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Assessment of Human-Related Driving Forces for Reduced Carbon Uptake Using Neighborhood Analysis and Geographically Weighted Regression: A Case Study in the Grassland of Inner Mongolia, China

Zongyao Sha [1,*] and Ruren Li [2]

1 School of Remote Sensing and Information Engineering, Wuhan University, Wuhan 430079, China
2 School of Transportation Engineering, Shenyang Jianzhu University, Shenyang 100168, China; cerrli@sjzu.edu.cn
* Correspondence: zongyaosha@whu.edu.cn; Tel.: +86-27-68778770

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Featured Application: The study assessed the reduced carbon uptake (RCU) due to human activities and highlighted the patterns of the impact on RCU from human-related driving forces so that optimized grassland management policies could be implemented to achieve more carbon sequestration from vegetation.

Abstract: The ever-rising concentration of atmospheric carbon is viewed as the primary cause for global warming. To discontinue this trend, it is of urgent importance to either cut down human carbon emissions or remove more carbon from the atmosphere. Grassland ecosystems occupy the largest part of the global land area but maintain a relatively low carbon sequestration flux. While numerous studies have confirmed the impacts on grassland vegetation growth from climate changes and human activities, little work has been done to understand the driving forces for a reduced carbon uptake (RCU)—a loss in vegetation carbon sequestration because of inappropriate grassland management. This work focused on assessing RCU in the grassland of Inner Mongolia and understanding the influential patterns of the selected variables (including grazing intensity, road network, population, and vegetation productivity) related to RCU. Neighborhood analysis was proposed to locate optimized grassland management practices from historical data and to map RCU. Ordinary least squares (OLS) and geographically weighted regression (GWR) models were applied to explore the driving forces for RCU. The results indicated that the human-related factors, including stock grazing intensity, population density, and road network were likely to present a spatially varied impact on RCU, which accounted for more than 1/4 of the total carbon sequestration.

Keywords: zonal analysis; carbon sequestration; grassland; land management; NPP

1. Introduction

Increased greenhouse gas (GHGs) emissions from human activities have caused significant concerns around the world [1]. As the largest component in GHGs, more than 10 PgC (1PgC = 10^{15}gC) is released into the atmosphere each year from human-related activities such as fossil fuel combustion and cement manufacture [2]. Green vegetation, on the other hand, absorbs carbon dioxide (CO_2) through a biotic process called photosynthesis, which sequesters CO_2 out of the atmosphere [3,4]. However, a significant increase in GHGs emissions in the past few decades has broken this emission–absorption balance and led to increased atmospheric CO_2 concentration, which is believed to be the main cause for global warming [5]. Facing such a challenge, international cooperation has been called for to cut down carbon consumption and reduce carbon release into the atmosphere [6]. Unfortunately, the increasing trend of the atmospheric CO_2 concentration did not stop. Along this track, it is forecasted that the global temperature would rise more than 3 °C by the end of the 21st century [6], which imposes a global catastrophic risk to human living environments. Hence, innovative work must be done to address the continuously accumulative CO_2 in atmosphere due to the imbalanced emissions and absorptions in GHGs. Improving carbon sequestration from vegetation may provide a prominent way to this goal.

The net carbon sequestration capacity from vegetation can be reflected from the dynamics of net primary productivity (NPP), which is the net amount of solar energy converted to plant organic matter through photosynthesis in a given period [3,7]. Terrestrial ecosystems are featured by vegetation biomes capable of sequestering varied amounts of carbon. For example, forestry usually but not necessarily produces more NPP than croplands given the same area [8]. Converting land-use types, e.g., from farmlands to forests, may help secure carbon sequestration [9]. However, it is impractical to resort to land-use transformation, because reduced farmland means less food supply, which is not acceptable to sustain a local economy. Whether it is possible to improve vegetation productivity without converting land cover use is a valuable topic that should be investigated. Furthermore, it is meaningful to know the sensitive area that possesses the most potential in the enhancement of carbon sequestration from vegetation.

Natural grasslands and savannas occupy nearly half of the terrestrial globe and provide important economic and ecological services to modern societies [10]. Unfortunately, a considerable proportion of the global grasslands shows degraded vegetation, e.g., reduced vegetation productivity [11], land desertification [12], or loss of biodiversity [13]. This could be attributed to climate constraints (e.g., shortage of precipitation) [14], natural environmental constraints (e.g., soils with poor nutrients which are required by vegetation growth) [15], and human activities (e.g., overgrazing) [16]. Historical data recording carbon sequestration flux of grasslands with dependent variables such as the climatic and environmental conditions and human footprint can be analyzed to assess the human-induced impact on vegetation carbon sequestration. While the climatic constraints and environmental constraints are difficult to be lifted in a short period of time, it is relatively easier to adjust human activities such as an exclusion of grazing or the restoration of abandoned mining lands so that more carbon could be sequestered. To measure the impact on vegetation carbon sequestration from human activities, we proposed the concept of reduced carbon uptake (RCU)—the amount of carbon that should have been sequestered but was actually not due to human impacts. Then, we assessed RCU and explored the influential factors related to human activities on RCU, aiming at making informed grassland management policies. To the best of our knowledge, the topic assessing RCU and modeling its driving factors has been rarely studied. The main purpose of this work was to model RCU and to analyze its driving factors linked to human activities.

2. Study Area, Methods, and Data Sources

2.1. Study Area

The Inner Mongolia Autonomous Region (IMAR) is an administrative region at the provincial level situated in the north-most part of China. It is characterized as one of the most typical grasslands in China and the world. Covering an area of $\approx 1.2 \times 10^6$ km^2, 60% of the area is occupied by grassland vegetation, and most of the area is characterized as arid and semi-arid regions. There are four main grassland vegetation types [17]: meadow steppe (including *Stipa baicalansis* and *Achnatherum splendens*, which occupy 13% of the total area), typical steppe (including *Stipa grandis* and *Leymus chinensis*, which take 28% of the total area), desert steppe (including *Stipa klemenzii, Sheep fescue,* and *Seriphidium gracilescens*, covering 12% of the total area) and steppe desert (mainly *S. sareptana* and *S. glareosa*, covering 6% of the total area). The average temperature in the vegetation growing season (from April to September) fluctuates between 12.1 and 25.2 °C. The study region presents an increasing elevation from east to west, ranging from 156 m below sea level to 2800 m above sea level, with significant local variation. The annual precipitation varies spatially from less than 200 mm in the west to 600 mm in the east. The western section in IMAR is commonly in severe shortage of water (annual precipitation <200 mm) and is primarily a desert, while the middle to eastern part is a semi-arid region, which is mainly covered by typical grasslands, steppes, or meadows.

