

Article

Spatial Inequality in Grassland Ecosystem Service Values and Fiscal Allocation Mismatch: A Meta-Regression Analysis of China

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Abstract

China possesses 400 million hectares of grasslands that provide regulating ecosystem services (ESs), including wind erosion control, water conservation, and carbon sequestration. The central government implemented the Grassland Ecological Protection Subsidy and Reward Policy (GERCP) in 2011, allocating 150 billion yuan (approximately \$23 billion) through 2020, while national vegetation coverage increased from 51.0% in 2011 to 56.1% in 2020. Existing valuation studies emphasize total economic value but rarely quantify the concentration of ES values across space or their alignment with fiscal allocation. We compiled 734 grassland ES valuation observations from 186 studies published between 2000 and 2024, and estimated a multi-level mixed-effects meta-regression model for benefit transfer. We projected standardized county-level ES values, decomposed spatial inequality using the Gini coefficient and Theil index, and assessed the mismatch between value-informed allocation weights and observed GERCP transfers. Predicted values exhibit high concentration (Gini coefficient = 0.58), and between-zone differences explain 52% of total Theil inequality. The mismatch analysis identifies 94 high-value and low-compensation counties concentrated in southern Qinghai and northern Tibet, where per-hectare values are 180 to 240% above national medians, and compensation is 35 to 55% below the median. The results support value-informed targeting and redistribution of fiscal weights across regions, while payment levels require pricing benchmarks based on opportunity cost or conservation cost rather than total economic value. We propose calibrating compensation rates through a tiered schedule based on ESV quantiles or standardized ecosystem-service bundles, and implementing county-level differentiated payments with periodic updating tied to monitoring and evaluation. As a minimum viable step, we recommend piloting this scheme in counties with high ESV yet low current compensation, and integrating it into existing ecological compensation funding channels to reduce administrative frictions.



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1. Introduction

1.1. The Paradox of Grassland Conservation

China possesses 400 million hectares of grasslands, which constitute the nation's largest terrestrial ecosystem and serve as a critical ecological barrier for wind erosion control in northern regions and water conservation in southern watersheds [1]. Grasslands provide regulating services, including erosion control and flood mitigation, that benefit downstream

populations [2]. The central government implemented the Grassland Ecological Protection Subsidy and Reward Policy (GERCP) in 2011, allocating 150 billion yuan (approximately \$23 billion) through 2020 for pastoral regions. National monitoring data indicate that comprehensive grassland vegetation coverage increased from 51.0% in 2011 to 56.1% in 2020, suggesting apparent conservation success [3]. Field surveys across Inner Mongolia, Qinghai, and Xinjiang demonstrate that the Grain to Green Program (GTGP) reduced grazing pressure on degraded grasslands by 28% and improved aboveground biomass by 15–22% over a decade [4].

This vegetation recovery, however, masks a deeper economic contradiction. While aggregate ecological quality improves through substantial fiscal investment, the distribution of economic benefits derived from these services remains poorly understood. Recent global meta-analyses highlight the complexity of grassland restoration outcomes and the role of methodological and temporal constraints in valuation studies [5]. China-specific meta-analysis estimates the total grassland ecosystem service (ES) value at 6.22 trillion yuan annually, equivalent to 6% of national GDP and 80% of agricultural GDP, with 84% of this value concentrated in regulating services rather than provisioning services [1]. These regulating services, particularly water conservation and soil retention, generate benefits that flow downstream to densely populated and economically developed eastern regions. The western pastoral regions that maintain these grasslands possess limited fiscal capacity and lower levels of public service provision. This situation creates a condition where economically disadvantaged regions provide ecological benefits for wealthier areas without adequate compensation [6,7]. Grassland restoration in western China generates substantial ecological returns but requires sustained fiscal transfers to bridge the gap between local costs and downstream benefits [8].

1.2. From Total Value to Spatial Inequality

Current literature extensively quantifies the total economic value (TEV) of grassland ecosystems through benefit transfer, contingent valuation, and market pricing approaches. Global-scale meta-analyses estimate grassland ES values exceed \$20 trillion annually [9], while China-specific studies document regional variations in per-hectare values ranging from 800 to 45,000 yuan per hectare per year, depending on grassland type, climate conditions, and service categories [1,10]. Regional assessments in the Tibetan Plateau and the Yellow River Source have examined spatiotemporal ecosystem service value (ESV) patterns and drivers [11,12]. These studies establish that grassland ES values vary substantially across space, but they primarily report mean values, aggregate totals, or provincial comparisons.

Two distinct concepts require clarification for this analysis. Spatial heterogeneity refers to the existence of differences in ES values across locations. Spatial inequality refers to the concentration and distributional structure of these differences, measured through indices such as the Gini coefficient and Theil index that quantify how values concentrate among spatial units. Spatial heterogeneity may reflect functional units shaped by abiotic conditions, including topography, climate, and soil characteristics [13]. Inequality measurement extends beyond documenting heterogeneity to assess whether value distributions exhibit high concentration comparable to income inequality in economic analysis. The Gini coefficient ranges from 0 (perfect equality) to 1 (maximum inequality), while the Theil index enables decomposition into between-group and within-group components. Moran's I statistic, by contrast, measures spatial autocorrelation rather than inequality structure and serves a complementary diagnostic role.

Recent high-impact studies on urban gross ecosystem product in China and ESV dynamics in the Yellow River Source region focus on spatiotemporal evolution patterns

and driving factors [12,14]. These studies do not quantify the structural concentration of ES values using inequality indices or assess alignment between value distributions and fiscal compensation allocation. This gap prevents the identification of which regions face systematic undercompensation relative to their ecological contributions. Improving the spatial targeting efficiency of payment for ecosystem services (PESs) requires incorporating degradation risk and value distribution patterns into allocation decisions [15].

Methodological heterogeneity in valuation studies constitutes a separate but related challenge. Market-based methods, including factor income and replacement cost approaches, rely on observable prices for ecosystem outputs or substitutes. Contingent valuation and choice experiments elicit stated preferences through surveys, which incorporate subjective perceptions, strategic responses, and hypothetical bias. Meta-analyses consistently demonstrate that valuation method choice explains 25–40% of variance in reported ES values after controlling for ecosystem characteristics [1]. The equivalence coefficient method, widely applied in Chinese ES valuation studies, assigns standardized value coefficients to different land cover types based on expert judgment or literature synthesis. These methodological differences generate systematic variation in reported values that must be distinguished from true spatial heterogeneity in service provision.

The relationship among ESV, TEV, and payment for ecosystem services (PESs) requires explicit specification. Researchers use ESV and TEV to characterize spatial distributions of ecological value and identify priority areas for conservation. PES mechanisms, by contrast, typically base payment levels on opportunity costs of conservation or protection costs rather than on full ecological value. The mismatch concept employed in this study refers to the deviation between the spatial distribution of ES values and the allocation structure of fiscal compensation. This analysis does not equate TEV directly with required compensation amounts, which would conflate value measurement with payment design.

Without a clear understanding of value distribution, uniform compensation policies risk creating spatial mismatches between ecological provision and fiscal allocation. Willingness-to-pay studies in arid northwest China reveal a counterintuitive pattern where residents in water-scarce regions express lower willingness to pay for water conservation services than residents in water-abundant regions, suggesting that resource scarcity does not automatically translate into higher perceived value [16]. Rangeland research in semi-arid regions identifies trade-offs between provisioning services (livestock production) and regulating services (carbon sequestration, erosion control), where moderate grazing maintains both services, but intensive grazing degrades regulating functions by 40–60% [17]. Compensation standard calculations demonstrate wide ranges in required payment levels. Analysis of Qilian Mountain National Park estimates the necessary compensation between 3.7 and 28.2 billion yuan annually, depending on assumed service values and beneficiary populations [18]. Priority sequence analysis in Zhijiang City ranks regions for compensation based on ES value provision and ecological risk, identifying target areas where compensation would generate maximum conservation impact [19]. International comparisons reveal substantial funding gaps, with grassland conservation in the United States requiring estimated annual compensation 57 times higher than current program budgets to maintain existing ES provision levels [20]. These findings imply that compensation mechanisms must account for complex spatial heterogeneity rather than applying blanket per-hectare payments.

1.3. Research Objectives and Contributions

This study addresses three critical gaps in the grassland ES valuation literature. First, researchers lack systematic quantification of spatial inequality in grassland ES values using formal inequality indices comparable to those employed in income distribution analysis.

While researchers recognize that values vary across regions, the degree of concentration and its implications for policy design remain unclear. Second, although meta-regression studies identify multiple drivers of valuation heterogeneity, including natural conditions, socioeconomic contexts, and methodological choices, these factors have not been translated into operational information for land management and compensation design. Existing coefficients from regression tables do not clarify which drivers contribute most to observed inequality or how much inequality would remain if certain factors were controlled for. Third, policy evaluations of grassland conservation programs measure success through vegetation coverage and livestock numbers, but they rarely assess whether compensation allocation aligns with the spatial distribution of monetized ES values. This disconnection prevents the determination of which regions face undercompensation relative to their ecological contributions.

Three research questions guide this study:

1. What is the degree of spatial inequality in grassland ES monetary values across China's grassland regions, and how does the Theil index decomposition partition total inequality into between-zone and within-zone components?
2. Which methodological factors (valuation method, service scope, publication characteristics) and contextual factors (climate, productivity, population density, conservation program participation) systematically drive cross-study variation in reported ES values, and what proportion of variance does each factor category explain in the meta-regression model?
3. How can the mismatch between predicted ES value distributions and observed GERCP compensation allocation be identified and classified, and what are the fiscal magnitudes of undercompensation and overcompensation across mismatch types?

This research contributes to the grassland ES literature in three ways. Methodologically, we estimate a multi-level mixed-effects meta-regression model that separates natural, socioeconomic, and methodological drivers of valuation heterogeneity, and we apply the Gini coefficient and Theil index decomposition to quantify spatial inequality structure. In terms of data contribution, we compile 734 grassland ES valuation observations from 186 studies published between 2000 and 2024, and we project standardized county-level ES values across China's major grassland regions using spatially referenced covariate data. For policy application, we operationalize a value-compensation mismatch framework that classifies counties into four types based on quartile rankings, we map 94 high-value-low-compensation counties and 73 low-value-high-compensation counties, and we quantify fiscal reallocation magnitudes for budget-neutral redistribution scenarios.

Figure 1 illustrates the conceptual framework linking natural endowments, socioeconomic pressures, and methodological factors through meta-regression to spatial value prediction, inequality decomposition, and policy mismatch assessment. The remainder of this paper proceeds as follows. Section 2 develops the theoretical framework and hypotheses linking valuation drivers to spatial inequality and policy mismatch. Section 3 describes the systematic review protocol, meta-database construction, meta-regression specification, and inequality measurement methods. Section 4 presents results including descriptive patterns, regression estimates, spatial projections, inequality decomposition, and mismatch analysis. Section 5 discusses implications for precision compensation policy design and acknowledges limitations. Section 6 concludes with recommendations for value-based payment mechanisms.

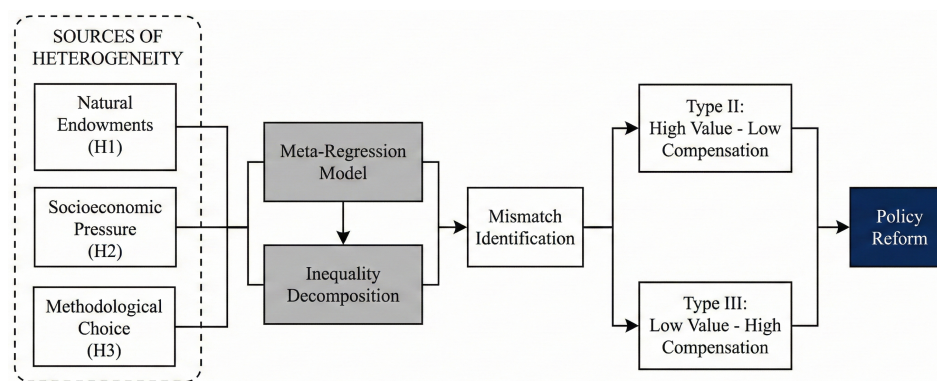


Figure 1. Conceptual framework for analyzing spatial inequality in grassland ecosystem service values and policy mismatch. The framework integrates natural, socioeconomic, and methodological drivers through meta-regression analysis to generate spatial value predictions, which are then analyzed for inequality patterns and compared with compensation allocation to identify policy mismatches.

