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Coupling Coordination and Influencing Mechanism of Ecosystem Services Using Remote Sensing: A Case Study of Food Provision and Soil Conservation

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Abstract: Understanding the trade-offs and synergies between ecosystem services is essential for effective ecological management. We selected food provisioning and soil conservation services to explore their intrinsic link and trade-offs. We evaluated these services in Minnesota from 1998 to 2018 using multi-source remote sensing data. The coupling coordination degree model (CCDM) was employed to quantify the relationship between these services. The CCDM evaluates the degree of coordination between systems by measuring their interactions. In addition, we used the geographically weighted regression (GWR) model to identify factors influencing this relationship. Our findings reveal that, while Minnesota's food provision services have shown a significant overall upward trajectory, distinct declines occurred in 2008 and 2018. In contrast, soil conservation services showed considerable variability from year to year, without a clear trend. Over time, the relationship between food provision and soil conservation services evolved from uncoordinated and transitional to more coordinated development. Our analysis indicates that climate–soil indicators (Z_1) exert the most significant influence on the coupling coordination degree (CCD), followed by topography (Z_3), vegetation quality (Z_4), and socio-economic indicators (Z_2). This suggests that natural environmental factors have a greater impact than socio-economic factors. Spatial analysis highlights that topography exhibits significant spatial heterogeneity and serves as the primary spatial driving factor. This study explores the trade-offs between food provision and soil conservation ecosystem services in Minnesota, enhancing the understanding of trade-offs among different ecosystem services and providing insights for global sustainable agricultural development.

Keywords: food provision; soil conservation; coupling coordination degree; sustainable agricultural development; ecosystem service

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1. Introduction

Food security is a critical global challenge, particularly as societies strive to maintain stable food supplies amidst population growth, climate change, and limited land resources [1,2]. Soil conservation enhances productivity, such as crop yield, and supports sustainable development [3–7]. However, soil erosion is occurring at an alarming rate of 13.5 tons per hectare per year globally, making it one of the significant factors affecting soil quality and productivity [8–10]. Economic development and population growth are likely to increase the demand for agricultural products, thereby intensifying agricultural activities [11]. Agricultural activities often lead to a series of issues for soil, including the loss of soil organic matter, structural degradation, and soil erosion [12,13]. Among these, soil erosion is one of the most widely recognized concerns [14,15]. A "trade-off" between agricultural and soil conservation services can be identified. Ideally, regional agricultural development should meet consumer demand while protecting ecological integrity by maintaining soil health, such as preventing soil erosion and water loss. Consequently, understanding and utilizing "trade-offs" between ecosystem services and identifying effective strategies to meet the balance is crucial for sustainable development.

Balancing the relationship between agricultural production and soil conservation is a critical issue for achieving sustainable agricultural development. Previous studies have investigated the "trade-offs" among population–agricultural-production–soil-erosion [16], agricultural-modernization–black-soil-protection [17], and food-production–agricultural-ecology [18]. These studies provide a significant theoretical foundation and empirical support for understanding the interactions among ecosystem services. However, research on the trade-off relationship between soil conservation services and food provision services remains insufficient. This study aims to systematically assess the trade-off relationship between these two ecosystem services. We will quantify food production as a measure of agricultural supply. For the assessment of soil conservation, we employ the sediment delivery ratio (SDR) used in the InVEST (Integrated Valuation of Ecosystem Services and Tradeoffs) model (InVEST-SDR) for quantitative evaluation. The InVEST-SDR model enhances the Universal Soil Loss Equation (USLE) [19–24] and has been widely applied by numerous scholars to estimate soil conservation and erosion in various regions [25–29]. Measuring the coupling relationship between soil conservation and food provision services offers theoretical support for the protection and restoration of agricultural ecosystems, while also improving the understanding of coordinated development strategies between social provisioning and ecological conservation.

With the advancement of spatial metrology theories and methods, along with the growing practical need for balanced regional development, the coordination among different systems has become a key area of interest for scholars worldwide [30–33]. The coupling coordination degree model (CCDM) has emerged as the most widely used method in this field. The CCDM analyzes equilibrium relationships among various elements by measuring the interactions and trends within a system [30,31]. The CCDM has been widely applied in empirical studies of "trade-off" relationships between two or more systems, due to its simple structure and ease of operation [34]. Existing research encompasses various aspects, including socio-economic–environmental [32], population–crop-production–soil-erosion [16], urbanization–ecological-environment [35], energy–economy–ecology [36], and economic-resource–environment [37]. Therefore, the CCDM was used to identify the "trade-offs" between food provision and soil conservation services in this study. Long-time-series changes in the coupled relationship between food provision and soil conservation were characterized.

Although the CCDM has been widely applied in various studies, there remain issues that require further investigation. Most studies employing the CCDM focus on the equilibrium state or coupling relationships between elements [23,38–42]. However, the analysis of the internal mechanisms of interaction among these elements remains relatively insufficient. Merely assessing the coupling state offers a superficial understanding of the social provision and ecological protection systems. Demonstrating the coupling coordination between these systems does not effectively guide policymakers and stakeholders towards specific actions to achieve designated goals [43]. Investigating the underlying mechanisms is essential for a deeper understanding of the coordinated development [44–46]. Previous studies have examined the influence of various socioeconomic factors on the coordination between food production and agricultural ecology [18,47]. However, few have integrated socioeconomic and ecological factors to quantitatively analyze their mechanisms affecting the relationship between soil conservation and food provision. The geographically weighted regression (GWR) model effectively captures variations in relationships between variables across different geographic locations, thereby elucidating local spatial relationships and spatial heterogeneity [44,48]. Therefore, we integrate social and ecological factors and adopt the GWR model to interpret the driving mechanisms of the coupling coordination degree from both quantitative and spatial perspectives.

In conclusion, this study innovatively explores the coordination and balance between soil conservation and food provision and investigates the influence mechanisms of their coupled coordination state. First, we quantitatively assess food provision and soil conservation in the study area from 1998 to 2018. Second, we evaluate the coupling coordination level between food provision and soil conservation using the CCDM. Third, we investigate the influencing mechanisms of the coupling coordination degree through GWR. Our findings aim to provide actionable insights for achieving ecosystem services coordination and sustainable agricultural development.