Under the provincial administration level, IMAR is composed of 12 city-level administrative regions and 103 county-level administrative regions under the city level. The capital city of IMAR, or Huhehot, is located in the south-western part of the area (Figure 1a). The net primary productivity (NPP) of the grassland vegetation from the NPP product of Moderate Resolution Imaging Spectroradiometer (MODIS) 17A3 (MOD17A3) showed significant spatial variation in the past two decades in IMAR [18]. Generally, NPP distribution is consistent with the precipitation belts in that NPP decreases from the east to the west. However, there is also a considerable local difference in NPP that cannot be simply explained by climatic factors. Other impacts on NPP from natural environments and socio-economic activities including grassland management practices could not be neglected. The natural environments such as soil types, terrain features, and vegetation biomes types have been proved to affect NPP significantly [19,20]. Human activities have a profound impact on NPP, both positively and negatively. For example, grassland restoration projects and fenced grazing practices have proven effective in improving NPP in some parts of the study area [21,22]; they could potentially be optimal grassland management practices (OGMPs) and transferrable to other locations. OGMPs specifically refer to any human-related management strategies that could produce high vegetation productivity and thus sequester more carbon from vegetation. Conversely, some other activities such as over-grazing [23], unplanned urbanization [24], or large-scale coal mining [25] may reduce NPP and should be avoided. By implementing OGMPs at locations having lower NPP, RCU, which represents the loss of carbon sequestration due to unimplemented OGMPs, could improve carbon sequestration in the future.

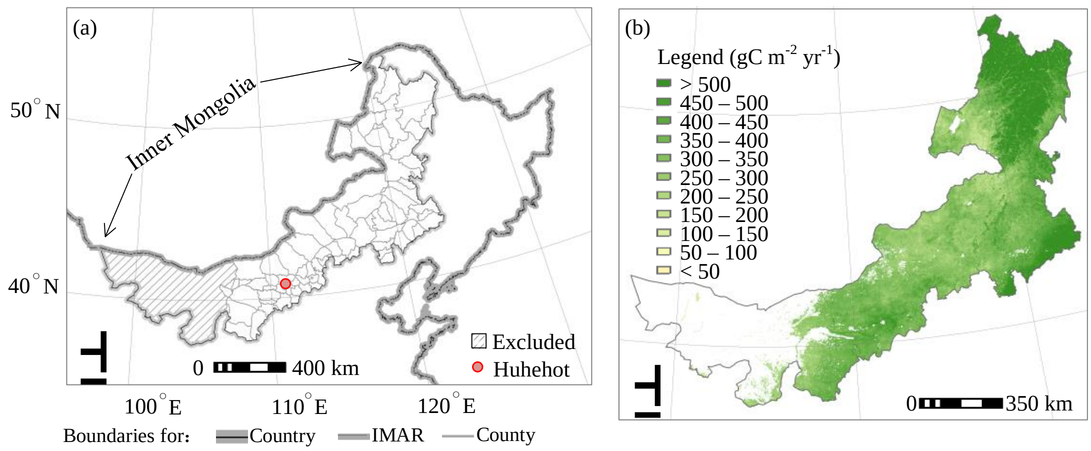

Figure 1. Study area. Some administrative units (counties) in the west mainly covered by desert or sandy areas or having very small vegetated area were excluded in the study. (**a**) Study area (Inner Mongolia) with administrative boundaries at the county level, and (**b**) Averaged NPP during 2001–2018.

2.2. Data Sources

To assess the reduced carbon uptake (RCU hereafter), the data sources included a soil map, digital elevation model (DEM), and vegetation cover, which were used to segment S-T-V patches, and climate dataset and annual NPP from MODIS (Moderate Resolution Imaging Spectroradiometer) 17A3 (MOD17A3), which were used to compute RCU along with the segmented S-T-V patches. The climatic variables were acquired from China's climate data-sharing platform (http://cdc.cma.gov.cn). Both the climate dataset and MODIS NPP were at an annual step in the time window during 2001–2018. RCU was assessed for each year during the time window. The explanatory variables grazing and population were compiled from yearbooks, and the road network was extracted from Open Street Map (OSM) [26]. All resultant raster layers were resampled to 1 km × 1 km if they were not at that resolution.

Vegetation cover types were extracted from the vegetation Atlas of China, which includes 55 vegetation types (http://www.nsii.org.cn/chinavegetaion). The non-vegetated area was excluded from further analysis. The soil map came from the Harmonized World Soil Database (ver. 1.2), which is the most up-to-date world soil map that incorporates data of 48,148 soil profile descriptions related to various soils associated with each mapping unit at a spatial resolution of ≈1 km at the equator [27]. Topography was prepared from DEM SRTM30 (http://earthexplorer.usgs.gov), which was resampled to the resolution at 1 km × 1 km and then reclassified to three groups, namely <500 m, 500–1500 m, and >1500m. The three layers were overlaid to segment the study area into S-T-V patches. RCU was assessed for each year during 2001–2018 based on the MOD17A3 time series and the climatic variables, and it was temporally averaged in the end.

The data sources for the explanatory variables, including grazing intensity and population, were compiled for 84 county-level administrative units (with the exclusion of those in sandy areas or having a very small vegetated area) from the yearbook of IMAR for each year during 2001–2018. This county-level yearbook covering the whole study area is the most consistent data available. The grassland has multiple grazing animals, for example, sheep, horse, buffalo, camel, and donkey. To uniformly measure grazing intensity, the impact from all other animals was converted into sheep units. Specifically, one horse is equivalent to 6 sheep and thus was multiplied by 6 to transform into the sheep unit. Similarly, cattle, camels, and donkeys were multiplied by 5, 7, and 3, respectively. The converted numbers were summed up to make a total value of sheep units, which was then divided by the vegetated area of each administrative unit to be grazing intensity. Similarly, population density was computed to be the total population divided by the area of administrative unit. Both the processed grazing intensity and population density were temporally averaged to represent an overall impact from each of them during the study period. Road network density, in the form of total road length in a square kilometer, was prepared using a line density algorithm with road network input from Open Street Map (OSM) [28].

