold, and extensive tracts of natural grasslands underwent conversion into urban land use, agricultural, and industrial. Apparently, the ecological compensation was not able to stop the trend of grassland ecological deterioration in IMAR.

This paper integrates the innovative conceptual frameworks of TSES [25] and social-ecological systems to examine the effectiveness of ESAP. It contributes to the current literature by filling the gaps for analyzing ecological systems' responses to ESAP, investigating its spatial heterogeneity, and exploring the meddling effects of integrated socio-environmental interactions on ESAP effectiveness. The novelty of the method reflects the integration of ecological, climate, and socioeconomic data, and several hierarchical linear mixed models (HLMM) to investigate how these factors affect ESAP effectiveness in IMAR from the perspectives of ecosystem biological responses, spatial disparities, and temporal dynamics. Section Two discusses the study area, the data, and the analytical method; Section Three presents the analysis results; Section Four discusses the findings and policy implications; and the conclusions are summarized in the last part.

2. Study Area, Data, and Analytical Method

2.1. Study Area

The Inner Mongolia Autonomous Region (IMAR), spanning latitudes from 37°24' to 53°23' North and longitudes from 97°12' to 126°04' East, is situated along China's northernmost border, encompassing the Inner Mongolia Plateau and boasting a total area of approximately 455,600 square miles (Figure 1). The study area, characterized by an average elevation ranging from 3280 to 3940 feet, is situated on the Inner Mongolia Plateau. The terrain is characterized by its flatness, bordered by the Greater Khingan Range in the eastern flank and the Yinshan and Henan Mountains to the south. The steppe area experiences a typical temperate continental climate, featuring annual precipitation

ranging from 50 to 450 millimeters and an annual average temperature varying between -1°C and 10°C. The climate undergoes a transformation from the east to the west, shifting from humid and semi-humid conditions to semi-arid and arid environments. The precipitation averages decrease progressively from the northeastern region towards the southwest, whereas the temperature exhibits an upward trend. The entire terrain spans diagonally from the northeast to the southwest, forming a lengthy and narrow expanse. Notably, IMAR constitutes the primary locale for temperate grasslands in China, occupying approximately 67% of the total regional area and 22% of the country’s overall grassland area.

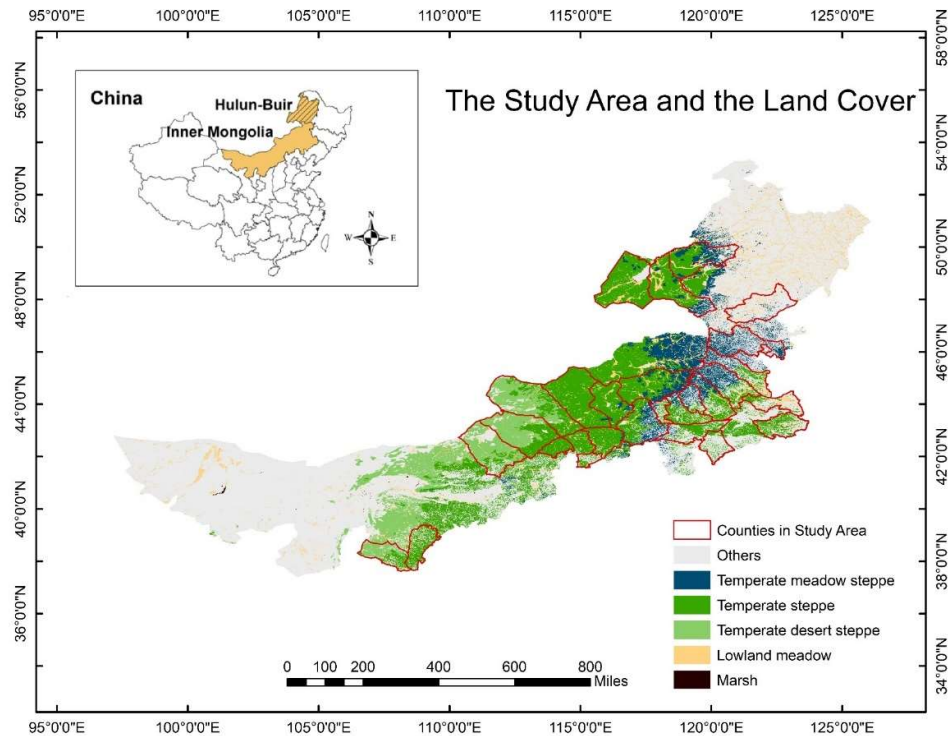


Figure 1. The Study Area: Inner Mongolia Autonomous Region of China and 26 Counties.

2.2. Data

The sample data were collected annually by the staff of county agricultural bureaus in IMAR in the peak growing month of August and compiled into an annual ArcGIS shapefile by the staff of the IMAR Institute of Grassland Surveying and Planning [17]. The attribute items include sample site index, longitude and latitude, county, town, data measurement time, vegetation characteristics (type, cover, height, above-ground biomass, etc.), soil characteristics, grassland utilization status (Table 1). The number of sampling sites gradually increased from around 500 in 2009 to over 1000 in 2015. However, the locations of sampling sites varied in a vicinity of 24.85 miles. Since ESAP was implemented in 2011, the most recent available data is the year of 2015. Three hundred ninety-two (392) pairs of samples were extracted based on the matched site locations between 2011 and 2015. These pairs of samples were distributed in 26 counties and 98 townships.