2. Material and Methods

2.1. Study Area

Minnesota is situated in the western-central United States (Figure 1), spanning latitudes from 43°30′N to 49°23′N and longitudes from 89°29′W to 97°14′W. The state comprises 87 counties and covers an area of 219,000 km^2. As a major agricultural state, more than 50% of Minnesota's land is used for farming [49], ranking it 7th nationwide for farm income [50]. Traditional agricultural practices often exacerbate soil erosion, leading to widespread soil degradation in farming regions [51]. The average annual erosion rate of cropland in Minnesota is about 2.1 tons per acre. Additionally, the spatial heterogeneity of soil loss in Minnesota is significant. Southeastern and northwestern regions have experienced erosion rates exceeding 5 tons per acre, affecting 45% of cropland [52]. Soil erosion reduces the organic matter content, nourishment, and fertility, adversely affecting crop yields [53,54]. Given the extensive agricultural activities and significant soil degradation issues in Minnesota, the state serves as an ideal research area. Investigating this region can provide valuable insights into sustainable agricultural practices and soil conservation strategies. Soil erosion is a widespread problem globally, particularly in agriculturally intensive regions. Research conducted in Minnesota can offer effective management strategies and solutions for other areas facing similar soil erosion challenges.

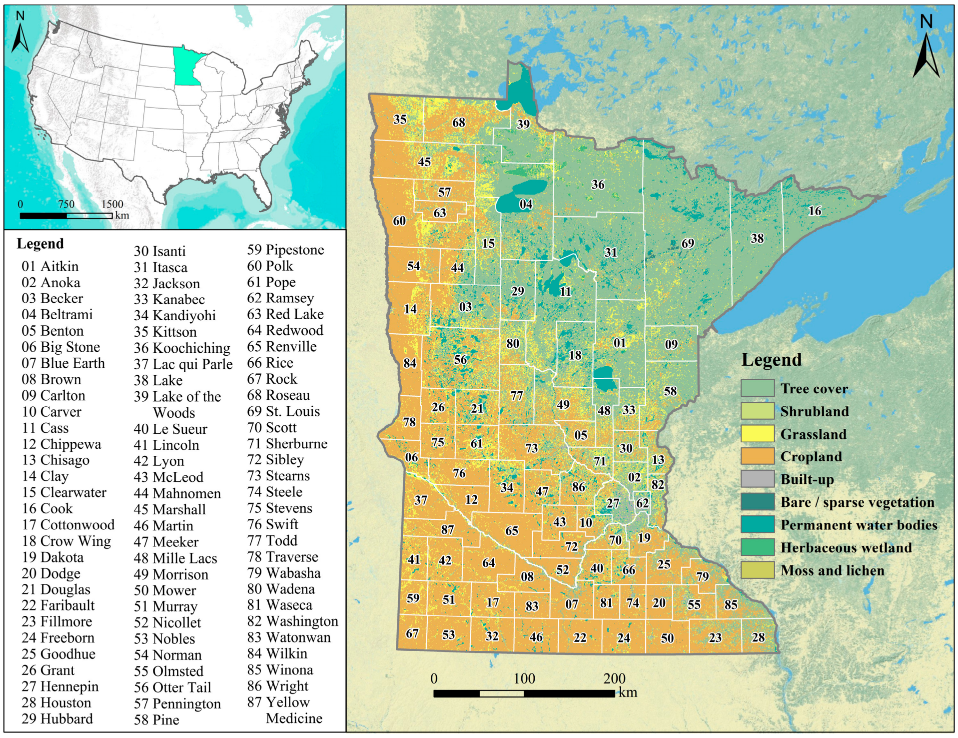

Figure 1. Study area.

2.2. Data Resources

2.2.1. Data on Food Provision and Soil Conservation

The data on major food crop production in Minnesota counties used in this study, spanning from 1998 to 2018, were sourced from the official U.S. Department of Agriculture website [55]. Additionally, a variety of remotely sensed data were necessary to calculate soil conservation services. This included land use data, digital elevation model (DEM) data, rainfall data, and soil composition information, which are detailed below, as follows:

Land use significantly impacts soil loss and directly influences the relevant model parameters. This study used land use data with the International Geosphere–Biosphere Program (IGBP) classification system. Minnesota's land use from 1998 to 2018 included building land, grassland, farmland, forest land, water bodies, and bare land. These data, with a resolution of 500 m, were obtained from the Google Earth Engine (GEE) public database provided by the Earth Resources Observation and Science (EROS) Center. The DEM data, with a resolution of 30 m, were provided by the Minnesota Office of Geographic Information. The rainfall data were downloaded from the DAYMET_V3 dataset in GEE. The soil composition information included data on soil texture, clay, sand, and surface soil organic carbon content. The soil powder content data were provided by the World Data Centre for Soils (ISRIC), and the soil clay, sand, and surface soil organic carbon content data were downloaded from GEE provided by the OpenLandMap dataset.