2. Theoretical Framework and Hypotheses

2.1. Valuation Drivers: Natural Endowments and Human Pressures

Ecological theory establishes that natural endowments set the potential ceiling for ecosystem service provision through climate, topography, and soil characteristics. This natural endowment channel operates through biophysical mechanisms that determine grassland productivity and service generation capacity. Mean annual precipitation (MAP) and temperature determine grassland productivity through controls on plant growth rates, species composition, and biomass accumulation [10]. Net primary productivity (NPP), derived from remote sensing observations, integrates these climatic factors into a measure of actual vegetation production capacity. Terrain characteristics, including elevation, slope, and aspect, influence water retention, soil formation, and microclimate conditions that affect service generation [21,22]. Alpine meadows at 3000–5000 m elevation in the Qinghai–Tibet Plateau receive 400–700 mm of annual precipitation and maintain high soil organic carbon stocks. These conditions generate substantial carbon sequestration and water conservation values despite lower aboveground biomass compared to temperate grasslands.

The natural endowment channel predicts that spatial variation in ESV reflects the underlying distribution of biophysical conditions. Regions with higher precipitation, greater NPP, and moderate elevations possess greater capacity to generate regulating services. This capacity translates into higher monetary valuations when downstream populations benefit from water purification or when carbon markets provide mechanisms to monetize sequestration. The testable implication states that ESV should increase with MAP, NPP, and elevation after controlling for human pressures and valuation methods. The natural endowment variables in subsequent empirical analysis include MAP, mean annual temperature (MAT), NPP, elevation, and grassland type classifications.

We hypothesize that natural endowments exert positive effects on per-hectare ES values after controlling for valuation methods and socioeconomic conditions (H1: Natural Endowment Hypothesis). Higher MAP, NPP, and moderate elevations should be associated with higher monetary valuations because these conditions support greater service flows that generate benefits for human populations. This relationship should hold most strongly for regulating services (water conservation, carbon sequestration) that depend directly on vegetation productivity and ecosystem functioning.

Socioeconomic activities constitute a second channel that either realizes or diminishes the potential value established by natural endowments. This human pressure channel operates through degradation, land use intensity, and disturbance frequency. Population

density introduces multiple opposing forces on ES values. Higher population density increases local demand for regulating services such as air purification and microclimate regulation, potentially raising willingness to pay. Simultaneously, dense populations generate land use pressures that degrade grassland quality through conversion to cropland, urban expansion, and overgrazing. Empirical evidence from western Jilin Province demonstrates that population density correlates negatively with per-hectare ES values, with each 100-person-per-square-kilometer increase in density associated with 12–15% reductions in value [23]. This negative relationship arises because population growth drives grassland degradation faster than it increases local demand for services.

Urbanization produces similar degradation effects through land conversion and intensified resource extraction [24]. Urban expansion in the Dunhuang Oasis reduced grassland area by 18% between 1990 and 2020, converting rangeland to built-up areas and cropland. This conversion eliminated regulating services valued at approximately 8400 yuan per hectare annually. Economic development level, measured through GDP per capita, generates competing effects. Higher income regions may express greater willingness to pay for environmental quality, but they also possess greater capacity to substitute natural services with technological alternatives such as water treatment facilities and soil conservation infrastructure.

Conservation interventions, including grazing restrictions, rotational grazing systems, and GTGP implementation, modify these human pressures. Moderate grazing restrictions that reduce livestock numbers by 20–30% below historical peaks allow vegetation recovery while maintaining some provisioning services from animal products. Complete grazing bans, however, may reduce certain services such as seed dispersal and nutrient cycling that depend on herbivore interactions with vegetation [17]. GTGP implementation generates positive effects on regulating services by converting degraded grassland and cropland to restored vegetation, increasing ES values by 15–25% over 10-year restoration periods [3].

The human pressure channel predicts that ESV decreases with population density and urbanization intensity, while conservation program participation increases ESV. The testable implication states that after controlling for natural endowments and valuation methods, areas with higher population density or urbanization rates exhibit lower per-hectare values, while areas participating in GTGP or GERCP exhibit higher values. The socioeconomic variables in subsequent empirical analysis include population density, GDP per capita, urbanization rate, and conservation program implementation indicators.

These considerations lead to the Land Use and Pressure Hypothesis (H2): Human population density and urbanization reduce per-hectare ES values through degradation effects, while conservation programs increase values through restoration, after controlling for natural endowments and valuation methods. This hypothesis implies a potential threshold relationship where moderate human activity maintains multiple services, but intensive pressure degrades regulating functions disproportionately.

2.2. Methodological Heterogeneity in Valuation

Beyond physical and socioeconomic drivers, the choice of valuation methodology introduces systematic bias into monetary estimates through a distinct methodological choice channel. Market-based methods, including factor income and replacement cost approaches, rely on observable prices for ecosystem outputs or substitutes. Contingent valuation and choice experiments elicit stated preferences through surveys, which incorporate subjective perceptions, strategic responses, and hypothetical bias. The equivalence coefficient method, widely applied in Chinese ES valuation studies, assigns standardized value coefficients to different land cover types based on expert judgment or literature synthesis [25].

Meta-analyses consistently demonstrate that valuation method choice explains 25–40% of variance in reported ES values after controlling for ecosystem characteristics [1]. Market-based methods typically generate higher valuations than stated preference approaches for provisioning services, while stated preference methods capture non-use values that market approaches exclude. The choice of discount rate, study duration, and spatial extent further affects final estimates. Studies using 3% discount rates report values 40–60% higher than studies using 8% rates when assessing long-term regulating services like carbon sequestration.

Scale effects introduce additional methodological variation. Per-hectare ES values decline with study area size due to diminishing marginal returns and spatial heterogeneity within large regions [26]. A 1000-hectare grassland plot may generate per-hectare values 50% higher than the average across a 100,000-hectare region because small plots typically represent optimal conditions, while large regions include degraded and marginal areas. Psychographic characteristics of survey respondents, including environmental attitudes and cultural values, systematically affect willingness to pay estimates by 30–50% [27].

The methodological choice channel predicts that observed spatial variation in reported ESV partly reflects differences in study design rather than true differences in service provision. The testable implication states that after controlling for natural and socioeconomic characteristics, market-based valuation methods generate higher ES value estimates than stated preference methods. Study-level characteristics, including publication year, journal quality, service scope, and geographic focus, systematically affect reported values. The methodological variables in subsequent empirical analysis include valuation method categories, service scope indicators, publication year, and journal quality classification.

These methodological factors lead to the Method Bias Hypothesis (H3): After controlling for natural and socioeconomic characteristics, market-based valuation methods generate higher ES value estimates than stated preference methods, and study-level characteristics, including publication year, journal quality, and geographic focus, systematically affect reported values. This hypothesis implies that observed spatial inequality in values partly reflects methodological artifacts rather than true differences in service provision or economic value.

2.3. *The Logic of Policy Mismatch*

The relationship between ecosystem service valuation and payment for ecosystem services (PESs) design requires explicit conceptual specification. TEV or ESV provides a measure of ecological contribution that informs targeting decisions and priority identification. Researchers use ESV to characterize which regions generate greater ecological benefits and deserve conservation attention. Opportunity cost or conservation cost, by contrast, provides the efficiency benchmark for determining payment levels. Opportunity cost measures the foregone returns from alternative land uses that landholders sacrifice when maintaining grassland cover. Conservation cost measures the direct expenditures required to implement protection activities. Opportunity cost provides an efficiency benchmark for differentiated payments, while TEV informs targeting priorities [28]. This distinction clarifies that value measurement and payment design serve complementary but separate functions in conservation policy.

Ideally, fiscal transfer payments for ecosystem services should account for spatial variation in both ecological value and protection costs. Regions that generate substantial regulating services with downstream beneficiaries represent high-priority targets for conservation investment. Payment levels, however, should reflect the costs required to secure conservation behavior rather than the full ecological value generated. Institutional rigidity often prevents this alignment through uniform per-hectare payment formulas,

administrative boundaries that ignore ecological flows, and political economy factors that privilege certain regions over others.

The current GERCP framework allocates subsidies based on grassland area and live-stock reduction targets rather than ES value provision or opportunity cost variation. Provincial governments receive budget allocations proportional to total grassland area within their jurisdiction, with additional funds for counties that achieve specified vegetation coverage improvements. This area-based approach assumes uniform per-hectare values and uniform opportunity costs across grassland types and regions, ignoring the 50-fold variation in actual values documented in the literature [1].

We define mismatch as the deviation between the spatial distribution of ES values and the allocation structure of fiscal compensation. This definition focuses on the weighting structure rather than absolute payment levels. A mismatch occurs when regions contributing high ES values receive disproportionately low shares of total compensation, or when regions contributing low ES values receive disproportionately high shares. Cost-based identification can improve the efficiency of ecological compensation allocation, which clarifies why a mismatch between value patterns and fiscal weights may generate efficiency losses [29]. Misalignment between value provision and compensation allocation creates two types of inefficiency. Undercompensated high-value regions face weakened conservation incentives and potential degradation. Overcompensated low-value regions absorb fiscal resources that could generate greater conservation impact elsewhere.

Compensation standard calculations in several provinces demonstrate wide ranges in required payment levels. Analysis of Qilian Mountain National Park estimates necessary compensation between 3.7 and 28.2 billion yuan annually, depending on assumed service values and beneficiary populations [18]. Priority sequence analysis in Zhijiang City ranks regions for compensation based on ES value provision and ecological risk, identifying target areas where compensation would generate maximum conservation impact [19]. International comparisons reveal substantial funding gaps. Grassland conservation in the United States requires an estimated annual compensation 57 times higher than current program budgets to maintain existing ES provision levels [20]. These findings suggest that undercompensation constitutes a widespread challenge.

These findings motivate the Value-Compensation Mismatch Hypothesis (H4): At the national scale, limited correlation exists between per-hectare grassland ES values and per-hectare compensation intensity, with systematic patterns of high-value-low-compensation and low-value-high-compensation regions. This mismatch implies that current PES mechanisms fail to align fiscal allocation with ecological contribution patterns efficiently, potentially undermining long-term conservation incentives in high-value regions while misallocating resources to lower-value areas.

2.4. Analytical Framework

We synthesize these theoretical components into an integrated framework linking valuation drivers, meta-regression analysis, and policy mismatch assessment. The framework operates through three sequential stages. First, we compile grassland ES valuation observations from published studies, extracting per-hectare monetary values along with natural characteristics (MAP, NPP, elevation, grassland type), socioeconomic attributes (population density, GDP per capita, conservation program presence), and methodological features (valuation method, service categories, study year) for each observation.

Second, we employ mixed-effect meta-regression where observed values depend on natural, socioeconomic, and methodological variables plus study-level random effects that capture unobserved heterogeneity. This model identifies how much each factor category contributes to explaining observed variance in values. We then predict standardized

values across China's grassland regions by holding methodological factors constant and varying natural and socioeconomic conditions according to spatial data. Third, we calculate inequality indices for the predicted value distribution and decompose total inequality into components attributable to different sources using the Theil index decomposition. We compare the spatial pattern of predicted values with actual compensation allocation data to identify mismatch types, including high-value-low-compensation (undercompensated), low-value-high-compensation (overcompensated), and well-matched regions.

This framework explicitly connects three analytical components: meta-regression to identify value drivers, inequality decomposition to quantify concentration, and mismatch analysis to assess policy alignment. The three theoretical channels (natural endowment, human pressure, methodological choice) map onto three groups of explanatory variables that subsequent sections operationalize and estimate. The integration allows determination of not only that inequality exists and what drives it, but also whether policy responses account for this inequality or exacerbate it through misaligned resource allocation. Figure 1 illustrates the conceptual framework linking natural endowments, socioeconomic pressures, and methodological factors through meta-regression to spatial value prediction, inequality decomposition, and policy mismatch assessment.