Table 1. Socioeconomic and sample data variables in the study.

Short Name	Long Name	Unit
cou_name	County name	
cid	County ID	
TID	Township ID	

cov	Coverage	percentage
height	Height	cm
n_s	Number of species	
bio	Biomass	kg m-2
g_type	Grass Type	
pre	total precipitation every 16-day period in the growing season)	mm
temp	averaged temperature every 16-day period in the growing season)	°C
DPop	county population density	100/Sq. Km
gdppc	per capita gross domestic product (GDP) by a county	1,000 Yuan pc
prpop	percent of rural population to total population by a county	%
iofp	net income of farmers and pastoralists by a county	%
lssk	the amount of livestock per square kilometer by a county	100 Head/Sq.Km
gpsk	grain production per square kilometer by a county	Ton/Sq.Km
Grass	percentage of grassland area to total land area	% in county
CropPG	percentage of crop area and planted grassland for harvest to grassland	% in county
Urban	percentage of urban area to total land area	% in county
gova	the gross output value of farming, forestry, animal husbandry, and fishery - share of GDP by a county	%
Paa	percent of the arable area to total land area by a county	%
fai	fixed assets investment - share of GDP by a county	%
lgr	local government revenue - share of GDP by a county	%
lohsk	the total length of highways per square kilometers by a county	Km/Sq.Km)
HMP	health & medical professionals per ten thousand people by a county	person/10,000 people
HPB	hospital beds per ten thousand people by a county	bed/10,000 people
MHT	middle & high school teachers per ten thousand people by a county	person/10,000 people
PTE	professional & technical employment per ten thousand people by a county	person/10,000 people
PcUDI	per capita disposable income of permanent urban residents by a county	1000 Yuan pc
PIO	primary industry output value - share of GDP by a county	%
SIO	secondary industry output value - share of GDP by a county	%

TIO	tertiary industry output value - share of GDP by a county	%
TCRV	total consumer retail value - share of GDP by a county	%

Source: IMAR Statistical Bureau, and IMAR Agricultural Bureau.

The selection of socioeconomic data is based on the literature review. The fundamental conditions pertaining to the land and people of the research area are disclosed through the total area, overall population, rural population, and arable area [18]. The traditional indicators that reflect the state of the grassland economy encompass gross domestic product (GDP), livestock volume, grain production, and agricultural income [19]. The state of regional economic growth is mirrored in local government revenues, state investment, and the length of highways [20]. The socioeconomic statistics for the years 2011 and 2015 were sourced from the statistical yearbooks published by the IMAR [21]. The total area and total population were used as the basis for normalizing the socioeconomic data. For example, population density (PopDen) was the normalized total population over the total area; rural population percentage was the normalized rural population by the total population. All other variables were normalized by the total population as per capitals (Table 1).

2.3. The Analytical Method

The conceptual frameworks of the analysis are the total socioenvironmental systems (TSES) [5]. TSES builds on the nature-society coevolution theory [22–24]. This coevolution accounts for interactions and feedback between the biological species, their abiotic environment, and their socioeconomic and cultural conditions. TSES supports a comprehensive and quantitative assessment of spatial disparities and temporal dynamics of a TSES system, an exploration of TSES’ interactions and trade-offs by uncovering the hidden causal relationships, and an investigation of multi-scaled spatial autocorrelations to reveal TSESs’ multi-scaled interactions and trade-offs [25].

TSES recommends the mixed panel data regression model for area-enumerated socio-environmental systems (statistical data are compiled over administrative or socioeconomic boundaries) and the hierarchical linear mixed model (HLMM) for samples-based socio-environmental systems [26]. Ecologists have adapted HLMM for over a decade to overcome random effects or non-normal distributions typically found in experimental and observational ecological information [27]. In ecological and environmental studies, random effects are frequently modeled statistically in order to investigate the variabilities that exist among communities, species, individuals, times, and regions [28]. The capability of HLMM in managing random effects is commensurate with the incorporation of grouping, categorical, or indicator variables within the framework of panel data regression modeling. Apart from modeling differences among communities, spatial and temporal dimensions, heterogeneous impacts of managerial, financial, and economic variables may be incorporated into HLMM as random effects or covariates of random effects. A hierarchical linear mixed model can be expressed as follows [29].

$$y_{ij} = x_{ij}\beta + z_{ij}\mu_i + e_{ij} \tag{1}$$

where y_{ij} is a matrix of the response variable observations across the i th subject and the j th repeated measure; β is a vector of regression coefficients for the fixed effect; x_{ij} is the $i \times j$ matrix of covariates for fixed effects; z_{ij} is the $i \times j$ matrix of covariates for random effects; μ_i is a vector of random effects over the j repeated measures; and e_{ij} are the residuals.

Eq. 1 reveals that HLMMs can account for the correlation caused by the repeated measures over the sampling sites [30], which are common in ecological and environmental studies [31]. HLMMs’ capability of handling random effects and repeated measures also enables GLMMs to analyze hierarchical (multilevel) models [32]. Repeated measures of individuals or samples are analyzed at the bottom level. Random effects over communities, locations, or times can be modeled at higher levels, consisting of a hierarchical model. Another strength of HLMM is that it deals with non-normal

distributions. Generalized linear models can handle non-normal response variables by linking them with logistic, Poisson, and ordered multinomial regression [28,33].