2.2.2. Data on Influencing Factors

Considering data availability, this study selected nine factors for the analysis of influencing mechanisms, as follows: population (POP), Gross Domestic Product (GDP), average daily rainfall (RF), normalized difference vegetation index (NDVI), diurnal temperature variation (DIF), average daytime temperature (T), slope (SLP), soil clay content (CLAY), and soil sand content (SAND). POP and GDP reflect human activities and socio-economic development, influencing both food production decisions and soil conservation practices [56–58]. Therefore, POP and GDP are essential for studying the coupled coordination of food provision and soil conservation. Rainfall serves as the direct source and supplement for crop water absorption and soil water retention. Additionally, rainfall impacts soil moisture and structure through its physical scouring action [59], altering surface runoff [60], and replenishing soil moisture [61]. Thus, there is a close relationship between rainfall, food production, and soil conservation. The NDVI is used to detect crop growth conditions and serves as a quantitative remote sensing indicator for estimating crop yield, widely applied in related research both domestically and internationally. Several studies have found that the NDVI positively influences soil conservation functions [62,63]. Temperature affects not only the photosynthesis and growth efficiency of crops, but also soil moisture retention [64]. As early as 1978, Wischmeier and Smith proposed that soil erosion typically increases with steeper slopes [65], a finding later confirmed by Mah and Fu, who demonstrated that erosion is a power function of slope [66,67]. Slope is also an important factor affecting crop growth. Soil structure is the foundation of soil conservation capacity and crop production, and it is closely related to their coupled coordination [68–71]. In addition, considering that the analysis of impact mechanisms in this study is based on a single year, indicators reflecting progressive and cumulative effects, such as advancements in agricultural technology and policy changes, were not selected. These influences typically do not manifest in the short term and require a longer duration to fully exert their effects. Descriptions and sources of each factor are detailed in Table 1.

Table 1. Description and sources of impact factors.

Factors	Description	Dataset and Resources
POP	Statistics on resident population by county	U.S. Census Bureau QuickFacts website
GDP	Gross Domestic Product statistics by county	U.S. Bureau of Economic Analysis website (BEA data)
RF	Average annual rainfall	GEE (DAYMET_V3)
NDVI	Normalized difference vegetation index	GEE (USGS Landsat 8)
DIF	Mean day/night temperature difference	GEE (MOD11A2.006)
T	Average daytime temperature	GEE (MOD11A2.006)
SLP	Slope (calculated from DEM data)	Minnesota Office of Geographic Information website (Elevation Data for Minnesota)
CLAY	Soil viscosity	GEE (OpenLandMap/SOL)
SAND	Soil sand content	

2.3. Methodology

2.3.1. Assessment of Ecosystem Services

Food Provision

Food provisioning ecosystem services were reflected by the number of harvested crops. In this study, we employed annual yields of dominated crops reported in Minnesota counties from 1998 to 2018 as a measure of food provision services.

Soil Conservation Services

We utilized the sediment delivery ratio (SDR) module of the InVEST model to estimate soil conservation services in Minnesota. The core of the SDR model is the Universal Soil Loss Equation (USLE), which is used to predict the long-term average annual soil loss A_i. The USLE comprises six factors, including the rainfall erosivity factor R_i, the soil erodibility factor K_i, the slope length-gradient factor L_i and S_i, the cover-management factor C_i, and the support practice factor P_i.

$$A_i = R_i \times K_i \times L_i \times S_i \times C_i \times P_i \tag{1}$$

The factors in the above equation are described as follows:

(1) Rainfall erosivity factor R: Represents the potential capacity of soil erosion caused by raindrops and confluence erosion.

$$F_f = \frac{\sum_{j=1}^{12} P_{ij}^2}{\sum_{j=1}^{12} P_{ij}} \tag{2}$$

$$R = \alpha F_f^{\beta} \tag{3}$$

where R denotes the average annual rainfall erosivity (MJ·mm(hm^2·h·a)$^{-1}$), P_{ij} denotes the rainfall in month j of grid i, and the parameters α and β are used with empirical values of 0.1833 and -1.9957, respectivley.

(2) Soil erodibility factor K: This factor indicates the sensitivity of the soil to erosion. Under consistent rainfall and similar conditions, areas with high soil erodibility factors are more susceptible to soil erosion than areas with low erodibility factors.

$$K_{EPIC} = \left[0.2 + 0.3 \times e^{-0.0256SAN(1-\frac{SIL}{100})}\right] \times \left(\frac{SIL}{CLA + SIL}\right)^{0.3} \times \left[1 - \frac{0.25C}{C + e^{3.72-2.95C}}\right] \times \left(1 - \frac{0.7SNI}{SNI + e^{22.9SNI-5.51}}\right) \tag{4}$$

$$SNI = 1 - \frac{SAN}{100} \tag{5}$$

where K_{EPIC} is the soil erosive force factor, SAN is the soil sand content, SIL is the soil powder content, CLA is the soil clay content, and C is the surface soil organic carbon content.

(3) Slope length-gradient factor L, S: The slope length and gradient are critical topographic and geomorphologic factors that influence soil erosion intensity. These elements

are typically combined to produce *LS* indicators. In this study, the *LS* index was calculated from DEM data using ArcGIS 10.8 following a data filling process.

(4) Cover-management factor *C*: This factor represents the impact intensity of various surface cover types on soil erosion and reflects historical land use, crop canopy, surface cover, and surface roughness. The *C* value ranges between 0 and 1.

(5) Soil and water conservation measures factor *P*: This factor reflects the impact of soil and water conservation measures, represented as the ratio of soil erosion under the two situations of taking corresponding measures and not taking any measures. The value of *P* ranges from 0 to 1, in which in the area where the corresponding measures are effective and no soil erosion occurs, the value of *P* is 0; while in the case where no protection measures are taken, the value of *P* is equal to 1.

In this study, the *C*-value and *P*-value for different land use types were determined using the look-up table method in Table 2, referencing existing studies and the actual land use types in Minnesota.

Table 2. Cover-management factor *C* and soil and water conservation measures factor *P* values for different land use types.

Land Use Type	Buildings	Grassland	Water Bodies	Bare Land	Forest	Cropland	Other
C-value	0.99	0.034	0	1	0.025	0.412	1
P-value	1	1	0	1	1	0.15	1

2.3.2. Mann–Kendall Test

The Mann–Kendall trend test is used to assess the long-term trend in time series data. It does not require the samples to follow a specific distribution and is insensitive to measurement errors and outliers [72–74]. The sample data are arranged according to the time series observations as $X_n = \{x_1,\ x_2, \ldots, x_n\}$, and its statistic S is denoted as follows:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sgn(x_j - x_i) \tag{6}$$

$$sgn(x_j - x_i) = \begin{cases} -1 & (x_j - x_i < 0) \\ 0 & (x_j - x_i = 0) \\ 1 & (x_j - x_i > 0) \end{cases} \tag{7}$$

If S is positive, it indicates that the observations tend to increase over the time series; if S is negative, it suggests that the observations tend to decrease over the time series.