3. Methodology

3.1. Data Collection and Screening

We conducted a systematic literature review following PRISMA guidelines to construct a comprehensive meta-database of grassland ES valuation studies in China. The search strategy employed multiple databases, including Web of Science (WoS), China National Knowledge Infrastructure (CNKI), and Google Scholar, using combinations of keywords: (grassland OR rangeland OR meadow OR steppe) AND (ecosystem service OR ecological value OR economic value) AND (China OR Chinese). We limited searches to studies published between January 2000 and December 2024 to capture the period of major policy interventions and methodological developments in ES valuation.

Inclusion criteria required that studies: (1) reported monetary valuations of grassland ecosystem services in China; (2) provided sufficient information to extract or calculate per-hectare annual values in yuan; (3) specified geographic location, grassland type, or ecological zone; (4) described valuation methods employed; and (5) appeared in peer-reviewed journals, books, or government reports. We excluded studies that: (1) reported only physical quantities without monetary valuation; (2) focused exclusively on non-grassland ecosystems; (3) provided aggregate values without per-hectare normalization; (4) lacked essential metadata on location or methods; (5) duplicated results from the same research site and time period.

Initial database searches yielded 3847 potentially relevant records. Title and abstract screening eliminated 2956 records that clearly failed the inclusion criteria. We retrieved and assessed 891 full-text articles, excluding 705 due to insufficient data, duplication, or quality concerns. The final database contains 734 valuation observations from 186 unique studies spanning all major grassland regions in China. Here, n denotes the number of valuation observations (valuation entries) in the meta-database, whereas studies refers to the number of distinct primary studies. Figure 2 presents the PRISMA flow diagram documenting the systematic review process.

Observations are distributed across grassland types as follows: alpine meadow ($n = 198$), temperate steppe ($n = 302$), alpine steppe ($n = 86$), meadow steppe ($n = 94$), desert steppe ($n = 54$). Service categories include regulating services ($n = 412$), provisioning services ($n = 178$), cultural services ($n = 89$), and supporting services ($n = 55$).

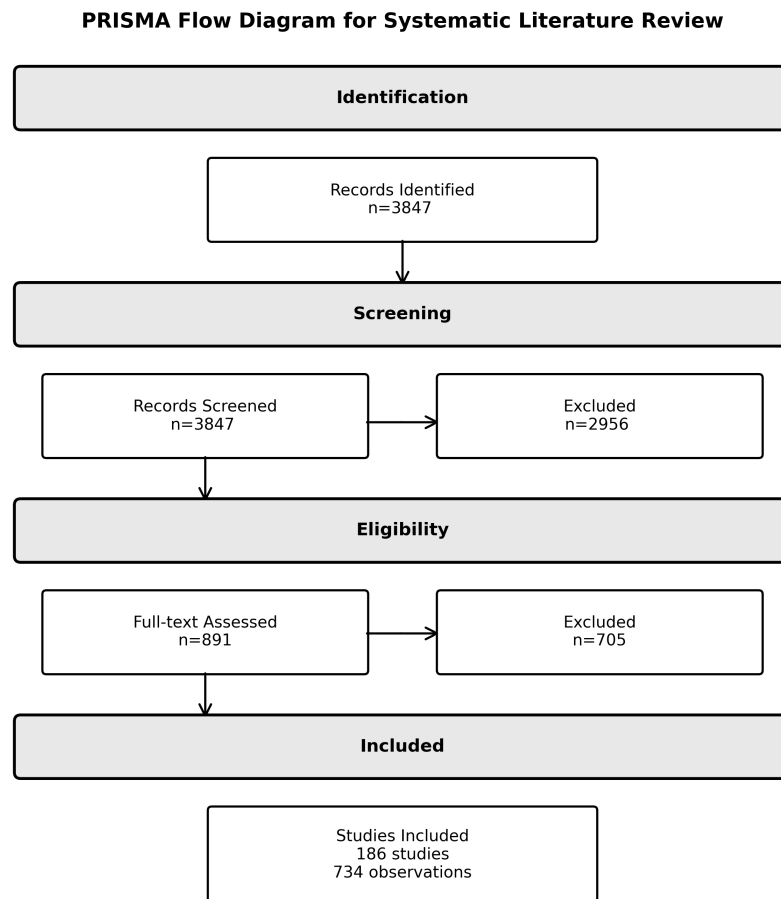


Figure 2. PRISMA flow diagram for systematic literature review and study selection. The diagram shows the identification, screening, eligibility assessment, and final inclusion of studies in the meta-database.

3.2. Variable Construction and Standardization

The meta-regression approach requires systematic specification of explanatory variables that capture distinct sources of spatial variation in ecosystem service values. We organize explanatory variables into three groups corresponding to the theoretical channels developed in Section 2. The natural endowment group includes climate, productivity, terrain, and vegetation type variables that determine biophysical service provision capacity. The socioeconomic and human pressure group includes population density, economic development, urbanization, and conservation program variables that modulate realized service provision through degradation or enhancement. The methodological and study design group includes valuation method, service scope, publication characteristics, and scale variables that introduce systematic variation in reported values independent of true service differences. These three variable groups jointly identify the sources of ESV spatial variation, with the meta-regression model estimating the marginal contribution of each group while controlling for the others.

The dependent variable, ecosystem service value (ESV), measures the monetary value of services provided per hectare per year. We standardized all values to 2020 constant yuan using the Consumer Price Index (CPI) published by the National Bureau of Statistics. For studies reporting values in other currencies, we converted to yuan using average annual exchange rates for the study year, then adjusted to 2020 constant yuan. When studies reported ranges or multiple estimates, we calculated the arithmetic mean. Total ES values were divided by the reported area to obtain per-hectare annual values. These conversions harmonize cross-study differences in currency units, price levels, and measurement

scales, while remaining heterogeneity in valuation protocols and study design is addressed through the methodological and context controls included in the meta-regression.

Natural endowment variables capture biophysical characteristics that determine service provision capacity. Mean annual precipitation (MAP, mm) and mean annual temperature (MAT, degrees Celsius) derive from meteorological station data matched to study locations using coordinates or place names. For studies covering large regions, we calculated area-weighted averages from gridded climate data. Net primary productivity (NPP, g C/m²/year) comes from MODIS satellite data products averaged over the study period. Elevation (meters above sea level) represents the mean elevation of study areas from digital elevation models. Grassland type classifies vegetation into five categories (alpine meadow, alpine steppe, meadow steppe, temperate steppe, desert steppe) based on the Chinese Grassland Classification System.

Socioeconomic variables characterize human pressures and economic contexts. Population density (persons/km²) measures residential population within the study area from census data or statistical yearbooks. GDP per capita (yuan, 2020 constant prices) represents the economic development level. Urbanization rate (percent of population in urban areas) quantifies the degree of urban influence. Conservation program implementation dummy variables indicate whether study areas participate in GTGP (1 if yes, 0 if no) or GERCP (1 if yes, 0 if no) during the study period. Grazing intensity, when reported, measures livestock density (sheep units per hectare).

Methodological variables control for valuation approach and study design heterogeneity. Valuation method classifies studies into six categories: market price method, replacement cost method, shadow price method, contingent valuation method, choice experiment method, and equivalence coefficient method. Service scope indicates whether studies value single services, multiple services, or total ecosystem value. Publication year captures temporal trends in valuation practice and economic conditions. Journal quality classifies studies published in international journals indexed in WoS as high quality versus domestic journals and reports as standard quality.

Table 1 presents descriptive statistics for all variables. The mean per-hectare ES value across observations is 8742 yuan with a standard deviation of 12,356 yuan, reflecting substantial heterogeneity. Natural condition variables show wide ranges: MAP varies from 89 mm in desert steppes to 782 mm in alpine meadows; NPP ranges from 98 to 876 g C/m²/year; elevation spans 342 to 4687 m. Socioeconomic variables exhibit similar variation with population densities from 2.3 to 547 persons/km² and GDP per capita from 8450 to 168,230 yuan. Approximately 38% of observations come from study areas participating in GTGP and 42% from GERCP areas.

3.3. Meta-Regression Model

We employ a multi-level mixed-effect linear regression model to analyze valuation determinants while accounting for the hierarchical structure of observations nested within studies. This approach follows established best practices for meta-regression benefit transfer (MRBT), which provide guidance on model specification, coefficient interpretation, and uncertainty communication [30]. The model specification is as follows:

$$\ln(ESV_{ij}) = \alpha + \beta_1 X_{nat,ij} + \beta_2 X_{soc,ij} + \beta_3 X_{met,ij} + u_j + \epsilon_{ij} \quad (1)$$

where ESV_{ij} represents the ecosystem service value for observation i from study j ; X_{nat} , X_{soc} , and X_{met} denote vectors of natural endowment, socioeconomic, and methodological variables as defined in Table 1; β_1 , β_2 , and β_3 are coefficient vectors; u_j represents study-level random effects distributed $N(0, \sigma_u^2)$; and ϵ_{ij} denotes observation-level errors

distributed $N(0, \sigma_\epsilon^2)$. We apply a natural logarithm transformation to ESV to address a right-skewed distribution and facilitate interpretation of coefficients as percentage changes.

Table 1. Descriptive statistics of variables in the meta-database (n = 734 observations).

Variable	Mean	Standard Deviation	Min	Max	Unit
Dependent Variable ES Value	8742	12,356	224	89,456	yuan/ha/year
Natural Endowment Variables					
Mean Annual Precipitation	438	186	89	782	mm
Mean Annual Temperature	4.2	5.8	−4.1	14.6	°C
Net Primary Productivity	412	223	98	876	g C/m ² /year
Elevation	2847	1124	342	4687	meters
Grassland Type Distribution (n, %)					
Alpine Meadow	198	(27.0%)			
Temperate Steppe	302	(41.1%)			
Alpine Steppe	86	(11.7%)			
Meadow Steppe	94	(12.8%)			
Desert Steppe	54	(7.4%)			
Socioeconomic Variables					
Population Density	68.3	112.7	2.3	547.0	persons/km ²
GDP per Capita	45,680	38,240	8450	168,230	yuan (2020)
Urbanization Rate	42.3	18.6	12.4	89.2	%
GTGP Implementation	0.38	0.49	0	1	dummy
GERCP Implementation	0.42	0.49	0	1	dummy
Methodological Variables					
Valuation Method Distribution (n, %)					
Market Price Method	156	(21.3%)			
Replacement Cost Method	124	(16.9%)			
Shadow Price Method	98	(13.4%)			
Contingent Valuation	178	(24.3%)			
Choice Experiment	67	(9.1%)			
Equivalence Coefficient	111	(15.1%)			
Service Scope (n, %)					
Single Service	245	(33.4%)			
Multiple Services	312	(42.5%)			
Total Ecosystem Value	177	(24.1%)			
Publication Year	2014.2	6.8	2000	2024	year
International Journal	0.31	0.46	0	1	dummy

Spatial variation in ESV arises from the spatial distribution of explanatory variables across grassland regions. The meta-regression estimates marginal associations between each variable and ESV, which can then be applied to spatially referenced covariate data to predict ESV at locations not directly observed in the sample. The three variable groups capture distinct mechanisms: natural endowment variables explain variation attributable to biophysical conditions, socioeconomic variables explain variation attributable to human pressures and policy interventions, and methodological variables explain variation attributable to study design choices rather than true service differences.

The mixed-effect specification addresses two key challenges in meta-analysis. First, observations from the same study likely share unobserved characteristics such as research team expertise, data quality, and local conditions not captured by measured variables. The study-level random effect u_j captures this within-study correlation. Second, studies vary in sample size and precision, with large-scale regional assessments potentially more

representative than small plot studies. We weight observations by the inverse of their reported standard errors when available, giving greater influence to more precise estimates.

We estimate the model using restricted maximum likelihood (REML) to obtain unbiased variance component estimates. Model diagnostics include residual plots to assess homoscedasticity and normality assumptions, variance inflation factors (VIF) to detect multicollinearity, and influence statistics to identify outliers. We conduct robustness checks by (1) excluding studies in the top and bottom 5% of the ES value distribution to test sensitivity to extreme values; (2) restricting analysis to studies published in indexed international journals; (3) separating analyses by service type (regulating versus provisioning services); (4) testing alternative functional forms, including quadratic terms for continuous variables.