We implement the analysis in several interconnected steps, as depicted in Figure 2. First, we constructed a unified socio-environmental dataset by combining the ecological samples with socioeconomic statistics collected at town and county administration units. The samples contained biological information about the sample sites, which is critical to assessing ecological responses to ESWP. We conducted a descriptive analysis of the ecological samples two times, in 2011 and 2015, to see how the ecological characteristics changed due to the ESWP implementation in 2011.

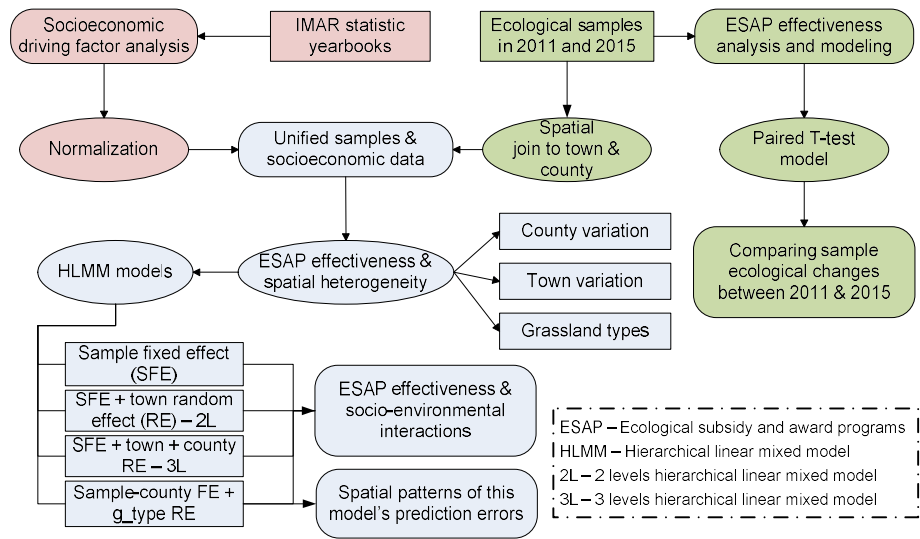


Figure 2. The flow chart of the analysis.

Afterward, we developed several HLMM models with three nested hierarchical spatial structures: samples, towns, and counties. The biological characteristics and socioeconomic factors were fitted into the HLMM models to examine causal relationships between biomass changes and their underlying driving factors. Furthermore, grassland types (g-types), along with towns and counties, were the random effects in these HLMM models, respectively, revealing spatial heterogeneity of biological characteristics and their interactions with socioeconomic driving factors at different scales.

3. Results

This section presents two sets of results: (1) the comparison of grassland biological characteristics before (the year 2011) and after (the year 2015) the adoption of ecological compensation policy in the study area and (2) the development of several HLMMs that explain the spatial heterogeneity of ecological compensation policy effectiveness and its main driving factors from perspectives of samples, townships, and counties.

3.1. Comparison of Grassland in 2011 and 2015

To explore the effectiveness of the ecological compensation policy in the study area, we first compared the grassland condition in 392 pairs of samples to see whether there were differences in coverage, height, number of species, and biomass in 2011 and 2015. The results in Table 2 show significant variations in the number of species, biomass, and height of vegetation conditions between these two years, while the coverage of grassland tends to stay the same over time. To further understand the 2-year grassland difference in social and ecological environments, we conducted pair sample tests to examine the biomass difference in 2011 and 2015 by grouping the samples based on grass type and county. The results are presented in Table 3. Overall, biomass differences in 2011 and 2015 vary over county and grass type. Specifically, in the temperate desert steppe region and seven

counties, biomass increased from 2011 to 2015, while in temperate meadow steppe, temperate steppe, marsh, and lowland meadow regions along with 18 counties, biomass illustrated decrease trends.

Table 2. Pair samples t-tests between 2011 and 2015 in 392 samples.

		Paired Difference	t	P value
Pair1	cov11 - cov15	3.613	.493	.622
Pair2	height11 - height15	4.0289	2.153	.032
Pair3	n_s11 - n_s15	2.190	4.254	.000
Pair4	bio11 - bio15	30.731962353	4.195	.000

Table 3. Biomass changes between 2011 and 2015 based on 26 counties and 5 grass types in the study area.

Summary	
Biomass Increase County:	368, 501, 884, 885, 2206, 2207, 2304
Biomass Increase grass type:	Temperate desert steppe
Biomass Decrease County:	366, 367, 368, 369, 372, 376, 876, 887, 2042, 2043, 2046, 2123, 2202, 2209, 2210,2211, 2212, 2301
Biomass Decrease grass type:	Temperate meadow steppe, Temperate steppe, marsh, and lowland meadow
Not Significant County	499 (small sample size)

3.2. Outcomes of SeveralHLMMs

Biomass measures from sample sites are used as the dependent variable. The observed biological characteristics of the samples (*cov*, *height*, *n_s*, *temp* and *pre*), including precipitation and temperature, are modeled as the fixed effects in HLMM. To examine the heterogeneities among communities, townships, and counties, three random effects models are built based on *CID*, *TID*, and *g_type*; one three-level hierarchical model is constructed with the nested spatial units, *TID* and *CID*. Furthermore, twenty-three socioeconomic variables (Table 1) are included in an expanded HLMM model (the added county-level explanatory variables as fixed effect with *g_type* random effect model) to explore how socioeconomic driving factors affect ecological compensation policy effectiveness.