The Mann–Kendall test statistic Z_c is defined as follows:

$$Z_c = \begin{cases} \frac{S-1}{\sqrt{Var(S)}}, & S > 0 \\ 0, & S = 0 \\ \frac{S+1}{\sqrt{Var(S)}}, & S < 0 \end{cases} \tag{8}$$

Var(S) is the variance. When $n \geq 8$, the variance statistic is calculated as follows:

$$\mathrm{Var(S)} = \frac{n(n-1)(2n+5) - \sum_{i=1}^{m} t_i(i-1)(2i+5)}{18} \tag{9}$$

Z_c follows a standard normal distribution and, for a given significance level of $P = 0.05$, when $|Z| \geq 1.96$, the change is indicated as significant. The Mann–Kendall trend test was implemented based on Python code.

2.3.3. Coupling Coordination Degree Model

The CCDM is a method used to analyze the correlation between systems, comprising two main components: coupling degree and coordination degree [30]. The coupling degree describes the extent of mutual influence of systems or elements, where a higher coupling degree indicates stronger interaction [75]. The coordination degree reflects the effect of coordinated development among systems. In this paper, the coupling coordination degree (CCD) is calculated to examine the interaction strength and coordinated development effect of soil conservation services and food provision services within farmland ecosystems.

The formula for calculating the coupling degree is as follows:

$$C_n = \left[\frac{u_1 * u_2 \cdots u_n}{\left(\frac{1}{n} \sum_{i=1}^{n} u_i \right)^n} \right]^{\frac{1}{n}} \tag{10}$$

where C_n denotes the coupling degree, and $u_1, u_2, \cdots, u_n$, denote the different subsystem scores, respectively.

When $n = 2$,

$$C = \frac{2\left(u_1 * u_2\right)^{\frac{1}{2}}}{u_1 + u_2} \tag{11}$$

where C denotes the degree of coupling and u_1 and u_2 denote soil conservation services and food provision services, respectively.

Since the coupling degree can only reflect the interaction among subsystems, it cannot capture the level of coordination development. Therefore, a single coupling degree is insufficient to explain the problem, and the CCD is used to reflect the degree of coordination in the interaction.

$$D = \sqrt{C * T} \tag{12}$$

$$T = \alpha u_1 + \beta u_2 \tag{13}$$

where D denotes the coupling coordination degree, taking values from 0 to 1. T denotes the comprehensive coordination index, and α, β are the weight coefficients of the subsystems, each set to 0.5 in this study.

Referring to the existing CCD classification criteria [30], the CCD is categorized into 10 levels, distinguishing three types of development stages along with their corresponding intervals (Table 3). The CCDM was implemented based on Python code.

Table 3. Classification system for CCD.

CCD	**[0.0, 0.1)**	**[0.1, 0.2)**	**[0.2, 0.3)**	**[0.3, 0.4)**	**[0.4, 0.5)**	**[0.5, 0.6)**	**[0.6, 0.7)**	**[0.7, 0.8)**	**[0.8, 0.9)**	**[0.9, 1.0]**
Degree	1	2	3	4	5	6	7	8	9	10
Progression	Uncoordinated state							Coordinated state		
Color										
Stage	Uncoordinated development				Transitional development			Coordinated development		

2.3.4. Principal Components Regression Analysis

Principal component analysis (PCA) is a statistical method that classifies the multiple variables into a few composite indicators. It serves as a means of dimensionality reduction, obtaining variables that adequately reflect the characteristics of the dataset but are not correlated with each other [76,77]. PCA categorizes numerous factors and extracts key information, eliminating information redundancy. This process facilitates a clearer analysis of the influencing mechanisms in the subsequent stages of the result analysis.

$$\begin{cases} z_1 = l_{11}x_1 + l_{21}x_2 + \cdots + l_{p1}x_p \\ z_2 = l_{12}x_1 + l_{22}x_2 + \cdots + l_{p2}x_p \\ \cdots\cdots\cdots\cdots \\ z_m = l_{1m}x_1 + l_{2m}x_2 + \cdots + l_{pm}x_p \end{cases} \tag{14}$$

$l_{ij}(i = 1, 2, \ldots, m; j = 1, 2, \ldots, p)$ represents the loading of the original variable x_j on the principal components z_j, which is the unit eigenvector corresponding to the m larger eigenvalues of the correlation coefficient matrices of x_1,x_2...,x_p. z_1, z_2, ..., z_m, which are the linear combinations of the uncorrelated $x_1,\ x_2,\ \cdots x_p$ arranged in order of variance from the largest to the smallest. The PCA was implemented based on SPSS 26.

2.3.5. Geographically Weighted Regression

Geographically weighted regression (GWR) is a local linear regression method that models spatially varying relationships [48]. It generates a regression model for each location within the study area, effectively capturing the local spatial relationships and spatial heterogeneity of variables.

$$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{m} \beta_k(u_i, v_i)x_{ik} + \varepsilon_i \tag{15}$$

where y_i represents the value of the dependent variable of sample point i; (u_i, v_i) is the center coordinate of sample point i; $\beta_0(u_i, v_i)$ refers to the intercept of sample i; $x_{ik}(k = 1, 2, \cdots, m)$ denotes the kth independent variable of sample i; $\beta_k(u_i, v_i)$ signifies the coefficient of the kth independent variable of sample point i; and ε_i is the error term. The GWR model was implemented based on ArcGIS 10.8.

3. Results

3.1. Minnesota Food Provision Services Assessment Analysis

3.1.1. Analysis of Temporal Changes in Food Provision

Food provision services in Minnesota exhibited a fluctuating upward trend from 1998 to 2018. The Mann–Kendall trend analysis indicated a statistically significant increase, with Z_c = 2.5063, $|Z_c| > Z_{(1-\alpha/2)}$, $\beta > 0$. Over this 20-year period, the total provision increased from 36,296,600 tons in 1998 to 39,555,600 tons in 2018, reflecting an average annual growth rate of 0.43% (Figure 2).