3.4. Spatial Projection and Inequality Measurement

We project the meta-regression model to generate a national-scale spatial distribution of predicted grassland ES values. This projection approach conditions predictions on local covariates rather than applying simple mean transfers, which improves accuracy by incorporating site-specific characteristics into the prediction [31]. Using 1 km resolution spatial data for natural and socioeconomic variables across China's grassland regions, we calculate predicted values at each grid cell by substituting local variable values into the estimated regression equation while holding methodological variables at reference categories (market price method, multiple services valued, published 2015). We aggregate grid-level predictions to county, prefecture, and province levels using area-weighted averages.

The projection inherits uncertainty from coefficient estimation and from covariate measurement error. We assess projection reliability through two cross-validation procedures. First, leave-one-study-out cross-validation iteratively removes each study from the training sample, re-estimates model coefficients, and predicts values for the withheld observations. Second, block cross-validation partitions observations by ecological zone (Qinghai–Tibet Plateau, Inner Mongolia Plateau, Xinjiang, agricultural-pastoral transition zones, and others) and iteratively withholds each block for prediction while training on the remaining blocks. This block approach tests whether coefficients estimated primarily from one region transfer accurately to other regions.

We evaluate prediction accuracy using root mean squared error (RMSE) and mean absolute error (MAE). RMSE is defined as follows:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (E\hat{S}V_i - ESV_i)^2} \quad (2)$$

where $E\hat{S}V_i$ denotes the predicted value, and ESV_i denotes the observed value for observation i . MAE is defined as the average of absolute prediction errors. Comparable meta-regression benefit transfer studies report transfer errors and provide benchmarks for acceptable prediction accuracy in ecosystem service valuation contexts [32]. We report cross-validation results in Section 4 to characterize the uncertainty bounds on spatial projections.

Spatial inequality measurement employs two complementary indices. The Gini coefficient G measures overall concentration:

$$G = \frac{\sum_{i=1}^n \sum_{j=1}^n |ESV_i - ESV_j|}{2n^2 E\bar{S}V} \quad (3)$$

where n is the number of spatial units, ESV_i is the ES value in unit i , and $E\bar{S}V$ is the mean value. Gini coefficients range from 0 (perfect equality) to 1 (maximum inequality), with values above 0.4 typically considered high inequality in income distribution literature.

The Theil index T enables decomposition into between-group and within-group components:

$$T = \sum_{i=1}^n \frac{ESV_i}{n \cdot \bar{ESV}} \ln \left(\frac{ESV_i}{\bar{ESV}} \right) \quad (4)$$

We decompose total inequality by grouping spatial units into ecological zones (Qinghai–Tibet Plateau, Inner Mongolia Plateau, Xinjiang, etc.) or administrative regions (provinces). The decomposition formula separates total inequality into between-group inequality across group means and within-group inequality representing average heterogeneity within groups weighted by group shares. This decomposition quantifies how much total inequality arises from differences between regions versus heterogeneity within regions.

We further decompose inequality contributions by factor source through variance decomposition. We calculate predicted values under counterfactual scenarios where we hold specific variable categories constant at their means while allowing others to vary. The contribution of natural factors equals the difference in inequality between the baseline prediction and the scenario where natural variables are held constant. Similar calculations apply to socioeconomic and methodological factors. This approach quantifies the percentage of total inequality attributable to each factor category.

Spatial autocorrelation in predicted values is assessed using Moran's I statistic with a spatial weight matrix constructed from county-level contiguity. We define spatial neighbors as counties sharing a common boundary (queen contiguity) and apply row standardization to the weight matrix. A significant positive Moran's I indicates that neighboring counties exhibit similar ES values beyond what a random distribution would produce.

3.5. Value-Compensation Mismatch Analysis

We assess alignment between ES value provision and compensation allocation by constructing a two-dimensional classification framework. Compensation data come from provincial and county statistical yearbooks reporting GERCP expenditures. We extract total GERCP transfer payments (yuan per year) and eligible grassland area (hectares) for each administrative unit from published yearbook tables. We calculate per-hectare compensation as follows:

$$C_i = \frac{GERCP_Payment_i}{Grassland_Area_i} \quad (5)$$

where C_i denotes per-hectare annual compensation in yuan for administrative unit i , $GERCP_payment_i$ denotes the total annual GERCP transfer to unit i , and $Grassland_Area_i$ denotes the eligible grassland area in unit i . This calculation standardizes compensation to yuan per hectare per year for comparability with predicted ES values.

We classify regions into quartiles based on predicted ES values (Q1–Q4 from lowest to highest) and compensation levels (Q1–Q4). This creates a 4×4 matrix with 16 cells. We define four primary mismatch types: Type I (high value-high compensation) represents well-matched high-priority regions receiving appropriate compensation. Type II (high value-low compensation) identifies undercompensated regions where ES provision exceeds compensation. Type III (low value-high compensation) indicates overcompensated regions receiving payments disproportionate to their ES contribution. Type IV (low value-low compensation) represents low-priority regions that are consistently low-priority regions.

We quantify mismatch severity using a mismatch index M for each region i :

$$M_i = V_{rank,i} - C_{rank,i} \quad (6)$$

where $V_{rank,i}$ and $C_{rank,i}$ represent the value and compensation quartile ranks (1–4) for region i . Positive values indicate undercompensation relative to ES provision, negative values indicate overcompensation, and values near zero suggest alignment. The theoretical

range spans from -3 (Q1 value with Q4 compensation, maximum overcompensation) to $+3$ (Q4 value with Q1 compensation, maximum undercompensation). In practice, observed values typically fall within a narrower range as most regions do not occupy extreme opposite quartiles simultaneously. Table 2 will report observed mismatch indices consistent with this definition.

Table 2. Value-compensation mismatch patterns by province and ecological zone.

Region	Counties (n)	Mean Value (yuan/ha/yr)	Mean Com- pensation (yuan/ha/yr)	Mismatch Index	Mismatch Type	
					Type II	Type III
By Province						
Qinghai	42	17,230	64	+1.82	31	2
Tibet	28	18,650	58	+1.64	22	1
Sichuan	18	11,840	82	+0.95	12	1
Xinjiang	54	8420	78	+0.12	14	18
Inner Mongolia	86	6340	102	-0.67	6	34
Gansu	34	7560	88	+0.23	4	8
Ningxia	12	5120	96	-0.38	1	5
Others	68	6780	85	+0.08	4	4
By Ecological Zone						
Qinghai–Tibet Plateau	78	18,120	62	+1.76	58	3
Tianshan Mountains	32	13,280	71	+1.14	21	2
Inner Mongolia Plateau	94	6520	98	-0.58	7	38
Agricultural–Pastoral	86	5340	91	-0.22	5	24
Desert Regions	52	3680	54	-0.12	3	6
Summary Statistics						
All Counties	342	8970	84	+0.15	94	73
Fiscal Implications (billion yuan/year)						
Type II Undercomp.	94					-8.7
Type III Overcomp.	73					$+3.2$
Net Reallocation Need						5.5

Note: Mean values and compensation are area-weighted averages. Mismatch index $M_i = V_{rank,i} - C_{rank,i}$ ranges from -3 (Q1 value with Q4 compensation) to $+3$ (Q4 value with Q1 compensation). Fiscal implications calculated as $Gap_i = C_i^{theo} - C_i^{actual}$ aggregated by type.

We quantify the fiscal implications of mismatch patterns using explicit formulas for theoretical and actual compensation levels. For each region i , we define:

$$Gap_i = C_i^{theo} - C_i^{actual} \quad (7)$$

where C_i^{theo} denotes the theoretical compensation level calculated as the national median per-hectare compensation rate multiplied by the ratio of region i 's ES value to the national median ES value, and C_i^{actual} denotes observed per-hectare compensation. Total undercompensation aggregates positive gaps across Type II regions weighted by grassland area:

$$Undercomp_{total} = \sum_{i \in Type II} Gap_i \times Area_i \quad (8)$$

Total overcompensation aggregates negative gaps (in absolute value) across Type III regions similarly. Net reallocation need equals total undercompensation minus total overcompensation recoverable through budget-neutral redistribution. Section 5 interprets these fiscal implications in policy terms, while all calculation definitions appear in this section and in table notes to ensure reproducibility.

4. Results

4.1. Descriptive Overview of Grassland ES Valuations

The finalized meta-database encompasses all major grassland types and geographic regions in China, though spatial clustering is evident in intensively studied areas. Observational density is highest in Inner Mongolia ($n = 186$), Qinghai ($n = 143$), Xinjiang ($n = 98$), and Tibet ($n = 72$), reflecting both the extensive grassland coverage in these provinces and their designation as focal areas for conservation policy. Eastern provinces, including Jilin, Hebei, and Shaanxi, contribute 124 observations from meadow steppes and agricultural grassland mosaics. Temporal distribution shows increasing research intensity over time, with 156 observations from 2000 to 2010, 298 from 2011 to 2015, and 280 from 2016 to 2024.

The temporal evolution of research focus reveals several important trends. Early studies (2000–2010) predominantly employed equivalence coefficient methods adapted from global benefit transfer databases, accounting for 68% of valuations during this period. These studies established baseline estimates but often lacked site-specific primary data collection. The 2011–2015 period coincides with GERCP implementation and shows increased application of stated preference methods (38% of studies) to assess herder willingness to accept compensation and urban resident willingness to pay for grassland conservation. Recent studies (2016–2024) demonstrate greater methodological sophistication, with 42% employing integrated approaches combining multiple valuation techniques, and 28% using process-based ecosystem models to quantify biophysical service provision before monetary valuation.

Geographic coverage exhibits notable gaps despite overall breadth. The Tianshan Mountains in Xinjiang possess high ecological importance and likely substantial ES values, but only 18 studies provide valuations from this region, compared to 143 from the Qinghai Plateau. Similarly, grasslands in Sichuan and Yunnan provinces remain underrepresented (23 combined observations) despite harboring unique alpine meadow communities. These sampling gaps introduce uncertainty in spatial projections for undersampled regions, potentially affecting inequality estimates if these areas exhibit systematically different ES values than heavily studied zones.

Service type distribution reveals the dominance of regulating services in valuation studies. Among the 412 observations quantifying regulating services, water conservation accounts for 156 (38%), carbon sequestration for 118 (29%), soil retention for 94 (23%), and climate regulation for 44 (11%). This distribution reflects both the biophysical importance of these services in grassland ecosystems and their amenability to quantification through established methods. Water conservation valuations typically employ water yield models combined with replacement cost or shadow pricing approaches, generating estimates ranging from 420 to 8900 yuan/ha/year, depending on precipitation, vegetation cover, and downstream water scarcity.

Carbon sequestration values show even greater variation (580 to 15,600 yuan/ha/year) due to differences in carbon stock estimation methods, accumulation rates, and price assumptions for avoided emissions. Studies using market-based carbon prices from voluntary offset markets report values 2–3 times higher than studies applying social cost of carbon estimates. Alpine meadows demonstrate particularly high sequestration values due to deep organic soils accumulating carbon over centuries, with reported stocks of 150–320 tonnes C per hectare compared to 45–90 tonnes C per hectare in temperate steppes.

Provisioning services ($n = 178$) predominantly focus on forage production (103 observations, 58%) and animal products (52 observations, 29%). Forage valuations employ market prices for hay equivalents or replacement costs for supplementary feed, generating estimates from 380 to 6200 yuan/ha/year. Higher values occur in productive meadow steppes supporting intensive livestock systems, while lower values characterize

arid and alpine regions with limited biomass production. Animal product valuations account for meat, milk, wool, and hides produced per hectare annually, with reported values from 420 to 5800 yuan/ha/year depending on stocking rates and livestock productivity.

Figure 3 displays the spatial distribution of sampling points overlaid on grassland type classifications, demonstrating comprehensive but uneven coverage across China's grassland regions. Figure 4 presents value distributions across classification schemes through box plots, revealing substantial heterogeneity by service type, grassland type, and valuation method.