2.3. Methodology

The study schema is composed of two parts, i.e., assessing RCU by applying neighborhood analysis and exploring the driving factors by the regression models through OLS and GWR (Figure 2). Much work related to RCU has been detailed in the previous work [18]. Both parts in the workflow are described in detail in this section.

2.3.1. Reduced Carbon Uptake by Neighborhood Analysis

Factors affecting carbon sequestration from vegetation are grouped into the following: (1) climatic factors (e.g., precipitation and temperature), (2) non-climatic natural conditions, such as the provision of nutrients from soil, topography, and vegetation types, and (3) human-related factors ranging from vegetation disturbances to grassland management such as enclosure fencing, fertilizing, and irrigation [18]. After deducting the impact on carbon sequestration from climatic and non-climatic factors, the spatial variation in the carbon sequestration will be attributed to human-related factors only. Accordingly, the flowchart for assessing RCU is designed as shown in Figure 2a. First, the study area is segmented into areal patches considering soil (S), topography (T), and vegetation (V), so that each S-V-T patch has no internal variations in terms of soil, terrain, and vegetation types; thus, there is no significant difference in the impact on RCU from the natural conditions. Second, the impact from the climatic factors (monthly precipitation and temperature) is rectified among the locations (pixels) in each S-V-T patch using potential NPP (PNPP) from the Miami model, which is a widely applied empirical NPP model driven by climate data [29]. The PNPP reflects the impact from the climatic variables only, and the relative magnitude in PNPP reflects the contribution of the climatic factors on NPP. By analyzing the spatial variation of PNPP in the S-V-T patch, the climate-rectified NPP (NPP_{CR})

was derived from the observed NPP and PNPP. The variation of NPP_{CR} within each S-V-T patch is attributed solely to human impact. Lastly, the within-patch variation of NPP_{CR} is analyzed using zonal statistics to derive RCU and to locate the optimal grassland management practices (OGMPs) within each S-T-V patch.

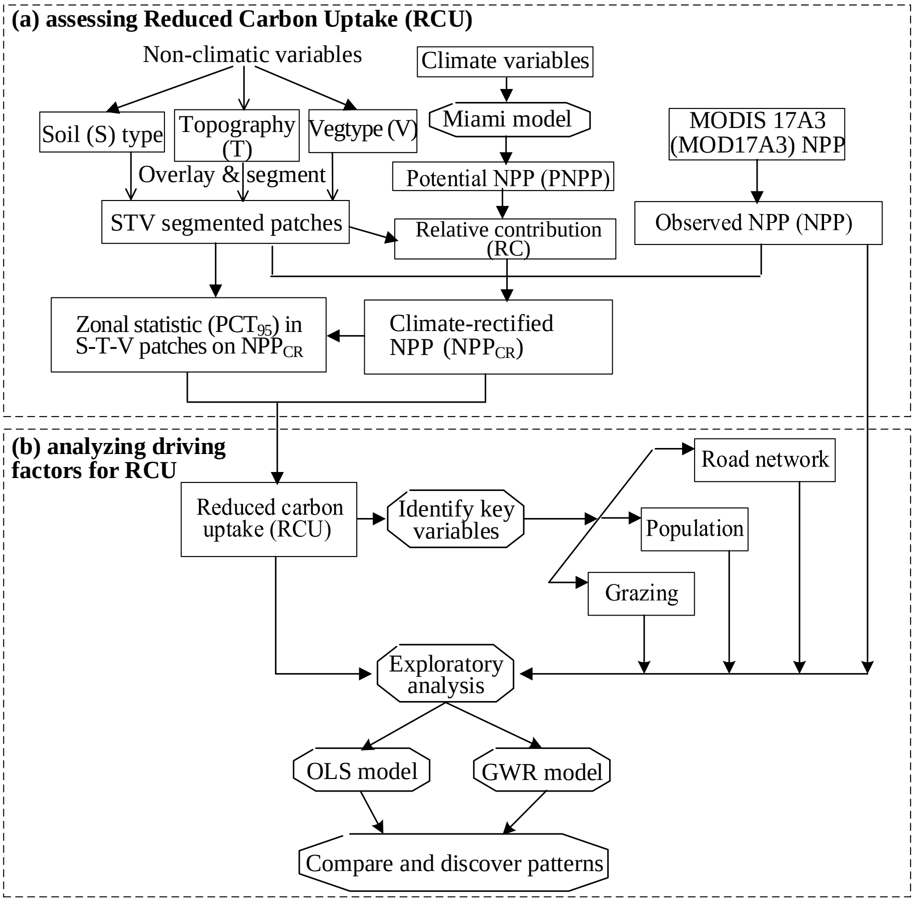

Figure 2. Flowchart of the study.

The Miami NPP model, which is widely recognized as a benchmark for NPP models, is applied to map grassland PNPP [29,30], in the form of,

$$\text{PNPP} = 0.45 \times \min\{\frac{3000}{1 + e^{1.315 - 0.119t}}, 3000 \times \left(1 - e^{-0.000664r}\right)\} \tag{1}$$

where t is the annual average temperature (°C), r is the annual precipitation (mm), and the coefficient 0.45 converts the PNPP to a carbon unit (gC m^{-2} yr^{-1}) from dry matter. The PNPP for arid regions increases by 1.0 gC/m^2 for every mm of precipitation, and productivity doubles every 10 °C between −10 and 20 °C [31].

Then, given an S-T-V patch g, which contains a set of k pixels (locations) homogeneous in soil, topography, and vegetation cover type, a relative contribution (RC) index at location i reflecting the differed impact from the climatic factors is written as

$$\text{RC}(i,g) = \text{PNPP}(i,g) - \text{PNPP}_{\text{Mean}}(g) \tag{2}$$

where $\text{PNPP}_{\text{Mean}}(g)$ is the averaged PNPP in g, $\text{PNPP}(i,g)$ is the PNPP at location i in g, and $\text{RC}(i,g)$ is the deviated PNPP at location i from the mean PNPP ($\text{PNPP}_{\text{Mean}}(g)$). A relatively more favorable climatic condition (e.g., more precipitation or temperate temperature) will promote PNPP (higher

PNPP), resulting a positive RC(i,g) at location i in g. Conversely, less favorable climate (shortage of precipitation or high temperature) results in a negative RC(i,g). Clearly, the total RC(i,g) for all i (i = 1, 2, . . . , k) makes 0—that is, $\sum_{i=1}^{k} RC(i,g) = 0$ in g.