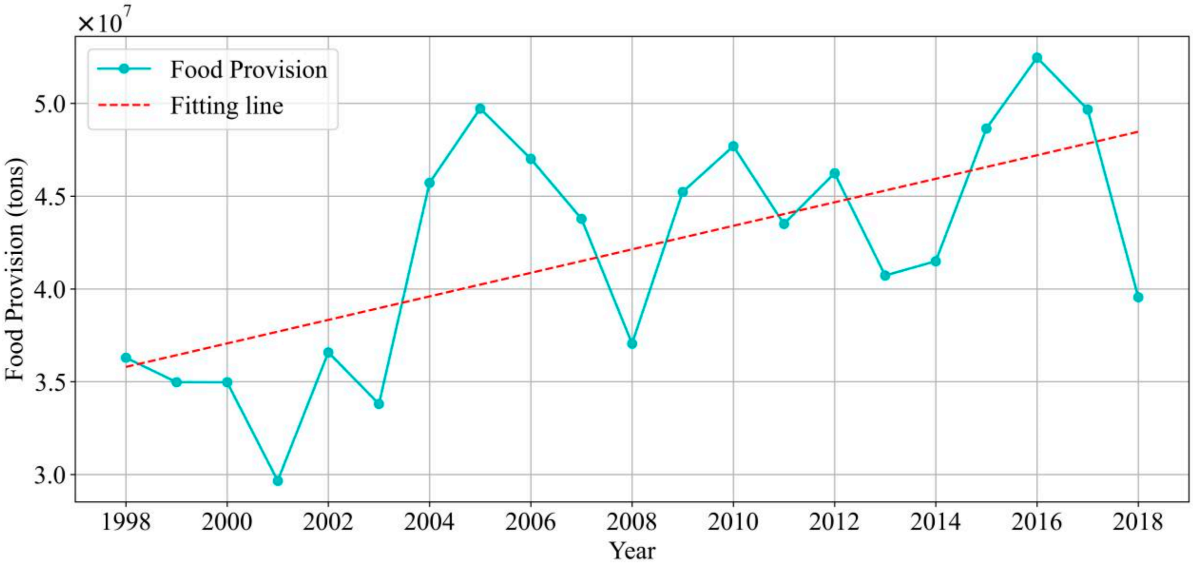

Figure 2. Changes in Minnesota's food provision services.

Throughout these years, the trend experienced episodes of rapid growth and decline. Notably, from 2001 to 2005, food provision services sustained a relatively high growth rate. However, from 2005 to 2008, a substantial decline in food production occurred, potentially linked to the increased frequency of extreme weather events in the United States. During this period, the U.S. faced disasters such as Hurricane Katrina, flooding, and heatwaves across the central and southern regions, resulting in frequent declines in the yields of wheat, corn, and soybeans [78–81]. Simultaneously, food prices surged significantly. During the summers of 2005 to 2008, international prices for wheat and corn tripled, while rice prices increased fivefold [82]. Fluctuations in agricultural product prices and demand also influenced farmers' planting decisions and levels of input. In the subsequent decade, food production showed a recovery. In both 2017 and 2018, a decline in food production was observed, which may be related to global climate change and the reduction in agricultural land in the U.S. Data from the Economic Research Service of the U.S. Department of Agriculture indicate that the total number of wheat farms in the U.S. has decreased by over 40% since 2002 [83]. In 2018, Minnesota experienced summer heatwaves and unusual blizzards [84,85].

3.1.2. Spatial Distribution of Food Provision Services

From 1998 to 2018, Minnesota's food provision services exhibited a stable spatial pattern, characterized by lower levels in the northeast and higher levels in the southwest (Figure 3). Counties with high food production, producing between 0.9 and 1.3 million tons, were consistently located in the southwestern region of the state. Over time, these areas expanded northward and increased in number. Meanwhile, counties with lower food provision services remained stable in the northeastern region, with little change in their numbers.

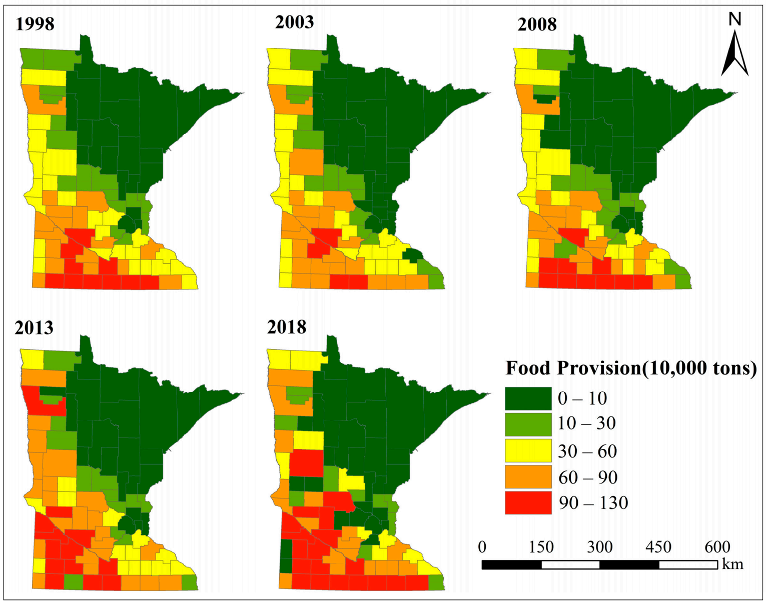

Figure 3. Spatial distribution of food provision services in Minnesota.

This spatial distribution aligns with Minnesota's land use patterns, as follows: the western part of the state is largely farmland, the northeast is characterized by forests and prairies, and the southeast has more urban areas. Thus, the spatial distribution of food provision services can be summarized as having no anomaly zones, with a stable geographic pattern of being "higher in the southwest and lower in the northeast". Additionally, there was an increase in the number of high-production counties, indicating a trend of positive development.