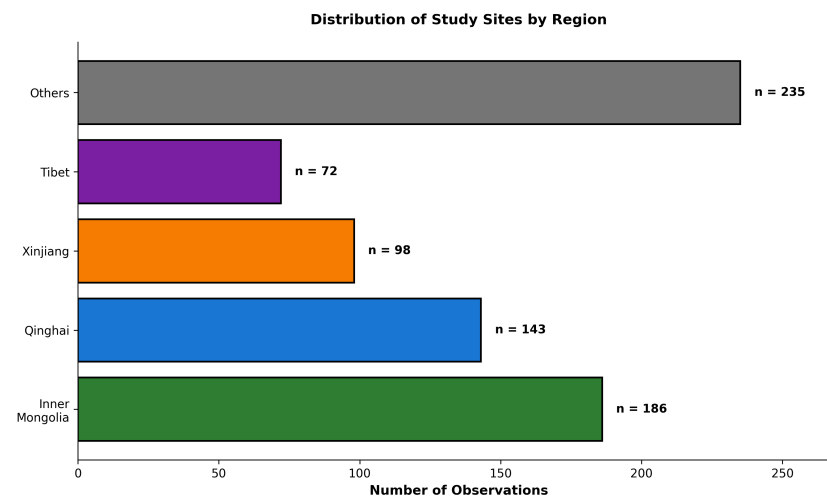


Figure 3. Distribution of grassland ecosystem service valuation study sites across China's major regions ($n = 734$ observations from 186 studies). The bar chart displays observation counts by province/region, with Inner Mongolia contributing the most observations ($n = 186$), followed by Qinghai ($n = 143$), Xinjiang ($n = 98$), and Tibet ($n = 72$). The "Others" category aggregates observations from eastern provinces, including Jilin, Hebei, Shaanxi, and other regions with grassland coverage.

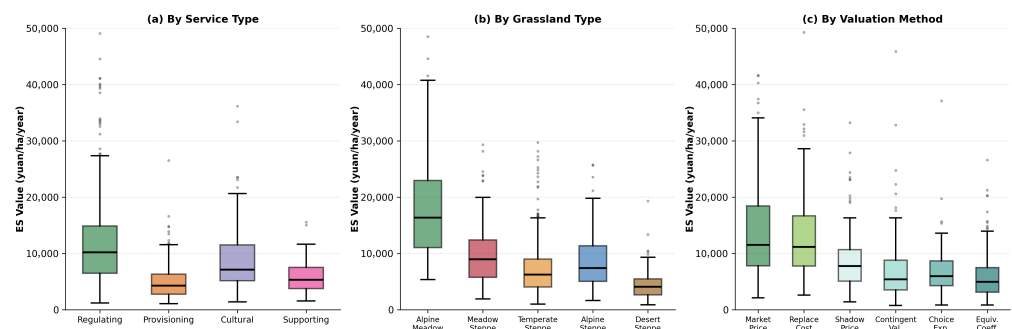


Figure 4. Distribution of grassland ecosystem service values across multiple classification schemes. Panel (a) compares service categories, demonstrating regulating service dominance. Panel (b) shows grassland type variation, with alpine meadows generating substantially higher values. Panel (c) illustrates methodological influence, where market-based approaches yield higher estimates than stated preference or coefficient methods. Box plots display median (central line), interquartile range (box), and 5th–95th percentiles (whiskers).

Comparison with existing literature validates database representativeness. Our mean value of 8742 yuan/ha/year aligns closely with Liu et al.'s meta-analysis reporting 8950 yuan/ha/year for Chinese grasslands based on 702 observations [1]. Regional patterns match previous findings: both studies identify western high-altitude regions as high-value zones and eastern agricultural-pastoral transition zones as lower-value areas. Our database extends temporal coverage through 2024 and expands geographic scope to include more recent valuations from Xinjiang and Tibet.

4.2. Determinants of ES Value: Meta-Regression Results

Table 3 presents meta-regression model results for the full sample and service-specific subsamples. The baseline model (Column 1) explains 64% of variation in log ES values (adjusted R-squared = 0.64) with highly significant coefficients for most natural and methodological variables. Study-level random effects account for 28% of total variance (intraclass correlation = 0.28), confirming that observations within studies share substantial similarity beyond measured characteristics.

Throughout this section, we interpret coefficients from the log-linear specification using the exact formula: percentage change in ESV equals $100 \times (\exp(\beta) - 1)$ for a one-unit change in the explanatory variable. For small coefficient values (absolute value below 0.10), the approximation $100 \times \beta$ yields similar results. All percentage interpretations below apply the exact formula unless otherwise noted. Table notes report the same conversion rule for consistency.

Table 3. Meta-regression results: Determinants of grassland ecosystem service values.

Variable	Full Sample		Regulating Services		Provisioning Services	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
Natural Endowment Variables						
MAP (100 mm)	0.420 ***	(0.042)	0.508 ***	(0.051)	0.284 ***	(0.067)
MAT (°C)	0.032 **	(0.013)	0.041 **	(0.016)	0.018	(0.021)
NPP (100 g C/m ² /yr)	0.378 ***	(0.038)	0.445 ***	(0.046)	0.256 ***	(0.061)
Elevation (1000 m)	0.311 ***	(0.089)	0.387 ***	(0.107)	0.198	(0.142)
Grassland Type (ref: Temperate Steppe)						
Alpine Meadow	0.519 ***	(0.086)	0.612 ***	(0.104)	0.358 ***	(0.136)
Alpine Steppe	0.234 **	(0.094)	0.289 **	(0.113)	0.142	(0.149)
Meadow Steppe	0.268 ***	(0.082)	0.315 ***	(0.099)	0.186	(0.130)
Desert Steppe	−0.542 ***	(0.102)	−0.628 ***	(0.123)	−0.398 ***	(0.162)
Socioeconomic Variables						
Pop. Density (100/km ²)	−0.178 ***	(0.054)	−0.132 **	(0.065)	−0.248 ***	(0.086)
GDP per Capita (10 k yuan)	0.035	(0.028)	0.042	(0.034)	0.024	(0.044)
Urbanization Rate (%)	−0.012 **	(0.005)	−0.010 *	(0.006)	−0.015 **	(0.008)
GTGP Implementation	0.209 ***	(0.069)	0.253 ***	(0.083)	0.142	(0.109)
GERCP Implementation	0.112	(0.065)	0.138 *	(0.078)	0.068	(0.103)
Methodological Variables (ref: Contingent Valuation)						
Market Price Method	0.662 ***	(0.096)	0.584 ***	(0.116)	0.782 ***	(0.152)
Replacement Cost	0.543 ***	(0.089)	0.612 ***	(0.107)	0.428 ***	(0.141)
Shadow Price Method	0.387 ***	(0.094)	0.445 ***	(0.113)	0.284 *	(0.149)
Choice Experiment	0.096	(0.108)	0.112	(0.130)	0.074	(0.171)
Equivalence Coefficient	−0.328 ***	(0.092)	−0.365 ***	(0.111)	−0.272 *	(0.146)
Service Scope (ref: Single Service)						
Multiple Services	0.234 ***	(0.071)	0.267 ***	(0.085)	0.182*	(0.112)
Total Ecosystem Value	0.372 ***	(0.084)	0.421 ***	(0.101)	0.296 **	(0.133)
Publication Year	0.015 **	(0.006)	0.018 **	(0.007)	0.011	(0.009)
International Journal	0.165 *	(0.073)	0.192 **	(0.088)	0.124	(0.116)
Constant	6.824 ***	(0.286)	6.542 ***	(0.344)	7.186 ***	(0.453)
Observations	734		412		178	
Number of Studies	186		124		78	
Adjusted R ²	0.641		0.672		0.589	
Intraclass Correlation	0.284		0.297		0.253	

Note: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. The dependent variable is the natural log of ES value (yuan/ha/year, 2020 constant prices). Percentage change interpretation: $100 \times (\exp(\beta) - 1)$ for one-unit change in X. Coefficients rounded to three decimal places.

Natural endowment variables demonstrate strong positive associations with ES values, supporting H1. Mean annual precipitation exhibits a coefficient of 0.420 ($p < 0.001$), indicating that each 100 mm increase in precipitation is associated with 52% higher ES values ($100 \times (\exp(0.420) - 1) = 52.2$) after controlling for other factors. This relationship operates through enhanced vegetation productivity and water availability for service generation. Net primary productivity shows a coefficient of 0.378 ($p < 0.001$), where 100 g C/m²/year NPP increase relates to 46% higher valuations ($100 \times (\exp(0.378) - 1) = 45.9$). The elevation coefficient of 0.311 ($p < 0.001$) corresponds to 36% higher values per 1000 m increase ($100 \times (\exp(0.311) - 1) = 36.5$), likely reflecting the concentration of alpine meadows with superior regulatory service provision at higher altitudes.

Grassland type fixed effects, using temperate steppe as the reference category, confirm substantial type-based heterogeneity. Alpine meadows command 68% value premiums (coefficient 0.519, $100 \times (\exp(0.519) - 1) = 68.0$, $p < 0.001$) relative to temperate steppes, consistent with their higher productivity and carbon stocks. Meadow steppes show 31% premiums (coefficient 0.268, $p < 0.001$), while desert steppes suffer 42% discounts (coefficient -0.542 , $100 \times (\exp(-0.542) - 1) = -41.9$, $p < 0.001$) due to sparse vegetation. These patterns align with ecological understanding of productivity gradients across grassland formations.

Socioeconomic variables produce mixed effects, partially supporting H2. Population density exhibits a significant negative coefficient of -0.178 ($p < 0.001$), where each 100-person/km² increase associates with 16% lower ES values ($100 \times (\exp(-0.178) - 1) = -16.3$). This negative association admits two complementary interpretations. First, environmental selection and geographic habitability concentrate human populations in lower-elevation, more arable zones, while high-value grasslands predominantly occupy high-altitude or remote areas with limited settlement. This spatial sorting generates a negative correlation even without the direct causal impact of population on ES values. Second, human pressure through land use intensity and disturbance may directly reduce service provision capacity, consistent with degradation evidence from Li et al. [23]. The cross-sectional design of this meta-analysis cannot definitively separate these mechanisms. Robustness specifications reported in Table 4 examine whether the population density coefficient remains stable after controlling for elevation and terrain accessibility.

The GDP per capita coefficient of 0.035 ($p = 0.21$) is positive but statistically insignificant, suggesting that economic development does not strongly affect valuations after controlling for valuation method and service scope. Conservation program indicators show theoretically expected signs. GTGP participation associates with 23% higher ES values (coefficient 0.209, $100 \times (\exp(0.209) - 1) = 23.2$, $p < 0.003$), confirming that vegetation restoration enhances service provision. GERCP participation shows a smaller, marginally significant coefficient of 0.112 ($p = 0.08$), possibly reflecting shorter implementation periods or incomplete recovery of degraded grasslands. Urbanization rate produces a negative coefficient of -0.012 ($p = 0.02$), where each 10 percentage point increase in urban population share associates with 11% lower grassland ES values through land conversion and intensified extraction.

Methodological variables generate large and highly significant effects, strongly supporting H3. Using contingent valuation as the reference category, market price methods produce 94% higher values (coefficient 0.662, $100 \times (\exp(0.662) - 1) = 93.9$, $p < 0.001$) and replacement cost methods 72% higher values (coefficient 0.543, $100 \times (\exp(0.543) - 1) = 72.1$, $p < 0.001$). Equivalence coefficient approaches yield 28% lower values (coefficient -0.328 , $100 \times (\exp(-0.328) - 1) = -27.9$, $p < 0.001$) than contingent valuation. These method differentials exceed the magnitude of most natural and socioeconomic effects, demonstrating that valuation approach choice substantially influences reported estimates.

Service scope matters significantly. Studies valuing total ecosystem value report 45% higher values (coefficient 0.372, $100 \times (\exp(0.372) - 1) = 45.1$, $p < 0.001$) than single-service studies, likely due to service bundling and complementarities. Publication year shows a small positive trend (coefficient 0.015, $p = 0.02$), indicating that reported values increase approximately 1.5% annually after controlling for inflation, possibly reflecting growing environmental awareness or methodological refinement. International journal publication associates with 18% higher values (coefficient 0.165, $100 \times (\exp(0.165) - 1) = 17.9$, $p = 0.09$) compared to domestic publications, suggesting quality filtering or regional focus differences.