To level off the difference of climatic impact within an S-T-V patch g, climate-rectified NPP, or termed as NPP_{CR}, at location i in g is computed as

$$NPP_{CR}(i,g) = NPP(i,g) - RC(i,g). \quad (3)$$

The internal variation of $NPP_{CR}(i,g)$ in an S-T-V patch g will be attributed to human-related impact only. Locations presenting the highest (target) NPP_{CR} in the S-T-V patch are under optimal grassland management practices (OGMPs); conversely, locations showing relatively lower NPP_{CR} in the S-T-V patch suggest that they experience RCU. By copying the OGMPs to locations presenting low NPP_{CR}, it is expected that NPP_{CR} can also be promoted to the target level given that all the locations in an S-T-V patch have similar natural (or non-climatic) environments. Here, the target level of NPP_{CR} for each S-T-V patch is computed by neighborhood analysis [32], which is a spatial analytical routine finding a zonal statistic (e.g., maximum value) from a set of NPP_{CR} inputs for locations within a neighborhood, i.e., the S-T-V patch. Rather than computing a statistic of the maximum value from the input data, we decided on a zonal statistic of 95% percentile (95%PCT), which may provide a more robust estimation of the target NPP level within each S-T-V patch considering possible noise in the patch segmentation [18]. Here, 95%PCT corresponds to an NPP_{CR} value such that NPP_{CR} out of 95% cases is below the value, while 5% of the cases are above it. Therefore, by referencing 95%PCT as the target NPP_{CR} level, the RCU at any location i in an S-T-V patch g can be computed as,

$$RCU_{95\%PCT}(i,g) = \mathit{Greatest}\{95\%PCT(g) - NPP_{CR}(i,g), 0\} \quad (4)$$

where $RCU_{95\%PCT}(i,g)$ is the reduced carbon uptake at location i by using zonal statistic 95% percentile (95%PCT) as the target NPP_{CR} and *Greatest* is a function that selects a non-negative value for the gap from the current NPP_{CR} to the target (95%PCT). The locations having NPP_{CR} over 95%PCT are to be referenced for obtaining OGMPs in g.

2.3.2. Explanatory Factor Analysis Using GWR

Few studies have examined the factors that are related to the spatial variation in RCU. There are several considerations in deciding the explanatory factors for RCU. Since the impacts from climatic factors and environmental (non-climatic) factors have been excluded from RCU, our focus was on the human-induced factors. Grazing has been identified as a key force degrading vegetation in the study area [10,33]. Over-grazing accounts for 35% of the degraded grasslands in the world [34] and has caused significant vegetation degradation and land desertification in the study area [35]. Urban sprawl is another important human-related factor [14,36]. Urban sprawl is closely correlated to the road network. In the rural areas, the road network may have an unneglectable impact on the grassland vegetation. Thus, access to a road network was taken to indicate the impact on vegetation for urban sprawl and to reflect the impact of road in rural areas. In vast grassland, the increase of population has imposed some negative impact on grassland vegetation [37]. In this study, population density was included as the third factor related to human activities. The listed factors may not be fully accountable for the RCU variation across the region, but they represent the typical human-related factors in the study area. Lastly, NPP was also taken as a variable in the explanatory factor analysis because RCU is directly related to NPP. It can be seen from Equation (4) that RCU is computed based on NPP distribution within an S-T-V patch (not only NPP at the current location but the NPPs located in the S-T-V patch, which are used to infer 95%PCT or the target carbon NPP_{CR}).

The flowchart analyzing the driving factors for RCU is shown in Figure 2b. Exploratory analysis was conducted first to understand the spatial distribution pattern in RCU. Global Moran's I is a useful indicator to detect whether RCU is in a random or clustered pattern. A clustered pattern usually indicates there are underlying mechanisms explaining RCU clustering. Analytical models can be applied to understand the impact from the selected explanatory variables on RCU. Ordinary least square (OLS), or a global regression model, was adopted first to reveal the relationship between RCU and the selected variables without reflecting the possibly spatial varied patterns in the relationships by the function,

$$y = \beta_0 + \sum_{k=1}^{p} \beta_k \cdot x_k + \varepsilon \quad (5)$$

where y is the observed outcome, β_0, β_1, ... , β_p are the fit model coefficients, x_k are explanatory variables k (k = 1, 2, ... , p, where p is the number of explanatory variables), and ε is the residual with zero mean and homogenous variance σ^2. Geographically weighted regression (GWR) is a local regression model that can estimate parameters to vary across regions to accommodate potential spatial dependencies [38]. A GWR model takes the form of,

$$y_s = \beta_0(s) + \sum_{k=1}^{p} \beta_k(s) \cdot x_{k,\ s} + \varepsilon_s \quad (6)$$

where y_s is the response variable (RCU) at location s, $x_{k,s}$ and $\beta_k(s)$ (k = 0, 1, 2, ... , p, and p is the number of variables) are the observed value and spatially varied coefficient for the k^{th} variable at s, respectively, and ε_s is a random error at location s. Compared to the global OLS, all the parameters (coefficients) and the error term (ε) in the local regression model (GWR) are location dependent and vary at different locations. Gaussian kernel using corrected Akaike Information Criterion (AICc) to determine the optimal number of neighbors was specified for the model. Global Moran's I on the regression residuals was applied to test if they are spatially clustered or random, which is a necessary step to verify that the GWR model is correctly specified.

Multicollinearity or strong correlation among the input variables should be avoided in either OLS or a local model. The variance inflation factor (VIF) and condition number (CN) are indicators for checking global multicollinearity and local multicollinearity, where a VIF greater than 7.5 in OLS or CN greater than 30 indicates multicollinearity [39,40]. An adjusted coefficient of determination (adjusted R^2) and AICc can be taken to decide whether the global or local model interprets the data better. The model with a higher adjusted R^2 and lower AICc is a preferred one that better reveals the relationship between the response variable and explanatory predictors. Both OLS and GWR were applied to fit the relationship between RCU and the selected variables.

3. Results

3.1. Descriptive Analysis of the Carbon Gap and the Explanatory Factors

RCU was distributed unevenly across the study area. A high RCU appeared in the eastern part of the study area, while a low RCU was observed mainly in the middle section of the area (Figure 3a). RCU averaged 58.9 ± 2.3 gC m^{-2} yr^{-1} in flux during the years, which is more than 1/4 of the NPP flux (averaged 195.6 gC m^{-2} yr^{-1}). A high RCU means that there was more carbon loss, which could have been sequestered from vegetation if given optimal grassland management practices (OGMPs); in other words, the areas with high RCU should be given more attention because they presented high potential in the carbon sequestration enhancement. The aggregated RCU at the administrative-unit scale is shown in Figure 3b. The high global Moran's I statistic (I = 0.31) indicates a significant spatial clustering pattern in RCU distribution ($p < 0.01$). Thus, there might be explanatory factors that lead to such non-random distribution in RCU.