3.2. Minnesota Soil Conservation Services Assessment Analysis

3.2.1. Analysis of Temporal Changes in Soil Conservation

Minnesota's total soil conservation services exhibited a trend of localized fluctuations and a slight overall increase from 1998 to 2018. The results of the Mann–Kendall trend analysis showed that $Z_c = 0.4530$, $|Z_c| < Z_{(1-\alpha/2)}$, indicating that there was no significant upward or downward trend in total soil conservation services in Minnesota during this 20-year period.

The amount of soil conservation fluctuated considerably from year to year. The lowest point occurred in 2006, when the amount of soil conservation services was 180 million tons. The highest point occurred in 2017, with a total soil conservation service of 225 million tons (Figure 4). The fluctuating increase in soil conservation in Minnesota may be attributed to the combined effects of long-term agricultural production activities and the implementation of soil protection initiatives. For instance, the One Watershed, One Plan initiative and various forestry planting or management projects [86,87] have played significant roles in this process.

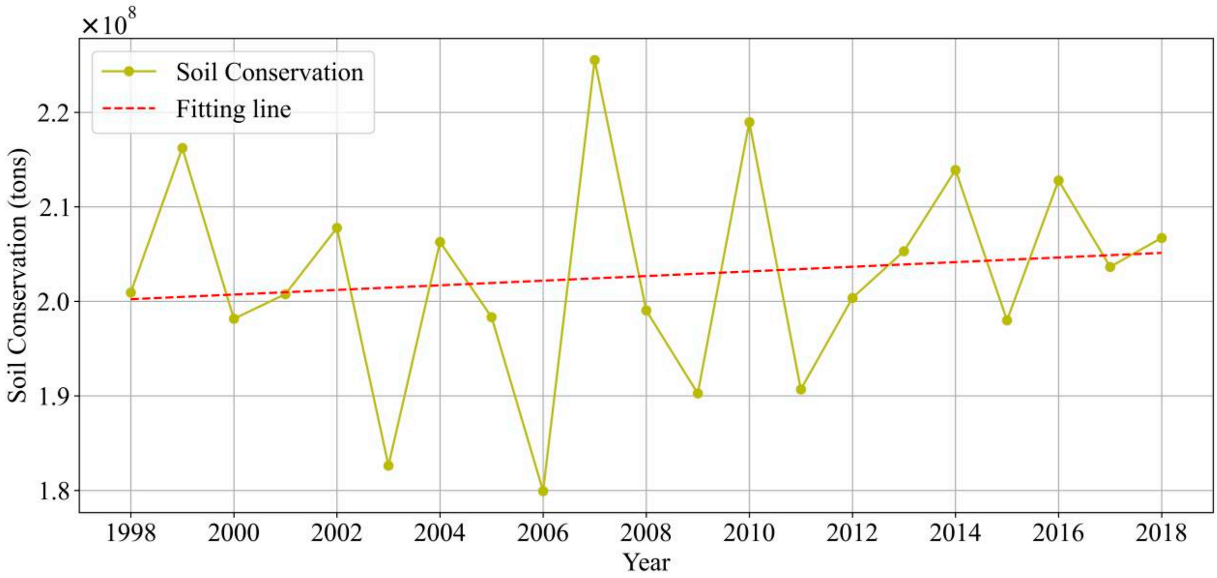

Figure 4. Changes in Minnesota's soil conservation services.

3.2.2. Spatial Distribution of Soil Conservation Services

The soil conservation services in Minnesota exhibit a stable geographic distribution pattern. High-value areas are concentrated in the northeastern and southeastern regions, while low-value areas are found in the southwestern and central regions. Overall, there is a gradient of soil conservation services that increases from low values in the southwest to high values in the northeast. This spatial distribution can be categorized into three distinct regions. The low-value region, with soil conservation levels below 1.5 million tons, is located in parts of southwestern and central Minnesota, particularly around the "Twin Cities". This area is primarily characterized by farmland in the southwest and urban development in the central region. The transition zone, where soil conservation ranges from 1.5 to 6.0 million tons, extends in a strip from northwestern to southeastern Minnesota, encompassing the northwestern farmland and the northeastern forest–steppe transition area. The high-value region, with soil conservation exceeding 6.0 million tons, is found in the northeastern and a small portion of the southeastern part of the state and is predominantly forested. Over time, the low-value region has shrank, the transition zone has expanded southward, and the high-value zone has experienced slight growth (Figure 5).

In summary, the geographical distribution of the total amount of soil conservation services is characterized by several key features, as follows: a stable pattern with "high-value zones dominating in the northeast and low-value zones dominating in the southwest"; a tendency for low-value zones to shrink, while the high-value zones tend to expand; and a strong correlation between the amount of soil conservation services and the type of land use.

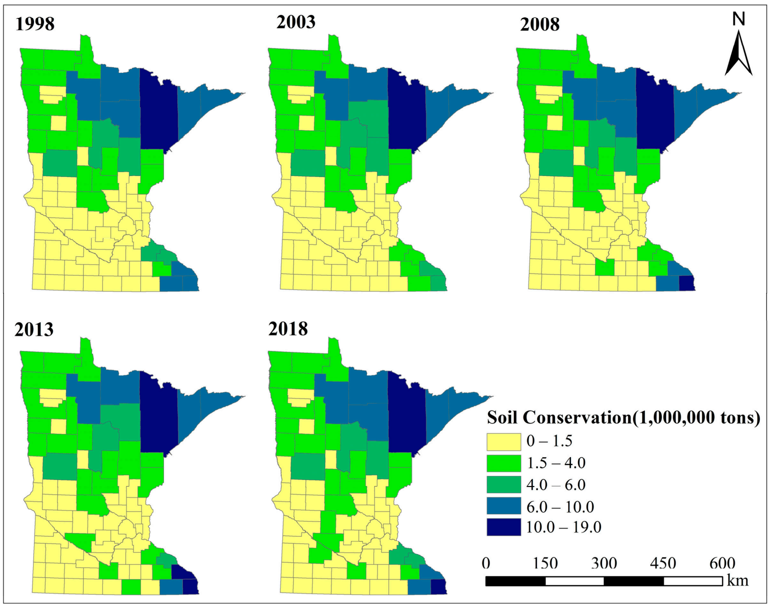

Figure 5. Spatial distribution of soil conservation services in Minnesota.