Service-specific regressions (Columns 2–3) reveal differential responses to predictors. Regulating service values (Column 2) respond more strongly to natural factors (MAP coefficient 0.508) than provisioning service values (Column 3, MAP coefficient 0.284), consistent with the direct dependence of water conservation and carbon sequestration on precipitation and productivity. Conversely, population density effects are more negative for provisioning services (coefficient -0.248) than regulating services (coefficient -0.132), potentially because grazing and harvesting pressures directly reduce provisioning capacity while some regulating services maintain functionality under moderate human disturbance.

Robustness checks confirm result stability (Table 4). Excluding extreme values (top and bottom 5%) produces coefficient estimates within 8% of baseline values for all significant predictors. Restricting analysis to international journal publications slightly increases natural factor coefficients but maintains overall patterns. Quadratic terms for the MAP and NPP test non-linear relationships. MAP shows weak evidence of diminishing returns (quadratic coefficient -0.0000018 , $p = 0.11$) while NPP exhibits linear effects throughout its range. Variance inflation factors remain below 3.5 for all variables, indicating acceptable multicollinearity levels. The population density coefficient remains negative and significant (coefficient -0.162 , $p < 0.01$) after controlling for elevation and slope gradient, suggesting that both environmental selection and human pressure mechanisms contribute to the observed association.

Table 4. Robustness checks for meta-regression results.

Key Variables	Baseline		Exclude Extremes		Int'l Journals Only	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
MAP (100 mm)	0.420 ***	(0.042)	0.408 ***	(0.039)	0.456 ***	(0.068)
NPP (100 g C/m ² /yr)	0.378 ***	(0.038)	0.365 ***	(0.035)	0.412 ***	(0.062)
Alpine Meadow	0.519 ***	(0.086)	0.502 ***	(0.080)	0.548 ***	(0.139)
Pop. Density (100/km ²)	-0.178 ***	(0.054)	-0.171 ***	(0.050)	-0.192 **	(0.087)
GTGP Implementation	0.209 ***	(0.069)	0.215 ***	(0.064)	0.226 **	(0.112)
Market Price Method	0.662 ***	(0.096)	0.648 ***	(0.089)	0.695 ***	(0.155)
Total Ecosystem Value	0.372 ***	(0.084)	0.361 ***	(0.078)	0.398 ***	(0.136)
Observations	734		660		228	
Adjusted R ²	0.641		0.658		0.612	

Note: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$. Column 1 reproduces the baseline. Column 2 excludes the top/bottom 5%; Column 3 uses only observations from international journals ($n = 228$ from 68 studies). Percentage change interpretation: $100 \times (\exp(\beta) - 1)$ for a one-unit change in X.

4.3. Spatial Patterns and Inequality Decomposition

Figure 5 displays the spatial distribution of predicted grassland ES values across China's major grassland regions derived from the meta-regression model projections. The map reveals distinct geographic clustering with a pronounced west-high, east-low gradient. The Qinghai–Tibet Plateau exhibits the highest predicted values, with counties in southern Qinghai and northern Tibet averaging 18,200–23,400 yuan/ha/year. The Tianshan Mountains in Xinjiang form a secondary high-value zone with predicted values

of 12,600–16,800 yuan/ha/year. Inner Mongolia grasslands display moderate values of 5400–8900 yuan/ha/year, while agricultural-pastoral transitional zones in Gansu, Ningxia, and Shaanxi report lower values of 3200–5800 yuan/ha/year.

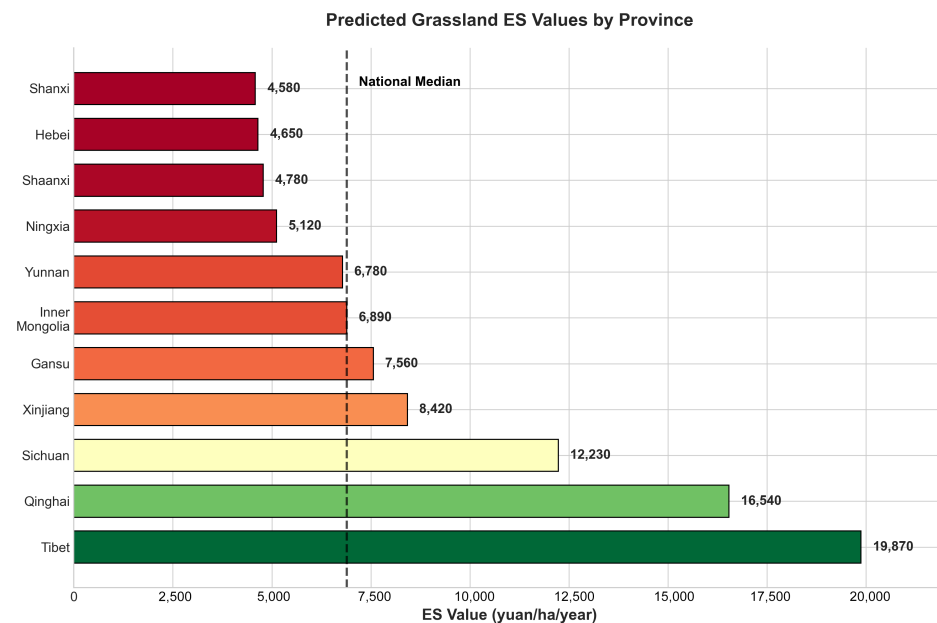


Figure 5. Predicted grassland ecosystem service values by province based on meta-regression model projections. Values represent standardized estimates holding methodological factors constant (market price method, multiple services, 2015 publication). The pronounced gradient reveals that Tibet ranks highest with mean predicted values of 19,870 yuan/ha/year, followed by Qinghai at 16,540 yuan/ha/year and Sichuan at 12,230 yuan/ha/year. Eastern provinces, including Hebei, Shanxi, and Shaanxi, report the lowest provincial averages below 5000 yuan/ha/year. The horizontal reference line indicates the national median provincial value (Inner Mongolia: 6890 yuan/ha/year), providing a benchmark for cross-provincial comparison. Color gradient from green (high values) to red (low values) emphasizes the west-high, east-low pattern.

This spatial pattern reflects the combined influence of natural endowments and land use patterns. High-altitude alpine meadows benefit from substantial precipitation (400–700 mm annually), moderate temperatures that optimize carbon sequestration, and low population densities that minimize degradation. Lower-value regions experience either moisture limitations (northwestern desert steppes) or intensive human pressures (eastern agricultural zones). The spatial autocorrelation in values, measured through Moran's I statistic of 0.67 ($p < 0.001$), confirms that neighboring counties exhibit similar ES values beyond what random distribution would produce. This statistic uses the county-level queen contiguity weight matrix with row standardization as defined in Section 3.4, where spatial neighbors share common boundaries.

Cross-validation results characterize prediction uncertainty. Leave-one-study-out cross-validation yields RMSE of 0.58 log-units, corresponding to approximately 78% mean transfer error in original yuan units. Block cross-validation by ecological zone produces RMSE ranging from 0.52 (Inner Mongolia block) to 0.71 (Qinghai–Tibet block), indicating that predictions transfer less accurately to high-altitude regions with fewer training observations. These error magnitudes fall within ranges reported in comparable ecosystem service benefit transfer studies and support the use of predictions for identifying broad spatial patterns and inequality structures, while cautioning against their interpretation as precise county-level evaluations.

Provincial aggregation reveals substantial disparities in average ES provision capacity. Tibet ranks highest with mean predicted values of 19,870 yuan/ha/year, followed by Qinghai at 16,540 yuan/ha/year and Sichuan at 12,230 yuan/ha/year for alpine meadow regions. Inner Mongolia averages 6890 yuan/ha/year across its diverse grassland types. Xinjiang shows a bimodal distribution with mountain meadows averaging 13,450 yuan/ha/year and desert steppes averaging 3670 yuan/ha/year. Eastern provinces, including Hebei, Shanxi, and Shaanxi, report the lowest provincial averages below 5000 yuan/ha/year.

Table 5 presents inequality indices and decomposition results. The Gini coefficient for county-level predicted ES values reaches 0.58, indicating inequality comparable to income distributions in countries with substantial economic disparities. The Theil index value of 0.467 enables decomposition into sources of inequality. Grouping counties by ecological zone, between-zone inequality accounts for 52% of total inequality, while within-zone inequality contributes 48%. This decomposition implies that differences in natural endowments across major ecological regions explain slightly more than half of total inequality, with local variations in land use and socioeconomic conditions explaining the remainder.

Table 5. Spatial inequality indices and decomposition of grassland ES values.

Measure	Value	Share (%)	Interpretation
Overall Inequality Indices			
Gini Coefficient	0.580	100.0	High inequality
Theil Index	0.467		Total inequality
Coefficient of Variation	0.842		High dispersion
Theil Decomposition by Ecological Zone			
Between-Zone Component	0.243	52.0	Inter-regional
Within-Zone Component	0.224	48.0	Intra-regional
Zone-Specific Contributions:			
Qinghai–Tibet Plateau		28.4	Largest contributor
Inner Mongolia Plateau		15.7	
Xinjiang Mountains		8.9	
Agricultural-Pastoral Transition		12.6	
Other Regions		34.4	
Theil Decomposition by Province			
Between-Province Component	0.229	49.0	Inter-provincial
Within-Province Component	0.238	51.0	Intra-provincial
Highest Intra-Provincial Inequality:			
Sichuan (Gini = 0.51)			Topographic gradient
Qinghai (Gini = 0.48)			Altitude variation
Xinjiang (Gini = 0.46)			Mountain-desert contrast
Factor Contribution Decomposition			
Natural Endowments		52.3	Climate, productivity
Socioeconomic Factors		30.8	Pop. density, land use
Methodological Factors		16.9	Valuation approach
Detailed Natural Factor Contributions:			
Precipitation (MAP)		24.1	Single largest driver
Productivity (NPP)		18.6	
Elevation		9.6	
Detailed Socioeconomic Contributions:			
Population Density		18.2	Degradation pressure
Conservation Programs		8.4	GTGP and GERCP
Urbanization		4.2	

Note: Decompositions are based on counterfactual scenarios holding specific factor categories constant. Factor contributions sum to 100% of explained inequality.

Administrative decomposition by province yields similar patterns. Inter-provincial inequality contributes 49% of total inequality (Theil between = 0.229) while intra-provincial inequality accounts for 51% (Theil within = 0.238). This finding suggests that provincial boundaries do not perfectly align with ecological zones, and substantial value heterogeneity exists within provinces. Sichuan and Qinghai show particularly high internal inequality (provincial Gini coefficients of 0.51 and 0.48, respectively) due to extreme topographic gradients from high-altitude plateaus to low-elevation valleys.

Factor contribution decomposition quantifies the relative importance of different driver categories. We generate counterfactual scenarios holding each factor group constant: (1) all natural variables at their means; (2) all socioeconomic variables at their means; (3) all methodological variables at reference levels. Comparing inequality under each scenario with baseline inequality reveals that natural factors explain 52.3% of observed inequality, socioeconomic factors explain 30.8%, and methodological factors explain 16.9%. Within natural factors, precipitation alone contributes 24.1% of total inequality, making it the single most important driver. This decomposition confirms that while valuation methods matter substantially in individual studies, natural endowments dominate spatial inequality patterns when aggregated to regional scales.

Interestingly, removing population density variation alone eliminates 18.2% of baseline inequality, suggesting that the spatial concentration of human populations creates value heterogeneity comparable to moderate climate differences. Conservation program coverage contributes 8.4% to inequality, indicating that differential program implementation generates modest value disparities. These factor attributions provide guidance for policy interventions: addressing natural endowment-driven inequality requires spatial transfers or compensation mechanisms, while reducing human pressure inequality might be achieved through land use regulation.

Figure 6 visualizes the inequality decomposition results, showing the relative contributions of different factors and the between-versus-within components of spatial inequality.