1) A two-level model of biomass with County or Town Boundary effects

This study will commence by examining the simplest multilevel model, incorporating random effects of county or town boundaries on biomass without the inclusion of regressors (covariates or explanatory variables). The primary focus of this model lies in investigating the spatial heterogeneity inherent in biomass distributions. This two-level null model is written as,

$$Biomass_{ij} = \beta_o + \mu_{oj} + \varepsilon_{ij}$$

(1)

Where *Biomass_{ij}* is the biomass weight of Sample *i* in County (or Town) *j*, *β_o* is the overall mean biomass across Counties (or Towns); *μ_{oj}* is the effect of County (or Town) *j* on *Biomass_{ij}*, and *ε_{ij}* is the Sample site level residual. The County (or Town) effects, *μ_{oj}* are also called County (or Town, or level 2) residuals. This model for the County outcome is reported in Table 4.

Table 4. The outputs of the two-level null model at the Sample and County levels.

Mixed-effects ML regression	Number of obs	=	784
Group variable: cid	Number of groups	=	26
Obs per group:			

					min	=	2
					avg	=	30.2
					Max	=	80
					Wald chi2(0)	=	.
Log likelihood = -4385.769		Prob > chi2			=	.	
bio	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]	
cons	83.867	7.069	11.860	0.000	70.012	97.721	
Random-effects Parameters		Estimate			Std. Err.	[95% Conf.	Interval]
cid: Identity							
var(_cons)		1024.84			.	.	.
var(Residual)		3976.57			.	.	.

LR test vs. linear model: chibar2(01) = 91.88 Prob >= chibar2 = 0.0000.

The overall mean biomass (across Counties) is estimated as 83.87. The biomass at County j is calculated as $83.87 + \mu_{oj}$, where μ_{oj} is the County residual stated in Table 3. When a County has a $\mu_{oj}>0$, its biomass exceeds the average, while $\mu_{oj}<0$ for a below-average County. For example, Sonid Right Banner (苏尼特右旗, cid=2206) had an estimated residual of -46.71, ranked 1, i.e., the first place from the bottom. For this county, we estimate a mean biomass of $83.87 - 46.71 = 37.16$, the lowest biomass in Inner Mongolia, China. Sonid Right Banner is positioned in the western sector of Xilingol grassland, and it has been rated “very serious alerts” or “serious alerts” because of its severely deteriorated ecosystem security [34]. On the other hand, the highest biomass occurs in Horqin Left Back Banner (科尔沁左翼后旗). Its biomass is estimated as $83.87 + 62.67 = 146.54$. This county is located on the eastern border of Inner Mongolia, adjacent to China’s Northeast Plain. It has a semi-humid climate and vast grasslands. With the ecological compensation policy, this county reversed the trend of ecological deterioration, and its grasslands were recovering [35]. The biomass rankings over 26 counties are graphed in Figure 3. In combination with Table 5, they tell how spatial patterns of sample biomass were distributed over Inner Mongolia.

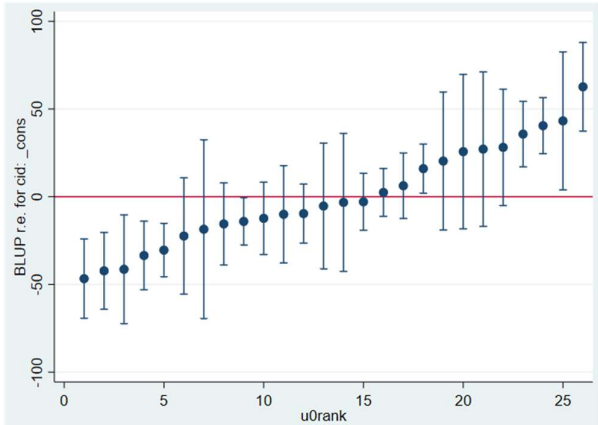


Figure 3. The ranking graph of the County random effects.

Table 5. Estimates of County random effects and standard errors.

Name	cid	μ_{oj}^1	μ_{oj}^{rank}	ε_{ij}^2
苏尼特右旗 (Sonid Right Banner)	2206	-46.707	1	11.536
	2301	-42.256	2	11.168

	2123	-41.383	3	15.824
	2207	-33.477	4	9.986
	2211	-30.435	5	7.769
	2208	-22.372	6	16.926
	499	-18.537	7	26.005
	372	-15.518	8	11.943
	2202	-14.082	9	6.885
	2212	-12.328	10	10.528
	369	-10.030	11	14.143
	2043	-9.609	12	8.591
	368	-5.314	13	18.295
	501	-3.232	14	20.062
	2210	-2.893	15	8.289
	876	2.452	16	6.969
	2304	6.260	17	9.520
	885	16.003	18	7.146
	376	20.344	19	20.062
	2209	25.727	20	22.464
	887	27.133	21	22.464
	367	28.136	22	16.926
	884	35.701	23	9.520
	2046	40.513	24	8.149
	366	43.231	25	20.062
科尔沁左翼后旗 (Horqin Left Back Banner)	2042	62.674	26	12.904

¹ the estimates of the County random effects using empirical Bayes predictions. ² the standard errors of the empirical Bayes estimators.