3.3. Status of Coupling Food Provision and Soil Conservation Services

The CCD of food provision and soil conservation services in Minnesota showed an overall increasing trend from 1998 to 2018. The Mann–Kendall trend results indicated that $Z_c = 2.3856$, $|Z_c| > Z_{(1-\alpha/2)}$, $\beta > 0$. This suggests that the CCD in Minnesota exhibited a statistically significant upward trend over the 20-year period.

The results from the CCD analysis indicate a noticeable improvement in the coordinated relationship between food provision and soil conservation services in Minnesota. In most years, the CCD was above 0.4, signifying a state of transitional to coordinated development. The CCD fell below 0.4 in 2001, 2003, and 2006, indicating an uncoordinated status (Figure 6). Temporally, the CCD can be divided into two phases. During the first phase (1998 to 2011), the CCD experienced significant fluctuations. In the second phase (2011 to 2018), fluctuations were smaller, and a stable upward trend emerged. After 2012, the CCD consistently remained above 0.7, reflecting a basic level of coordinated development between food provision and soil conservation services. This suggests that, post-2012, Minnesota successfully met food demands while protecting its soil resources.

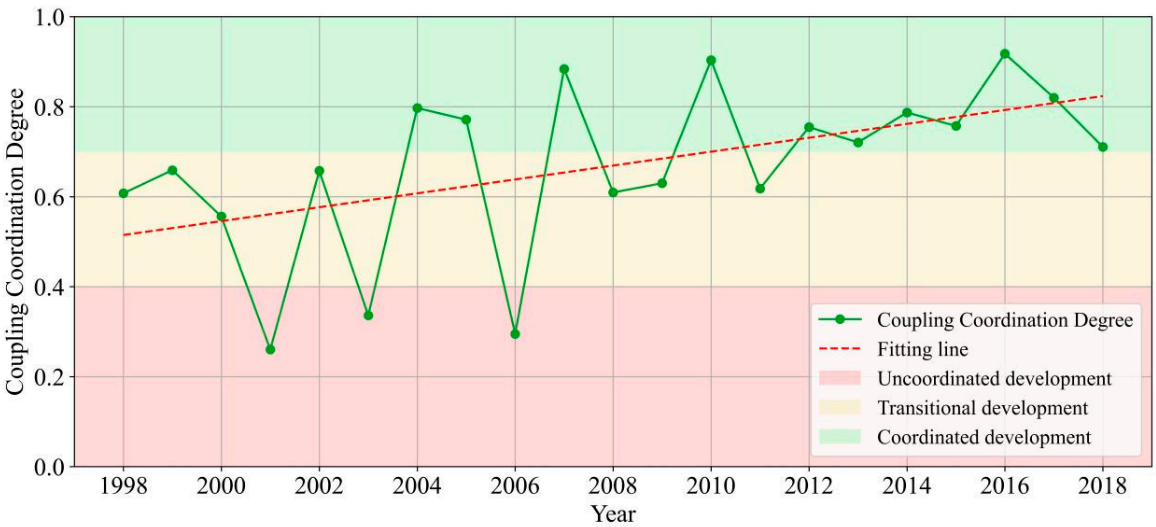

Figure 6. Food provision and soil conservation services coupling coordination degree in Minnesota.

The combined results of food provision and soil conservation services reveal that, as food production increased, the soil conservation levels remained stable, indicating the absence of severe soil erosion. This stability may be attributed to rising ecological awareness in Minnesota, with an emphasis on balancing increased food production and ecological protection.

3.4. Analysis of the Influence Mechanism of CCD

3.4.1. Principal Component Analysis of Impact Factors

The valid information from the nine impact factors can be summarized into four main components, with a cumulative contribution exceeding 93%. The first principal component (Z_1) is strongly correlated with DIF, T, CLAY, SAND, and RF, with a contribution of 39.55%. Z_1 shows positive correlations with DIF, T, CLAY, and RF, and a strong negative correlation with SAND. This indicates that Z_1 is a comprehensive indicator of soil quality. Soil quality involves multiple dimensions, including soil health, erosion risk, and agricultural productivity. DIF, T, and RF influence soil moisture and temperature, affecting its biological and chemical processes. CLAY and SAND impact structure and stability, influencing erosion risk and plant growth. By integrating these factors, Z_1 effectively evaluates the overall state of soil quality, making it a key indicator. The second principal component (Z_2) exhibits a strong positive correlation with POP and GDP, accounting for 23.52% of the variance. This suggests that Z_2, as an indicator of socio-economic conditions, increases with rising population and GDP. Consequently, Z_2 serves as a comprehensive measure of socio-economic development, reflecting regional prosperity. The third principal component (Z_3) is strongly correlated with SLP, contributing 17.09%, representing basic terrain indicators. The fourth principal component (Z_4) positively correlates with NDVI, contributing 12.94%, and representing vegetation quality (Figure 7).