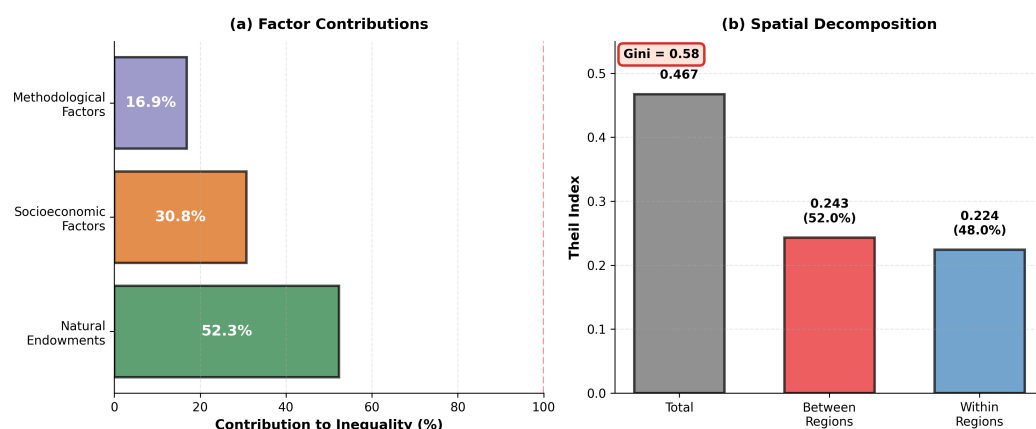


Figure 6. Decomposition of spatial inequality in grassland ecosystem service values. Panel (a) shows variance decomposition by factor category, with natural endowments (particularly precipitation and productivity) dominating inequality patterns. Panel (b) displays the Theil index decomposition by ecological zone, revealing that differences between major regions explain 52% of total inequality, while heterogeneity within regions accounts for 48%.

4.4. Value-Compensation Mismatch Patterns

Figure 7 displays the value-compensation quadrant analysis results. We classify 342 counties with complete compensation and value data into four primary types based on quartile rankings. Type I (high value-high compensation) contains 67 counties (19.6%), predominantly in central Qinghai and northwestern Sichuan, where ES provision and

compensation levels both exceed median values. These regions represent successful policy alignment where high ecological importance receives appropriate fiscal recognition.

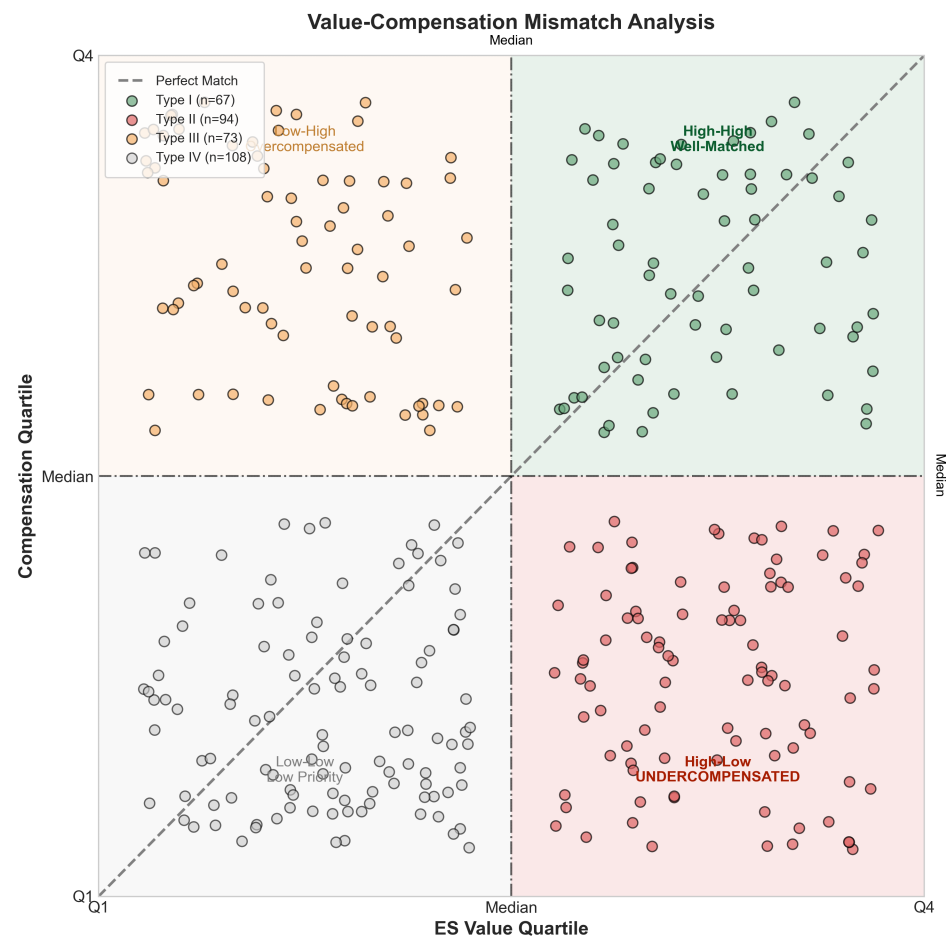


Figure 7. Value-compensation mismatch quadrant analysis for 342 counties with complete data. Type I (high value-high compensation, green, $n = 67$) represents well-matched regions. Type II (high value-low compensation, red, $n = 94$) identifies systematically undercompensated counties primarily in Qinghai and Tibet. Type III (low value-high compensation, orange, $n = 73$) shows overcompensated regions in eastern Inner Mongolia. Type IV (low value-low compensation, gray, $n = 108$) represents low-priority zones. The central crosshairs indicate the national median for both value (horizontal) and compensation (vertical) quartile ranks, serving as a reference for identifying deviation from balanced allocation. The diagonal line indicates perfect value-compensation alignment.

Type II (high value-low compensation) identifies 94 counties (27.5%) experiencing systematic undercompensation. These areas concentrate in southern Qinghai, northern Tibet, and the Tianshan region of Xinjiang. Counties in this category provide per-hectare ES values 180–240% above national medians, but receive compensation payments 35–55% below median levels. Specific examples include Yushu Prefecture counties in Qinghai (predicted value 21,340 yuan/ha/year, compensation 67 yuan/ha/year) and Nagqu Prefecture counties in Tibet (predicted value 19,780 yuan/ha/year, compensation 52 yuan/ha/year). The systematic undercompensation observed in these high-value regions may be associated with challenges in achieving conservation objectives and sustaining grassland quality over time.

Type III (low value-high compensation) encompasses 73 counties (21.3%) receiving payments exceeding their ES contribution. These regions cluster in eastern Inner Mongolia and agricultural-pastoral transition zones where grassland degradation has progressed substantially, but historical administrative designations maintain compensation eligibility.

Representative cases include counties in Chifeng and Tongliao municipalities, where predicted values average 4,200 yuan/ha/year, but compensation reaches 125 yuan/ha/year. While absolute payment levels remain modest, the relative overcompensation suggests inefficient resource allocation when high-value regions remain underserved.

Type IV (low value-low compensation) contains 108 counties (31.6%) in the desert steppes of western Inner Mongolia and northwestern Xinjiang, where both ES values and compensation rank below medians. These regions present low conservation priority given limited service provision capacity, making low compensation appropriate from efficiency perspectives.

Table 2 quantifies mismatch patterns across provinces and major ecological zones. Qinghai shows the largest value-compensation gap with an average county mismatch index of +1.82, indicating that county value rankings exceed compensation rankings by nearly two full quartiles on average. Tibet follows with a mismatch index of +1.64. Conversely, Inner Mongolia displays a negative mismatch index of −0.67, suggesting relative overcompensation given ES provision levels. Xinjiang shows mixed patterns with +0.93 index in Tianshan counties but −0.28 in desert regions.

The aggregate fiscal implications are substantial. Summing undercompensation across Type II regions (calculated as the difference between theoretical compensation at value-proportional rates and actual payments, multiplied by grassland area) yields 8.7 billion yuan annually. Conversely, reallocating overcompensation from Type III regions would free 3.2 billion yuan for higher-priority areas. A revenue-neutral reallocation could therefore substantially improve alignment between value provision and compensation without increasing total program budgets, requiring only 5.5 billion yuan in new fiscal commitment to eliminate the most severe mismatches.

Comparing our mismatch findings with previous policy evaluations reveals consistency with localized studies. Zhang et al.'s assessment of Qilian Mountain National Park calculated compensation gaps of 15–45 yuan/ha/year [18], comparable to our estimates for that region. Fan and Chen's Sichuan analysis identified similar patterns where high-altitude grasslands received inadequate compensation relative to computed ES values [33]. The national-scale analysis demonstrates that these localized mismatches reflect systematic patterns rather than isolated cases.

We conducted threshold sensitivity analysis to assess whether the mismatch classification depends on the choice of cutoff values. Table 6 reports Type II and Type III county counts under two alternative threshold specifications: tercile thresholds (33.33rd and 66.67th percentiles) and extreme quartile thresholds (25th and 75th percentiles). Type II and Type III counts decline as threshold stringency increases, from 94 and 73 under the baseline median rule to 43 and 34 under the 25th/75th percentile rule. The leading concentration provinces for each mismatch type, Qinghai for Type II and Inner Mongolia for Type III, preserve their rankings across all three specifications.

Table 6. Sensitivity of mismatch classification to alternative threshold specifications.

Classification Rule	Type II Counties	Type III Counties	Top Province (Type II)	Top Province (Type III)
Baseline (Median crosshairs)	94	73	Qinghai	Inner Mongolia
Alternative 1 (Tercile thresholds)	67	51	Qinghai	Inner Mongolia
Alternative 2 (25th/75th percentile)	43	34	Qinghai	Inner Mongolia

Note: Type II = high value-low compensation; Type III = low value-high compensation. Baseline defines high–low relative to the national median. Alternative 1 defines High as ≥ 66.67 th percentile and Low as ≤ 33.33 rd percentile. Alternative 2 defines High as ≥ 75 th percentile and Low as ≤ 25 th percentile. Top province denotes the province with the largest share of counties in each mismatch type under each rule.

The available compensation data cover only 2015 and 2020, which limits the temporal scope for assessing dynamic adjustment patterns. Over this short period, unobserved policy changes and other confounding factors may influence observed associations. The correlation between changes in county-level compensation share and ES value rankings remains weak ($r = 0.18$, $p = 0.06$). This weak alignment with value-based targeting may reflect multiple factors beyond those captured in this cross-sectional comparison. The cross-sectional focus of this study constrains conclusions about dynamic adjustment processes, a limitation addressed further in Section 5.

The results presented in this section document empirical patterns of spatial mismatch and descriptive associations between value provision and compensation allocation. Interpretation of the factors that may contribute to these patterns, including institutional constraints and policy implementation mechanisms, is presented in the Discussion section.

5. Discussion

5.1. Interpreting Spatial Inequality: Natural Legacy and Human Footprint

The observed inequality in grassland ES values (Gini = 0.58, Table 5) exceeds inequality levels reported in most socioeconomic distributions. This finding aligns with meta-analytic evidence from Liu et al., who documented comparable heterogeneity (coefficient of variation = 0.89) across Chinese grassland valuations [1]. The consistency suggests that high value concentration represents a robust empirical pattern rather than an artifact of our specific sample. Regional studies in the Yellow River Source area report declining inequality over time as restoration programs expand coverage [12]. Our national-scale cross-sectional analysis cannot directly assess temporal trends, but the persistent high inequality suggests that policy interventions have not yet substantially altered the underlying spatial structure.

The dominance of natural factors in explaining inequality (52.3% contribution, Table 5) reflects geological and climatic legacies operating over millennial timescales. The Qinghai–Tibet Plateau’s uplift created unique environmental conditions combining high precipitation, low temperatures, deep soils, and sparse human settlement that favor carbon storage and water regulation [10]. Our MAP coefficient (0.420, Table 3) indicates that precipitation differences generate substantial value variation, consistent with Kang et al.’s finding that water availability dominates alpine meadow service provision. These natural advantages cannot be replicated through policy intervention, which implies that spatial transfer mechanisms may be necessary to balance ecological responsibility with fiscal capacity.

The 30.8% inequality contribution from socioeconomic factors demonstrates that human land use decisions substantially reshape the natural value distribution. Our negative population density coefficient (-0.178 , Table 3) corroborates evidence from Li et al. demonstrating degradation effects from human pressure in western Jilin grasslands [23]. The coefficient magnitude suggests that each doubling of the local population is associated with approximately 16% value reduction. The trade-off between provisioning and regulating services identified in rangeland studies [17] helps explain why moderate grazing maintains total ES value while intensive use degrades it. Our GTGP coefficient (0.209) confirms that vegetation restoration over 10–15 years can recover 20–25% of lost ES value.