Now, let’s assess the performance of this two-level null model. When we delve into the statistical analysis, the initial metric under consideration is the Variance Partition Coefficient (VPC). Specifically, we estimate the variance in biomass at the between-cid level (Level 2), denoted as $\text{var}(_cons)$, to be 1024.84. Furthermore, the variance within individual cids across samples (Level 1), referred to as $\text{var}(Residual)$, is estimated at 3976.57. Therefore, the total variance is $1024.84 + 3976.57 = 5001.41$. VPC is $0.205 (=1024.84 / 5001.41)$, which represents that 20.5% of the variance in biomass can be attributed to the differences between Counties. The likelihood ratio serves as the second statistic. To test the significance of county effects, we can conduct a likelihood ratio test comparing with a null single-level linear model: LR test vs. linear model, which is 91.88 on one d.f. (the two models vary from each other by exactly one parameter, accounting for the distinction.). Given that the critical value for a 5% significance level in a chi-squared distribution with one d.f. is 3.84, it is evident that 91.88 far exceeds this threshold. Thus, we are confident in concluding that there is overwhelming evidence that biomass shows an evident variation over counties.

Furthermore, the spatial variation of biomass over towns is also significant. We ran a two-level null model at the Sample and Town levels (Table 6). The town model’s variance partition coefficient (VPC) is slightly lower than its counterpart of the county model. The between-cid (level 2) variance in biomass, $\text{var}(_cons)$, is estimated as 917.59, and the within-TID between samples (level 1) variance, $\text{var}(Residual)$, is estimated as 3943.01. As a result, the total variance is 4860.60. VPC is 0.189

(=917.59/4860.60), which represents that 18.9% of the variance in biomass can be attributed to the differences between Towns within Counties.

Table 6. The outputs of the two-level null model at the Sample and Town levels.

Mixed-effects ML regression			Number of obs	=	784
Group variable: TID			Number of groups	=	98
Obs per group:					
			min	=	2
			avg	=	8
			Max	=	30
Wald chi2(0)				=	.
Log likelihood = -4403.68		Prob > chi2		=	.
bio	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]
cons	83.990	4.075	20.610	0.000	76.003 91.976
Random-effects Parameters			Estimate	Std. Err.	[95% Conf. Interval]
var(_cons)			917.587	.	.
var(Residual)			3943.009	.	.

LR test vs. linear model: chibar2(01) = 56.06 Prob >= chibar2 = 0.0000.

2) *A three-level model of biomass with both Towns and Counties effects*

The three-level biomass model is a direct extension of the two-level model. The intent is to explore how the county and the nested township affect the spatial heterogeneity of biomass distribution. Compared with Eq. 1, the three-level biomass variance model is formulated as the following.

$$Biomass_{ijk} = \beta_o + v_k + \mu_{jk} + \varepsilon_{ijk}$$

(2)

Where *Biomass_{ijk}* is the observed biomass for Sample*i*, Town*j*, and County *k*. *β_o* is the mean biomass across counties, *vk* is the effect of county *k*, *u_{jk}* is the effect of Town *j*, and *ε_{ijk}* is the Sample level residual error term. This model includes only an intercept, two random effects of Town and County, and a Sample level residual error term. The 3-level model simply decomposes the total variance in the Sample’s biomass into separate variance components over the county, town, and sample. It is assumed that the county and town effects, as well as the sample-level residual errors, are independently and normally distributed, each having a mean of zero and constant variances. The outcomes of this analysis are presented in Table 7.

Table 7. The county, town effects, and the sample level residual errors.

Group variable		Number of groups	Observations per Groups		
			Minimum	Average	Maximum
cid		26	2	30	80
TID		98	2	8	30
Total Observations = 784					
			Wald chi2(0)	=	.
Log likelihood	=	-4385.77	Prob > chi2	=	.
bio	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]
cons	83.867	7.069	11.86	0	70.01212 97.72111

Random-effects Parameters	Estimate	Std. Err.	[95% Conf.	Interval]
cid: Identity				
var(_cons)	1024.837	.	.	.
TID: Identity				
Var(_cons)	0.000	.	.	.
var(Residual)	3976.567	.	.	.

LR test vs. linear model: chibar2(02) = 91.88 Prob >= chi2 = 0.0000. Note: LR test is conservative and provided only for reference.

The top section of Table 7 reports two levels of grouping variables, cid (the county ID) and TID(the town ID), and the total observations. The second section shows the estimation log likelihood (in the terminology of the Stata software package). It reports ‘Log likelihood = -4385.77’. On the right-hand side, the Wald test ‘Wald chi2(0) = .’ assesses the current model against a constrained model to include only a constant in its fixed effects. This comparison has not been carried out as the current model does not include any fixed effect predictor variables. Thus, Stata reports a period ‘.’ (Stata’s syntax for a missing value) for the test statistic and the associated p-value ‘Prob > chi2 = .’.

The third section details the fixed effects. The intercept is 83.867, with a standard error of 7.069. Therefore, the mean biomass is estimated to be 83.867. The z-value, p-value, and 95% confidence intervals for this parameter estimate are also given. These statistics show that the mean biomass value is statistically significant.

The fourth section tells the estimated variance components. The first part is labeled ‘cid: Identity’, indicating that this section reports random parameters at the county level. The between-county variance is estimated as 1024.837. The second part, labeled ‘TID: Identity,’ shows that the estimated within-county-between-town variance is 0.000. The third part, labeled ‘var(Residual),’ exhibits that the estimated within-town-between-samples variance is 3976.567. We can now quantify the extent of variability at each level of our model hierarchy through the computation of variance partition coefficients (VPCs). These VPCs provide insight into the proportional contribution of counties, towns, and samples to the overall observed response variation in biomass observations. The three levels of VPCs are calculated as follows.