There are variations in the spatial distribution of the four explanatory variables (Figure 4). The intensive grazing (in sheep unit per square kilometer) scatters across the study area, particularly in the south-eastern section (Figure 4a). Population density presents high in the south-eastern and southern parts of the area (Figure 4b). Road network, as measured by total road length in a square kilometer, is much denser in the south and west-southern parts of the region, particularly around some key cities including the capital city Huhehot, as compared to the rest of the area (Figure 4c). In terms of the NPP, the north-eastern part has the highest NPP (Figure 4d); at the same time, this area also showed the highest RCU (Figure 3).

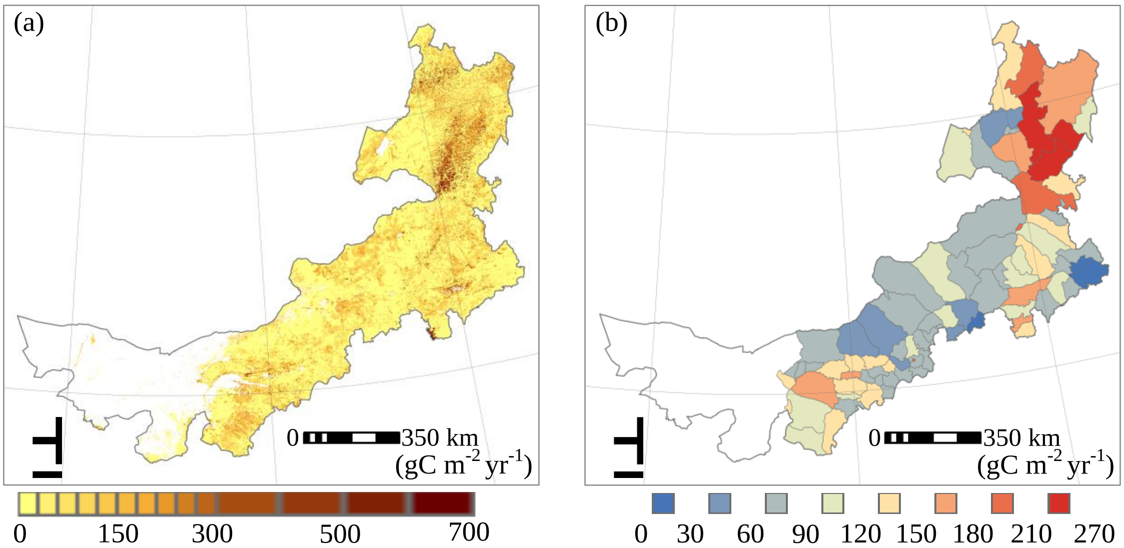

Figure 3. Distribution of reduced carbon uptake (RCU) at the pixel scale (with RCU_{mean} = 58.9 ± 2.3 gC m^{-2} yr^{-1}) and the aggregated administrative unit level. (**a**) Temporally averaged reduced carbon uptake (RCU) (2001–2018), and (**b**) Zonal average at the administrative-unit scale.

3.2. Model Result from OLS

The correlation matrix of the explanatory variables is shown in Table 1. The selected variables show no significant correlation (α = 0.01). All the coefficients (β) of the variables except for that of the grazing intensity show significance (p < 0.01), indicating that at the global scale, population density, road network density, and NPP all imposed a significant impact on RCU (Table 2). The positive coefficients from population and NPP reveal that a higher population density and NPP generally tend to contribute RCU or more loss in vegetation carbon sequestration. The negative coefficient from the road network density suggests that more road networks led to lower RCU or less carbon loss in carbon sequestration. Grazing intensity has for a long time been regarded as a factor affecting the grassland vegetation [41]. The positive coefficient (β = 0.65) of grazing intensity suggests that high grazing generally reduced carbon sequestration from vegetation; at the same time, the insignificance (p = 0.66) in the coefficient implies that the grazing might demonstrate local variation in the impact on vegetation productivity. The variance inflation factors (VIFs) all showed low value (<7.5), suggesting there is no problem of redundancy (multicollinearity) among the explanatory variables.

Table 1. Correlation matrix between the explanatory variables.

Variable #	Population	Road	NPP	Grazing
Population	1.00			
Road	0.27	1.00		
NPP	0.02	−0.17	1.00	
Grazing	−0.13	−0.06	−0.14	1.00

Population = population density; Road = road network density; Grazing = grazing intensity.