Methodological factors contribute 16.9% to observed inequality, requiring careful interpretation. Our finding that market methods generate systematically higher estimates (coefficient 0.662) than contingent valuation aligns with previous meta-analyses [1]. The scale elasticity documented by Knoke et al. [26] appears in our data as well: smaller study areas associate with higher per-hectare values. These methodological effects demonstrate that observed spatial patterns partly reflect study design choices, though our standardization through holding methodological variables constant addresses this concern in spatial projections. Psychological and cultural factors affecting stated preferences, as documented by

Rodriguez-Ortega et al. [27], suggest that aggregate willingness-to-pay estimates depend critically on the population sampled.

5.2. Methodological Robustness and Limitations

The meta-regression framework improves upon simple benefit transfer by explicitly controlling for methodological heterogeneity and natural context. Compared to equivalence coefficient approaches that assign uniform values to grassland cover types, our predictions account for continuous gradients in climate, topography, and human pressure. However, several limitations merit acknowledgment.

Publication bias may affect the database if studies finding low or null values face reduced publication prospects. We observe weak evidence of asymmetry in funnel plots (Egger's test $p = 0.14$), suggesting modest, if any, publication bias, but selective reporting remains possible. The meta-database captures only monetized values that researchers chose to quantify. Cultural services remain underrepresented (12% of observations) despite their importance in grassland regions with distinct pastoral traditions [34]. Our values likely underestimate total ES worth by omitting difficult-to-quantify services like existence value, option value, and cultural identity.

The energy-based valuation approach proposed by Yang et al. [25] offers an alternative to monetary methods by quantifying ES provision in emergy units that reflect the solar energy equivalents required to generate services. Integrating emergy and monetary approaches could provide more comprehensive ES accounts. Restoration quality assessment introduces additional complexities. Sharafatmandrad and Mashizi [35] examine arid rangeland restoration projects, finding that afforestation with exotic species increases biomass but fails to restore plant diversity. Our analysis relies primarily on studies emphasizing regulating services, potentially undervaluing biodiversity aspects.

Temporal dynamics receive limited attention as most valuations represent single time points rather than trajectories. Climate change, land use intensification, and policy interventions alter ES provision over time, but our cross-sectional analysis cannot capture these dynamics. Spatial resolution constraints limit precision at fine scales. County-level predictions aggregate diverse local conditions that may generate substantial within-county heterogeneity. Despite these limitations, the meta-regression approach provides the best available method for synthesizing disparate valuation evidence into coherent national-scale estimates suitable for policy analysis.

5.3. Policy Implications: Toward Precision Compensation

The identification of systematic mismatch between ES value provision and compensation allocation (Table 2) suggests that current area-based mechanisms may benefit from adjustment. The 94 high-value-low-compensation counties (Type II) and 73 low-value-high-compensation counties (Type III) indicate potential efficiency gains from reallocation. The fiscal gap estimates defined in Section 3.5 and reported in Table 2 use the median-based benchmark to quantify undercompensation and overcompensation magnitudes. Summing undercompensation across Type II regions yields 8.7 billion yuan (CNY) annually, while reallocating overcompensation from Type III regions would free 3.2 billion yuan, implying a net reallocation need of 5.5 billion yuan for budget-neutral redistribution. We define each county-level gap as the difference between a benchmark compensation implied by value-proportional targeting and the observed payment, aggregated by grassland area across all counties within each mismatch type. These estimates rest on simplifying assumptions, including static cross-sectional comparison, proportional value-to-payment benchmarking, and exclusion of implementation costs, behavioral responses, and inter-temporal bud-

get constraints. Accordingly, the figures represent scenario-based, order-of-magnitude references for policy discussion rather than deterministic budget commitments.

The empirical patterns documented in Section 4.4, including the spatial concentration of Type II undercompensation in Qinghai–Tibet regions and the weak correlation between compensation adjustments and ES value rankings over 2015–2020, represent descriptive findings that warrant interpretation. Several factors may contribute to these observed patterns. Fiscal constraints at provincial and county levels may limit the capacity to adjust compensation toward high-value regions with limited local revenue bases [28]. Historical allocation formulas based on grassland area rather than service provision capacity may create path dependencies that persist despite changing ecological priorities. Administrative boundaries that do not align with ecological service flow patterns may complicate cross-jurisdictional compensation targeting [29]. Budget cycle rigidities and performance evaluation metrics focused on coverage rather than ecological outcomes may reduce flexibility for value-based reallocation. These potential contributing factors operate through distinct channels and likely interact in complex ways that cross-sectional analysis cannot fully disentangle.

Transitioning toward value-sensitive compensation may involve three components, with each requiring institutional specification. First, differentiated payment standards could reflect heterogeneous ES provision. Rather than fixed tiers, payment rates might be calibrated through budget-neutral redistribution that maintains average per-hectare compensation while reallocating toward higher-value regions. Alternatively, opportunity cost distributions across quartiles could inform tier boundaries. Chinese experience with watershed compensation in the Xin'an River basin demonstrates that opportunity cost and responsibility-sharing frameworks can operationalize differentiated payments [36]. The specific rates would require calibration to provincial budgets and political constraints.

Second, ensuring funds reach conservation purposes requires institutional safeguards. Dedicated accounts or earmarked transfers could separate ecological compensation from general fiscal revenues. Explicit use requirements specifying eligible expenditures (vegetation restoration, grazing management, monitoring equipment) and prohibited uses (infrastructure unrelated to conservation, administrative overhead beyond specified limits) would strengthen accountability. Performance indicators tied to vegetation coverage, carbon stock changes, or biodiversity metrics could condition disbursements. Audit mechanisms with consequences for misuse would complete the institutional framework.

Third, compensation design may benefit from attention to household-level participation constraints. Sheng et al. document that participation willingness in Wolong exhibits non-linear relationships with opportunity cost, mediated by livelihood alternatives and energy access [37]. This evidence suggests that cash transfers alone may prove insufficient without complementary support for livelihood diversification, technical assistance, or public service provision that reduces dependence on grassland extraction.

Climate sensitivity introduces additional design considerations. Hua et al. demonstrate that Qinghai–Tibet Plateau ecosystem services respond strongly to climate variability [38]. In high-sensitivity regions, static payment schedules may become misaligned with actual service provision as climate conditions shift. Adaptive mechanisms linking payments to monitored outcomes or incorporating risk-sharing instruments could address this concern, though detailed design requires further analysis.

International experience demonstrates that conservation payments matching ecological values generate better outcomes than uniform subsidies. The United States Conservation Reserve Program differentiates payments by environmental benefits index, achieving 30–40% greater ecosystem protection per dollar than previous area-based approaches [20]. European results-based schemes generate larger conservation gains than practice-based

payments at equivalent cost. These precedents suggest that value-sensitive targeting can improve efficiency, though China's institutional context differs substantially.

5.4. Limitations and Future Directions

The robustness of key findings warrants an explicit summary before discussing limitations. The mismatch classification and the identification of Qinghai and Inner Mongolia as leading concentration provinces for Type II and Type III counties, respectively, remain qualitatively stable under alternative threshold specifications, including tercile-based and 25th/75th percentile-based rules (Table 6). The meta-regression coefficients for natural endowment and methodological variables retain consistent signs and relative magnitudes across robustness specifications that exclude extreme values or restrict the sample to international journal publications (Table 4). The fiscal gap estimates, however, depend on accounting assumptions including value-proportional benchmarking and static cross-sectional comparison, and should be interpreted as scenario-based magnitudes rather than deterministic quantities. These considerations frame the following discussion of limitations and directions for future research.

Several research directions could address current limitations. Incorporating high-resolution remote sensing data for continuous ES monitoring would enable annual value updates and trend analysis. MODIS NPP data provide annual vegetation productivity estimates, while soil moisture and land cover products track degradation and restoration dynamics. Expanding cultural service valuation through systematic surveys would provide more complete ES accounts. Cultural services likely contribute 10–20% of total grassland ES value based on analogous ecosystem studies, but current evidence remains sparse.

Developing integrated assessment models linking biophysical simulation with economic valuation would improve mechanistic understanding of how climate change, land use, and management alter ES provision. Process-based grassland models simulate vegetation dynamics, carbon cycling, and water fluxes under alternative scenarios. Coupling these models with valuation parameters would enable the projection of future ES values under climate change scenarios.

Examining heterogeneous treatment effects of conservation programs across grassland types would provide evidence on where interventions generate the greatest impact. Current program evaluations aggregate effects across diverse contexts, potentially missing important variation in effectiveness. Investigating governance arrangements and institutional factors affecting ES provision deserves attention. Collective grassland management institutions, land tenure security, and coordination across administrative boundaries all influence conservation outcomes. Comparative analysis of regions with different institutional configurations could identify governance factors that enhance ES provision.

6. Conclusions

This study provides a systematic measurement and decomposition of spatial inequality in China's grassland ecosystem service values. The meta-database synthesizes 734 valuation observations from 186 studies spanning 2000–2024 (Table 1). The analysis reveals that grassland ES values exhibit high concentration (Gini coefficient = 0.58, Table 5), comparable to income inequality in economically stratified societies.

Natural endowments, including precipitation, productivity, and elevation, explain 52.3% of observed inequality (Table 5). This finding establishes that ecological value distribution reflects geological and climatic legacies operating beyond policy control. Human population pressure and land use patterns contribute 30.8% of inequality (Table 5), demonstrating that management decisions substantially modulate the natural value distri-

bution. Valuation methodology choices account for 16.9% of observed variation (Table 5), highlighting persistent challenges in ES monetary assessment.

The spatial pattern reveals a pronounced west-high, east-low gradient (Figure 5). High-altitude alpine meadows of the Qinghai–Tibet Plateau generate per-hectare values 180–240% above national medians through superior water conservation and carbon sequestration capacity. These high-value regions maintain sparse populations and limited fiscal capacity. Current area-based payment mechanisms produce systematic mismatches between value provision and compensation allocation (Table 2). The analysis identifies 94 high-value-low-compensation counties (Type II) and 73 low-value-high-compensation counties (Type III). The mismatch index, defined as the difference between value and compensation quartile ranks with a theoretical range from -3 to $+3$, quantifies deviation from aligned allocation (Section 3.5; Table 2).

This research contributes to the grassland ES literature in four ways. Methodologically, the study moves beyond aggregate valuation to systematic inequality measurement using Gini and Theil indices with variance decomposition. The meta-regression benefit transfer approach conditions spatial projections on local covariates rather than applying simple mean transfers. Cross-validation procedures (leave-one-study-out and block cross-validation) characterize prediction uncertainty to bound the reliability of spatial projections for identifying broad patterns rather than precise county-level evaluations.

Theoretically, the framework integrates natural, socioeconomic, and methodological drivers into a unified analytical structure where different explanatory factors can be compared on a common scale through variance decomposition. Empirically, the study bridges ES valuation research with PES policy evaluation by overlaying value distribution maps with compensation allocation data. This approach provides a transferable template for natural capital accounting in other ecosystems where value inequality and policy alignment require assessment.

Several limitations warrant acknowledgment. The cross-sectional design constrains conclusions about temporal dynamics and causal mechanisms. The negative association between population density and ES values admits multiple interpretations, including environmental selection and human pressure, which the meta-regression cannot definitively separate (Section 4.2). Spatial projections inherit uncertainty from coefficient estimation and covariate measurement, with transfer errors documented in Section 4.3. Compensation data availability and comparability across provinces introduce additional measurement concerns.

Future research could address these limitations through several directions. Incorporating time-series data would enable analysis of how value distributions and mismatch patterns evolve under policy interventions. Finer-scale spatial data and stronger identification strategies could improve the local specificity of projections. Expanding opportunity cost measurement would strengthen the connection between value-based targeting and cost-based payment calibration. Integrating biophysical simulation with economic valuation could support the assessment of climate change impacts on ES provision and compensation needs.

The findings suggest that transitioning from uniform area-based subsidies toward value-sensitive compensation mechanisms may improve alignment between ecological contribution and fiscal allocation. Such a transition would require institutional safeguards, attention to household-level participation constraints, and adaptive capacity for climate-sensitive regions. Detailed policy design remains beyond the scope of this empirical analysis, but could build on the spatial patterns and mismatch typology documented here.

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