$VPC_v = \sigma_v^2 / (\sigma_v^2 + \sigma_u^2 + \sigma_\epsilon^2) = 1024.837 / (1024.837 + 0.000 + 3976.567) = 0.205$ (3)

$VPC_u = \sigma_u^2 / (\sigma_v^2 + \sigma_u^2 + \sigma_\epsilon^2) = 0.000 / (1024.837 + 0.000 + 3976.567) = 0.000$ (4)

$VPC_\epsilon = \sigma_\epsilon^2 / (\sigma_v^2 + \sigma_u^2 + \sigma_\epsilon^2) = 3976.567 / (1024.837 + 0.000 + 3976.567) = 0.795$ (5)

The VPCs confirm that 20.5% of the biomass variation lies between counties, 0.0% between towns within counties, and 79.5% between samples with towns. Therefore, the biomass variation across counties is moderate, and most biomass variations are present between samples within their towns. The VPCs also reveal that the variations between towns within counties are trivial (0.000).

Finally, the last two lines report a Log Ratio (LR) test, which compares the current model to a single-level model without county and town effects (i.e., linear regression). The LR test statistic is chi2(2) = 91.88 with a p-value that is almost zero ‘Prob > chi2 = 0.0000’ (p < 0.001, or more precisely p < 0.0005). Hence, the three-level model provides a markedly superior fit to the data compared to the single-level model. Notably, the final line of the output cautions that the ‘LR test is conservative in nature and serves merely as a reference point.’ This implies that the reported p-value actually represents an upper limit of the true p-value, thereby allowing us to reject the null hypothesis with even greater certainty and conviction.

3) *Adding sample-level explanatory variables as fixed effects with Town random effects*

We can add fixed effects to the samples (e.g., adding explanatory variables to Eq. 1):

$Biomass_{ij} = \beta_0 + \beta_1 cov_{ij} + \beta_2 height_{ij} + \beta_3 n_sij + \beta_4 temp_{ij} + \beta_5 pre_{ij} + u_{0j} + \epsilon_{ij}$ (6)

County (cid) or town (TID) works for the random effect. Based on the comparison, Eq. 6 performs better with the TID random effect. The outcome of Eq. 6 with TID is reported in Table 8.

Table 8. HLMM results for Biomass and related measurements with town as random effects.

Mixed-effects ML regression			Number of obs		=	784
Group variable: TID			Number of groups		=	98
			Obs per group:			
			min		=	2
			avg		=	8
			Max		=	30
			Wald chi2(5)		=	821.2
Log likelihood = -4123.26			Prob > chi2		=	0
bio	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
cov	1.512	0.100	15.140	0.000	1.316	1.708
height	1.996	0.146	13.620	0.000	1.709	2.283
n_s	0.045	0.409	0.110	0.913	-0.756	0.845
temp	1.919	0.944	2.030	0.042	0.069	3.769
pre	-0.065	0.017	-3.730	0.000	-0.099	-0.031
_cons	-30.323	7.554	-4.010	0.000	-45.129	-15.517
Random-effects Parameters			Estimate	Std. Err.	[95% Conf.	Interval]
TID: Identity						
Var(_cons)			344.332	.	.	.
var(Residual)			1965.023	.	.	.

LR test vs. linear model: chibar2(01) =46.04 Prob >= chibar2 = 0.0000.

First, the LR statistics report the performance of this random intersect model (Eq. 6) compared to the null model (Table 4). $LR = 2 \cdot (-4123.26 - -4403.68) = 280.42$ on 2 d.f. LR is much higher than the Chi-Square critical value at 95% with 2 degrees of freedom, 5.99. Consequently, compelling evidence underscores the profound and significant influence of these covariates (explanatory variables) on the sample biomass. Furthermore, the final entry in the table presents an additional LR test, contrasting it with the standard linear regression model. This second LR comparison reinforces the superiority of the town-level random effects model over its linear regression counterpart.

Second, we investigate the impact of the additional explanatory variables on the biomass. All five variables except for *n_s* (the number of species) statistically impact biomass based on $P > z$ (< 0.05). The variables, *cov* and *height*, strongly and positively affect biomass. Intuitively, biomass is higher when the grassland coverage is dense, or the plant height is tall. Two climate factors marginally affect the biomass. However, it was surprising to see a negative correlation between biomass and precipitation in this case study. When we looked at the annual precipitation changes, we found that precipitation was under the annual average and experienced a decline between the study period, 2011 – 2015, which led to a negative relationship between biomass and precipitation.

Third, adding these explanatory variables dramatically reduced the residual, *var(Residual)*, from 3943.01 in the null model (Table 6) to 1965.02 in the town random model.

4) Adding county-level explanatory variables with *g_type* random effects

We added county-level driving factors as the fixed effects and constructed an HLMM model using grass type as random effects, and the results are presented in Table 9. Based on the value and sign on the coefficients in the *g_type* random effect model, one unit of increase in the observations of *height* and *cov* would cause a rise in biomass by 2.154 and 1.30 units, respectively, assuming that other independent variables were held steady. The variables of *height* and *cov* showed the highest *z* values, which indicates that they are the most vital driving factor of biomass.

Table 9. HLMM results for Biomass with g_type as random effects.