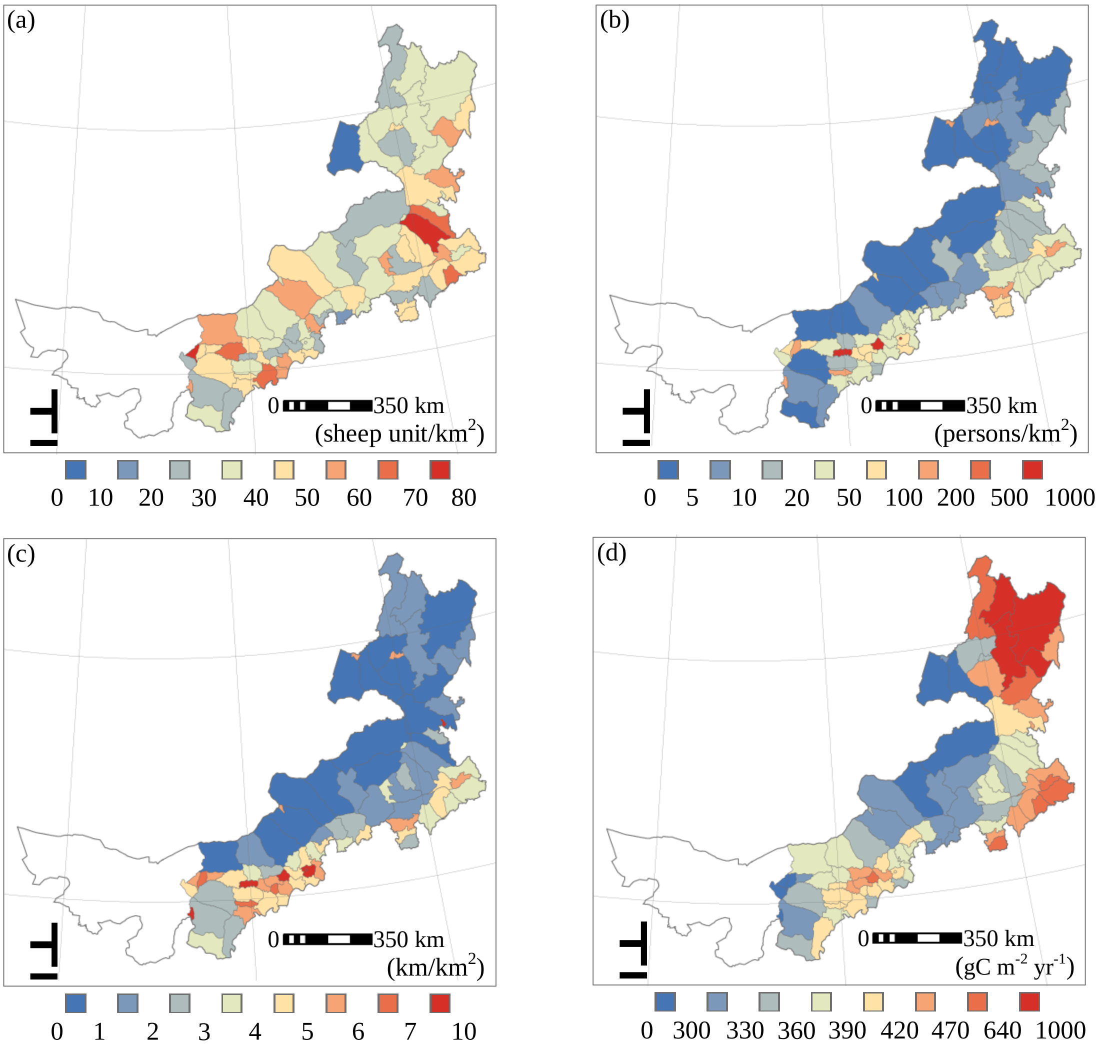

Figure 4. Distribution of selected explanatory variables for the reduced carbon uptake (RCU) from vegetation. (**a**) Grazing intensity, (**b**) Population density, (**c**) Road network density, and (**d**) Net primary productivity (NPP) at the administrative unit level.

Table 2. Statistics of the regression coefficient for the explanatory variables from ordinary least square (OLS) regression.

Variable	Coef. (β)	StdErr.	t-Statistics	Probability	Robust_SE	Robust_t	Robust_Pr	VIF
Intercept	51.49	43.80	1.17	0.24	45.80	1.12	0.27	
Population	0.35	0.13	2.62	<0.01 *	0.13	2.67	<0.01 *	4.87
Road	−0.91	0.44	−2.07	0.04 *	0.51	−1.79	0.08	4.82
NPP	0.30	0.08	3.95	<0.01 *	0.10	3.15	<0.01 *	1.04
Grazing	0.65	2.01	0.33	0.74	1.50	0.44	0.66	1.04

* Significance tested based on two-tailed hypothesis; VIF = variance inflation factor.

The overall performance of the OLS model is summarized in Table 3. The Jarque–Bera statistic, which is a goodness-of-fit test of whether the data present skewness and kurtosis, shows non-significance (p = 0.56), indicating that the residuals from the OLS model are not significantly different from normal distribution. The Joint Wald statistic confirmed the model significance (p<0.01). However, a rather low percentage, i.e., 21% (adjusted R^2 = 0.21), of the variation in RCU is explained from the explanatory variables by the OLS model. The significance of the Koenker (BP) Statistic (p < 0.01) suggests that a local regression such as GWR may be a better model candidate.

Table 3. The diagnostics from ordinary least square (OLS) regression.

Variable	Value	Probability	Value
R^2	0.25		
Adjusted R^2	0.21		
AICc	961.7		
Joint F-Statistic	6.71	Prob(>F), (4,79) DF	<0.01
Joint Wald Statistic	22.66	Prob(>chi-squared), (4) DF	<0.01
Koenker (BP) Statistic	9.01	Prob(>chi-squared), (4) DF	<0.01
Jarque-Bera Statistic	1.17	Prob(>chi-squared), (2) DF	0.56

DF = degrees of freedom.

3.3. Model Result from GWR

Although the OLS regression captured the relationships between RCU and the explanatory variables, nonstationary characteristics in the spatial RCU and the explanatory variables imply that the global model may fail to highlight the spatially variant patterns in the relationship [42]. Therefore, RCU was further analyzed by the GWR model, which is capable of reflecting the nonstationary characteristics in the relationship. Table 4 describes the result from GWR with 58 optimal neighbors suggested by the model. The improved performance, as opposed to that from the OLS model, confirmed that nonstationary patterns do exist among the relationship between RCU and the explanatory variables. For example, the adjusted R^2 had a significant improvement, which was 0.53 from GWR compared to 0.21 in the OLS model. Furthermore, the corrected Akaike's Information Criterion (AICc) is also a useful way to evaluate the performance of a regression model, and lower AICc means model improvement. The decrease of AICc to 951.6, as opposed to 961.7 from the OLS model, confirms that GWR is superior to the OLS model in capturing the variation of the dependent variable. The model residuals from the GWR regression did not show significant bias. In summary, it is evident that GWR improved the model performance compared to that by OLS.

Table 4. Statistics from a geographically weighted model (GWR) for the carbon gap using the explanatory variables.

#ID	Statistical Item	Value
0	Neighbors	58
1	Residual squares	274571.4
2	Effective number	15.5
3	Sigma	63.3
4	AICc	951.6
5	R-Squired (R^2)	0.62
6	Adjusted R^2	0.53
7	Depend variable	Reduced carbon uptake (RCU)
8	Predictors	Grazing (intensity), Road (network density), Population (density), NPP

AICc: Akaike's Information Criterion, corrected. Global Moran's *I* on residual map is 0.16, showing no significant clustering pattern ($p > 0.01$).