Mixed-effects ML regression			Number of obs		=	784
Group variable: g_type			Number of groups		=	5
Obs per group:						
			min		=	6
			avg		=	156.8
			Max		=	576
			Wald chi2(28)		=	962.3
Log likelihood = -4046.9207			Prob > chi2		=	0
bio	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
height	2.154	0.147	14.700	0.000	1.867	2.441
cov	1.299	0.105	12.410	0.000	1.094	1.504
temp	4.288	1.040	4.120	0.000	2.250	6.325
Paa	11.839	2.870	4.120	0.000	6.214	17.465
iofp	9.338	2.377	3.930	0.000	4.680	13.996
HMP	0.963	0.284	3.390	0.001	0.407	1.520
fai	0.204	0.104	1.960	0.050	0.000	0.407
pre	0.019	0.021	0.890	0.374	-0.023	0.061
HPB	0.217	0.253	0.860	0.392	-0.280	0.713
prpop	0.125	0.232	0.540	0.591	-0.330	0.579
PcUDI	0.003	0.025	0.130	0.895	-0.045	0.052
TIO	-0.016	0.327	-0.050	0.960	-0.658	0.626
DPop	-35.730	33.563	-1.060	0.287	-101.513	30.052
SIO	-0.331	0.207	-1.600	0.110	-0.736	0.075
n_s	-0.639	0.397	-1.610	0.108	-1.417	0.139
Urban	-44.100	21.852	-2.020	0.044	-86.929	-1.270
MHT	-0.826	0.358	-2.300	0.021	-1.529	-0.124
CropPG	-0.183	0.075	-2.430	0.015	-0.331	-0.035
lgr	-5.204	1.937	-2.690	0.007	-9.000	-1.407
PTE	-0.166	0.059	-2.820	0.005	-0.282	-0.050
lssk	-18.949	6.320	-3.000	0.003	-31.335	-6.562
gdppc	-0.289	0.092	-3.130	0.002	-0.470	-0.108
gpsk	-0.443	0.129	-3.430	0.001	-0.697	-0.190
gova	-0.529	0.144	-3.670	0.000	-0.811	-0.247
Grass	-1.071	0.291	-3.690	0.000	-1.640	-0.501
TCRV	-1.119	0.282	-3.970	0.000	-1.671	-0.566
PIO	-2.443	0.485	-5.040	0.000	-3.393	-1.493
_cons	193.436	39.618	4.880	0.000	115.786	271.086
Random-effects Parameters			Estimate		Std. Err.	[95% Conf. Interval]
g_type: Identity						

Var(_cons)	559.688	.	.	.
var(Residual)	1748.174	.	.	.

LR test vs. linear model: chibar2(01) =13.37 Prob >= chibar2 = 0.0001.

Based on the $P > z$ critical value, < 0.05 , the twenty-three socioeconomic variables could be divided into three groups: (1) positively and significantly impacting biomass; (2) negatively and significantly affecting biomass; and (3) no significant impacts on biomass. Paa (percent of the arable area to total land area), iofp (net income of farmers and pastoralists), and HMP (health and medical professionals) belonged to the first group and exhibited significant positive impacts on biomass. Paa indicates the available land resource and positively impacts the grassland size. High iofp means wealthy communities, or good grassland resources and management. A high concentration of HMP also confirms good socioeconomic development.

A dozen socioeconomic variables ($P > z$ values are < 0.05 with negative coefficients) negatively impacted biomass. Most of them reflected economic or market intensities such as urban (urban construction area), lgr (local government revenue), lssk (the amount of the livestock per square kilometers), gdppc (per capita gross domestic product), gova (the gross output value of farming, forestry, animal husbandry and fishery), etc. Intensive socioeconomic activities often lead to excessive exploitation of grasslands and deterioration of grass plants (lower biomass) [26]. For example, a one-unit increase in an urban area could lead to 44 units of biomass reduction when other variables held no change. One unit increase in the livestock amount could reduce 19 units of biomass. We noticed that a group of variables concerning retail and tertiary industries showed no significant impacts on biomass.

Furthermore, we delved into the spatial disparities in the influence of ecological and socioeconomic determinants on grassland productivity, scrutinizing the deviations in predicted biomass across the 392 sampled locations. Spatial interpolation is used to derive the continuous surface across 392 samples over 26 counties using the sample residuals from the HLMM model. Figure 4 shows the spatial patterns of the performance of the added county-level explanatory variables with g_type random effects model. The residuals are medium to low in the areas where the dominant grass types are temperate steppe and temperate desert steppe, indicating the HLMM overestimates the biomass. The GLMM tends to underestimate the lowland and temperate grassland grassland biomass.