The regression coefficient varied over the space, indicating a heterogeneous impact on the reduced carbon uptake (RCU) from each of the variables (Figure 5). The four variables together explain 53% of the variation in RCU (adjusted $R^2 = 0.53$, Table 4). The model coefficients from the variables differed not only in magnitude but also in directions (positive or negative). The positive coefficients of the grazing intensity in most of the study area, particularly the middle part, confirms that increasing grazing animals would increase RCU, which is a sign of negative impact on vegetation productivity; an opposite impact from grazing animals was identified in the northern and north-eastern part of the area, where grazing showed an improving effect on vegetation (Figure 5a). The population shows a consistently negative impact on RCU, meaning that a larger population would lead to more RCU (Figure 5b). The impact from road network density shows a complicated pattern over the area (Figure 5c). The coefficient distribution of the road network suggests that the impact of roads on RCU is closely related to vegetation density; the sparsely covered vegetation, which dominates mainly the middle and west part of the study area, is more likely to present RCU. This finding is consistent with the previous work stating that roads led to vegetation degradation (increased RCU) at densely covered vegetation, while convenient access to roads resulted in vegetation restoration when vegetation cover was sparse [43]. The coefficient distribution in NPP showed that for the majority of the study area, a higher RCU can be observed in areas with higher NPP (Figure 5d). This finding seems contradictory to our common sense that a higher NPP means more carbon sequestered and thus lower RCU. However, it is noteworthy that the computed RCU was derived from neighborhood analysis, which took not only the NPP_{CR} at a currently examined location but also a target NPP_{CR} statistic around it; i.e., RCU reflects the difference from its current NPP_{CR} to 95%PCT, or a target NPP_{CR} level in the neighborhood (refer to Equation (4)). Thus, a high RCU is usually observed in a neighborhood having a high 95%PCT, which also makes the spatially aggregated RCU high at the administrative unit level. At the same time, RCU is negatively related to the NPP itself, i.e., a location with higher NPP_{CR} means a lower RCU (refer to Equation (4)), which might be the case for the small part of the area having the minus NPP coefficient.

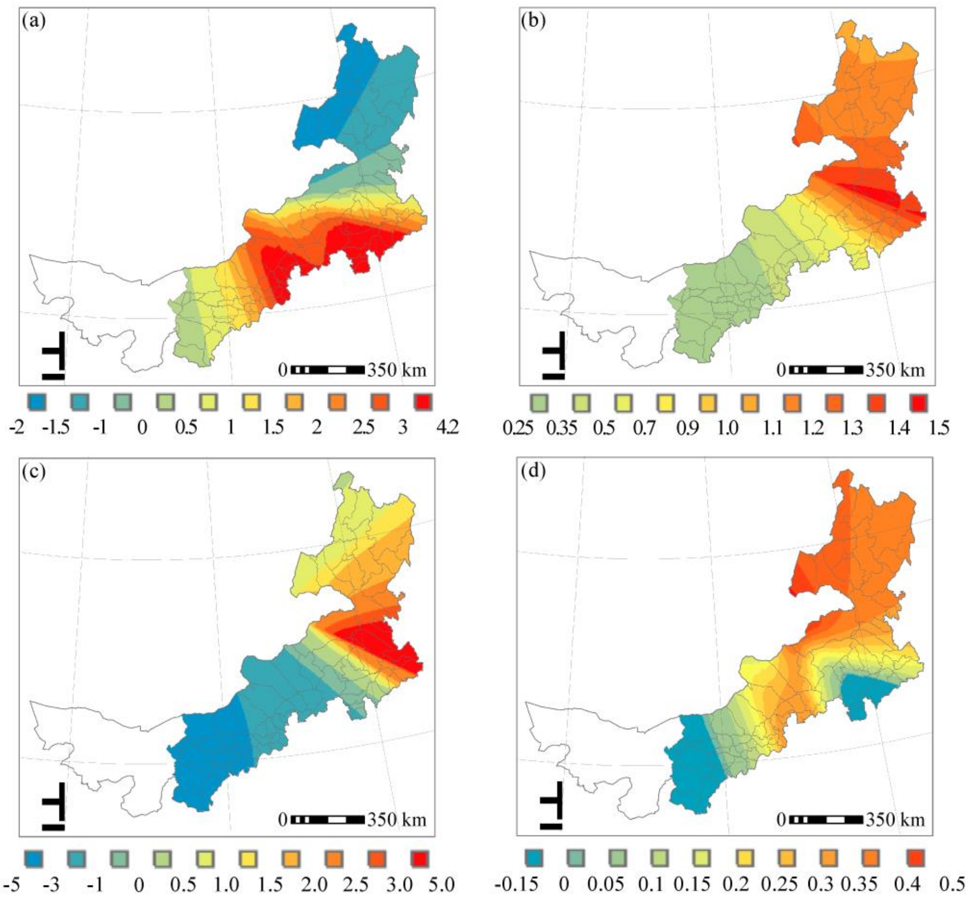

Figure 5. Regression coefficient of the explanatory variables against reduced carbon uptake (RCU) from GWR. Coefficient for (**a**) Grazing intensity, (**b**) Population density, (**c**) Road network density, and (**d**) Net primary productivity (NPP).

4. Discussions

4.1. Optimal Grassland Management Practices (OGMPs)

Optimal grassland management practices (OGMPs) refer to those grassland management strategies that have produced relatively higher vegetation productivity. Previous study showed that human activities could increase or decrease vegetation productivity [44], and adopting OGMPs means an improvement in vegetation productivity and thus carbon sequestration. RCU measures the loss of carbon sequestration from human impacts in the past or the potential of carbon sequestration to increase under OGMPs in the future. The current work identifies OGMPs through the neighborhood analysis; namely, OGMPs are referenced from the locations demonstrating high climate-rectified NPP (NPP_{CR}) within an S-T-V patch. It is advisable that OGMPs should be taken into account when making grassland management policies.

There exists no OGMPs that are applicable to all locations. The identified OGMPs are location-dependent and pertain to specific S-T-V patches. Taking grazing management as an example, the exclusion or restriction of grazing resulted in a significant improvement in vegetation density in Horqin sandy land located in the southeast of IMAR [45]. Rotational or nomadic grazing also helps reduce the negative impact on grassland vegetation [46]. Thus, fenced grazing (exclusion of grazing) and rotational grazing can be adopted as OGMPs for the S-T-V patches in those study regions. The current study identified the locations presenting the desired target NPP level within each S-T-V patch, and the locations with the target NPP should be extracted to build the candidate pool of OGMPs suitable for the local climatic and natural contexts. In addition, some of the other forms of OGMPs are listed in Table 5.

Table 5. Typical examples of optimal grassland management practices (OGMPs) in Inner Mongolia.

OGMPs	Main Practices and Results	Study Location	References
Rotating grazing	Grazing and protection rotationally improved NPP	Xilingol league in IMAR	[46]
Fenced grazing	Replacing direct grazing with grass-cutting improved NPP	Xilingol league in IMAR; Horqin sandy land in IMAR	[35,45,46]
Protection zone/belt against expansion of road/urbanization	Densely distributed roads/urbanization reduced NPP in areas with dense vegetation and protection zone/belt is recommended	Scattering across IMAR	[43]
Restoration and recovery projects	Restoration, recovery, and vegetation rehabilitation projects improved soil improvement, reduced erosion, and thus improved NPP	Scattering across IMAR	[37,47]
Vegetation protection from coal mining	Heavy coal or metal mining activities reduced NPP, and vegetation restoration should be followed after mining	Eastern IMAR	[25]
* Vegetation irrigation and fertilizing	Certain amount of irrigation improved NPP	Xilamuren grassland (in middle to western IMAR)	[48]
Maintain vegetation health by pesticide spaying	Pesticide application helped the improvement of NPP in some parts of the study area	Scattering across IMAR	[49]

* Irrigation is related to rainfall (a climatic factor) but is listed here as one typical practice belonging to human-related activities.

4.2. Driving Factors for Reduced Carbon Uptake (RCU)

The driving factors for RCU could be complex. In this study, along with NPP, the human-related factors, including grazing intensity, population, and road network density, were taken to examine their impact on RCU using both global (OLS) and local (GWR) regression models. As stated above, heavily grazing could degrade vegetation productivity. However, a recent meta-analysis of stock grazing on China's grasslands concluded that light and medium grazing was actually beneficial to grassland vegetation [50]. For example, light and moderate grazing could improve the top soil organic carbon, which is essential for vegetation growth [51]. The impact from grazing is also related to vegetation status and terrain features [35]. The above findings suggest that grazing may impose different effects on NPP under different local conditions. The current study verified that grazing intensity showed a positive impact on NPP in the northern and north-eastern parts of the study area (Figure 5a). Hence, optimal grazing intensity must be decided considering the location difference. The population or the total number of human inhabitants reflects the socio-economic development of the area. Densely distributed population was found to have reduced carbon sequestration from vegetation (i.e., increased RCU) in some parts of the grassland; this is understandable, because more population means a sprawl of human settlements and built-up areas, which could easily fragment and degrade grassland vegetation [52]. Previous work verified that the impact of roads on grassland vegetation depends on the nature of the resource (e.g., the density of vegetation cover) [43]. This study found that the grassland vegetation responded differently to the impact from roads at various locations, suggesting that the grassland management policy should reflect the location-dependent impact from the road network. The current work reveals the associations between the selected variables and RCU, but the patterns in the cause and effect need further field verification in the future.

This work is limited to examining the impact of some commonly recognized human-related factors on RCU; however, they together only explain slightly over half of the variance in RCU (53%), which could be further improved. There are other factors, including those human-related practices listed in Table 5, which might be similarly important and preferably included in the driving factor analysis. For example, rotating grazing, as a management practice recommended for improving vegetation productivity [46], was not indicated in the variable of grazing intensity and thus not reflected in the explained variance, although grazing rotationally or not could mean a significant difference on the impact of RCU. Moreover, while the included human-related factors, RCU, and their relationships were found to vary among administrative units, the analysis of the driving forces for RCU at the county level may generalize the effect between the selected variables and RCU. This work was unable to take all the key factors at a finer scale in the model because obtaining the fine-scale human-related factors require extensive data synthesis and most likely conducting field experiments, which would be our next step.

4.3. Further Note for Understanding Reduced Carbon Uptake (RCU)

The factors affecting carbon sequestration from grassland vegetation have been classified into three groups: climatic, non-climatic, and human-induced. After isolating the impact from climatic and non-climatic factors, RCU is equivalent to the amount of carbon that should have been sequestered from vegetation with appropriate grassland management practices and without negative human disturbances. Quantifying and mapping the spatial distribution of RCU can help understand the sensitive locations to human activities and thus informed policies regarding improving grassland management can be made for the future. Improving grassland management or reducing human disturbances improves vegetation photosynthesis. Adjusting human activities serves as a prominent measure that can promote carbon sequestration from the atmosphere. The study revealed that over 1/4 more carbon is to be sequestered under optimal grassland management practices. The study area presented high spatial variation in the distribution of RCU. Traditionally, severely degraded vegetation is believed to hold much potential in carbon sequestration improvement and is given more attention in terms of implementing new grassland management strategies. The study pointed out that grassland vegetation with a high NPP might also possess high enhancement potential in carbon sequestration and should be given sufficient attention.

We acknowledge there might be uncertainties in the result. The current work considers three elements, namely, soil, topography, and vegetation cover types in S-T-V patch segmentation, which may cover the most important factors differentiating grassland vegetation productivity in terms of the growing (non-climatic) environments. It is assumed that within each S-T-V patch, there is no internal variation in NPP attributed to the non-climatic conditions. Furthermore, the Miami model is taken to capture the difference in NPP from the varied impact of the climatic factors within each S-T-V patch.

Although the Miami model has been widely applied for deriving potential NPP, particularly in arid and semi-arid regions, the accuracy of the rectification in this study was not strictly verified due to unavailability of truth field data. With uncertainties in the computed variation of NPP from both the climatic and non-climatic factors, it is inevitable to lead to uncertainty in the isolated NPP variation from human activities. Thus, further work is needed to improve the accuracy of the contributed part from climatic and non-climatic factors.

5. Conclusions

The current work has applied spatial analytical models to reveal the reduced carbon uptake (RCU) from grassland vegetation due to inappropriate grassland management in the grassland of Inner Mongolia. Our work estimated that every year, there is a significant amount of carbon, i.e., more than 1/4 of the total NPP, that is not sequestered from the grassland vegetation due to ineffective grassland management. In other words, given improvement in the grassland management, the grassland vegetation would be able to sequester significantly more carbon. Improving grassland management strategies servers as a prominent measure to enhance the carbon sequestration service from the grassland vegetation. To explore the driving factors for RCU, human-related activities including grazing intensity, population density, and road network density along with vegetation NPP were analyzed using global regression OLS and local regression GWR. Both models reveal the patterns in the relationship between RCU and the variables, but GWR is superior to OLS in the model performance. The spatial varying effects of the selected explanatory variables from GWR provide a more useful guidance for making grassland management policies.

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