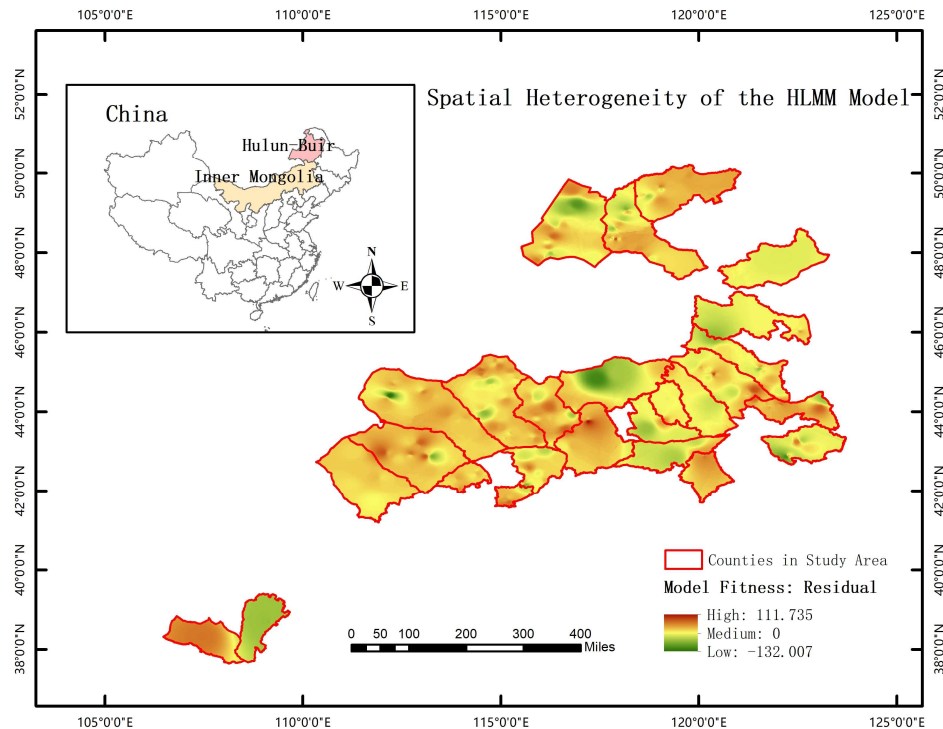


Figure 4. Spatial heterogeneity of the HLMM model. The figure is the map of residual interpolated in 26 counties.

4. Discussion

This research has significant findings. First, paired t-tests compared biomass in 2011 and 2015 from 392 samples across 26 counties in Inner Mongolia (IMAR). We found that the changes in biomass vary depending on the counties or grass types. The significance of annual precipitation stability in bolstering grassland productivity is readily apparent in arid and semi-arid areas akin to IMAR. We found that precipitation was declining during the study period, which complicates the effectiveness of the Ecological Subsidy and Award Program (ESAP).

Second, the sample biomass distributions and the ESAP show clear patterns. The county's administrative unit has a large spatial extent and contains complex geomorphological and ecosystem communities. Biomass responses to the ESAP vary significantly over counties. The ESAP is more effective in counties with better water conditions, developed local economies, or better management strategies. On the contrary, the ESAP is less effective in areas with adverse conditions. However, within counties, the differences between townships are less critical.

Third, the pivotal contributions of local communities, economic landscapes, and policy frameworks have been instrumental in safeguarding ecological systems and alleviating the impacts of natural disasters. We find that rapid urbanization, high grazing density, and large herds (sheep, horses, and cattle) cause disastrous damage to grassland vegetation and decrease biomass. Therefore, it is imperative to examine the key factors that affect the change in biomass. The HLMM models developed in this paper successfully reveal spatial heterogeneity of biomass distribution and the causal relationships between biomass change and main socio-economic driving factors.

Fourth, the HLMM models use county ID, town ID, and grass type as random effects and socioeconomic factors as the fixed effects. These models suggest that biomass changes to the ESAP differ spatially during the compensation policy implementation period. More importantly, the policy effectiveness behaves differently in different grass types and socioeconomic communities. Interestingly, at the county level, available land resources (the percent of arable land), hospital and

medical facilities, and net farmer and herdsman income are the most important factors contributing to grassland productivity.

On the contrary, high primary industries like mining (PIO), total consumer retail value (TCRV), the gross output value of animal husbandry, farming, forestry, and fishery value (gov), and GDP are the most damaging economic factors affecting biomass. This discovery carries significant policy weight regarding the effectiveness of ecological compensation. As IMAR is a key grazing region, excessive economic activity and intensified grazing severely cut grassland productivity, weakening the ESAP's impact. This should be considered together with government investment when considering how to implement ecological compensation policies at the local level.

Another worth noting point is that herdsman, whose livelihoods depend on the availability of pasture and water, require long-term assurance to maintain their traditional practices and sustain their herds. Short-term incentives, as elaborated on in literatures to be beneficial in the immediate term, often fail to address the underlying issues that herdsman face. These incentives might include temporary financial aid, short-lived subsidies, or limited access to resources, which do not provide the stability necessary for long-term planning and adaptation. Effective policy interventions should focus on creating sustainable and long-lasting solutions. Our work provides important insight for policymakers to integrate herdsman into a comprehensive TSES framework for instituting future ESAPs.

Note that the socioeconomic variables chosen for this study were confined solely to the statistical data published by the local statistical bureau. In certain scenarios, these indicators fall short of being comprehensive or adequate, potentially exhibiting limitations. To more accurately gauge the economic progression within IMAR communities, incorporating novel metrics and harnessing additional data sources, notably surveys, will become imperative in the impending future.

In summary, in this study, we integrated ecological modeling and socioeconomic analysis under the conceptual frameworks of total socio-environmental systems to examine the effectiveness of the Ecological Subsidy and Award Program (ESAP), analyze the responses of ecological systems to ESAP, investigate spatial heterogeneity of ESAP, and explore the meddling effect of integrated socio-environmental interactions on ESAP effectiveness. Our findings provided strong evidence that the above-ground biomass between 2011 and 2015 responds significantly to variations in both socioeconomic variables and different ecological communities, displays significant annual and regional variation, and reveals the heterogeneity of effectiveness of ESAP in the study area. Our study recommends a regionally or locally tailored ecological recovery policy to better incorporate government investment and local ecological characteristics and economic conditions, instead of a one-size-fits-all one, in the future effort to conserve grassland.

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