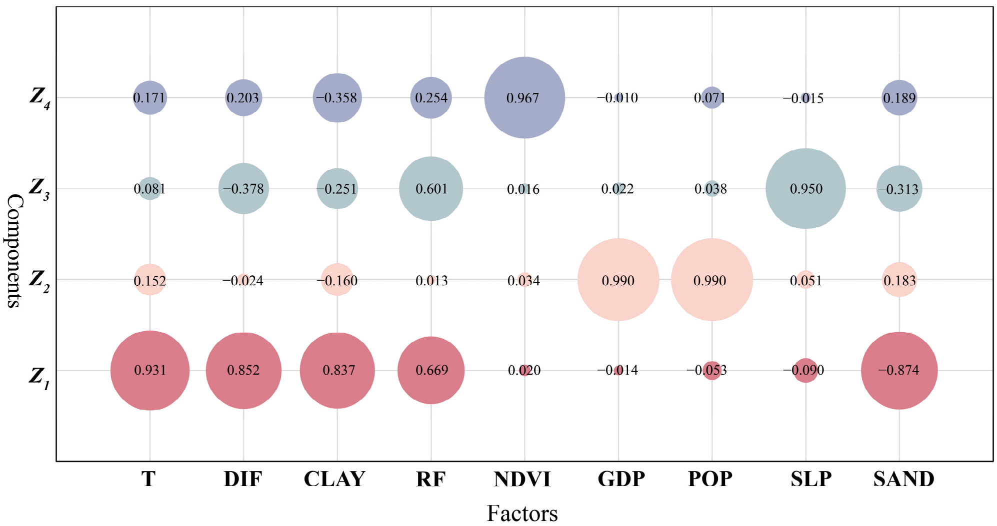

Figure 7. Result of the rotated component matrix.

Therefore, the four principal components—Z_1, Z_2, Z_3, and Z_4—characterize soil quality indicators, socio-economic indicators, topography indicators, and vegetation quality indicators, respectively.

The coefficients of the four principal components in relation to each factor are as follows:

$$Z_1 = 0.018 \times \mathrm{POP} + 0.031 \times \mathrm{GDP} + 0.174 \times \mathrm{RF} - 0.009 \times \mathrm{NDVI} + 0.251 \times \mathrm{DIF} + 0.269 \times \mathrm{T} - 0.048 \times \mathrm{SLP} + 0.248 \times \mathrm{CLAY} - 0.240 \times \mathrm{SAND} \tag{16}$$

$$Z_2 = 0.489 \times \mathrm{POP} + 0.498 \times \mathrm{GDP} - 0.011 \times \mathrm{RF} - 0.063 \times \mathrm{NDVI} + 0.015 \times \mathrm{DIF} + 0.093 \times \mathrm{T} - 0.009 \times \mathrm{SLP} - 0.012 \times \mathrm{CLAY} + 0.056 \times \mathrm{SAND} \tag{17}$$

$$Z_3 = -0.013 \times \mathrm{POP} - 0.020 \times \mathrm{GDP} + 0.355 \times \mathrm{RF} - 0.047 \times \mathrm{NDVI} - 0.276 \times \mathrm{DIF} + 0.013 \times \mathrm{T} + 0.613 \times \mathrm{SLP} - 0.157 \times \mathrm{CLAY} - 0.197 \times \mathrm{SAND} \tag{18}$$

$$Z_4 = -0.024 \times \mathrm{POP} - 0.091 \times \mathrm{GDP} + 0.164 \times \mathrm{RF} + 0.796 \times \mathrm{NDVI} + 0.178 \times \mathrm{DIF} + 0.109 \times \mathrm{T} - 0.070 \times \mathrm{SLP} - 0.282 \times \mathrm{CLAY} + 0.173 \times \mathrm{SAND} \tag{19}$$

3.4.2. Influencing Mechanisms of the CCD

To determine the effects of environmental conditions and socioeconomic factors on the coupling of food provision and soil conservation, we used GWR models to explore the quantitative relationships between CCD and indicators of soil quality, socio-economics, topography, and vegetation quality (Table 4).

Table 4. Statistics on variable coefficients.

Variables	Mean-Value	Std	Min-Value	Mid-Value	Max-Value
Z_1	0.43	0.05	0.34	0.43	0.59
Z_2	−0.32	0.02	−0.33	−0.33	−0.23
Z_3	0.40	0.21	−0.18	0.48	0.62
Z_4	−0.38	0.04	−0.43	−0.39	−0.22

Z_1 shows a positive correlation with CCD. The coefficient values range from 0.34 to 0.59, with an average value of 0.43 and a standard deviation of 0.05. This indicates that, for every 1-unit increase in Z_1, CCD increases by 0.43 units.

Z_2 primarily reflects the socio-economic conditions and exhibits a negative correlation with the CCD in Minnesota. The coefficients range from −0.33 to −0.23, with a mean of −0.32 and a standard deviation of 0.02. This suggests that, as Z_2 increases, i.e., population and GDP increase, CCD tends to decrease. Specifically, a 1-unit increase in Z_2 corresponds to an average decline of 0.32 units in CCD. Typically, a higher population and GDP drive increased food demand, which may necessitate the expansion of agricultural land, potentially compromising soil conservation services. In addition, regions with a higher population and GDP are often urban areas, where both food production and soil conservation are typically less effective.

Z_3 primarily reflects the influence of topographic elements, with coefficients ranging from −0.18 to 0.62, a mean of 0.40, and a standard deviation of 0.21. Overall, Z_3 appears to positively impact CCD. Specifically, for every 1-unit increase in Z_3, the CCD in Minnesota increases by 0.40 units.

Z_4 primarily reflects the effect of vegetation quality, with coefficients ranging from −0.43 to −0.22, a mean of −0.38, and a standard deviation of only 0.04. Overall, Z_4 shows a negative impact on CCD. When Z_4 increases by 1 unit, the CCD in Minnesota decreases by 0.38 units.

In terms of standard deviation, Z_1, Z_2, and Z_4 have small values, all below 0.05, indicating that the effects of these three principal components exhibit minimal spatial variation in Minnesota. Z_3 has a relatively large standard deviation, suggesting significant spatial heterogeneity in the effects of topographic elements.

Spatially, Z_1 has a positive effect on CCD throughout the region, exhibiting a strip-like distribution that increases from the southwest to the northeast (Figure 8a). This pattern indicates that changes in climatic conditions (precipitation and temperature) and soil composition in the southwest have a smaller impact on CCD. Conversely, variations in climatic and soil conditions in the northeast significantly influence CCD. This phenomenon is related to Minnesota's land types. In the southwest, where extensive agricultural land predominates, increased precipitation and temperature contribute less to the CCD. Conversely, the eastern region features more lakes and forests, with a more fragmented surface. As a result, changes in precipitation and soil conditions have a greater impact on coupled coordination in this area.

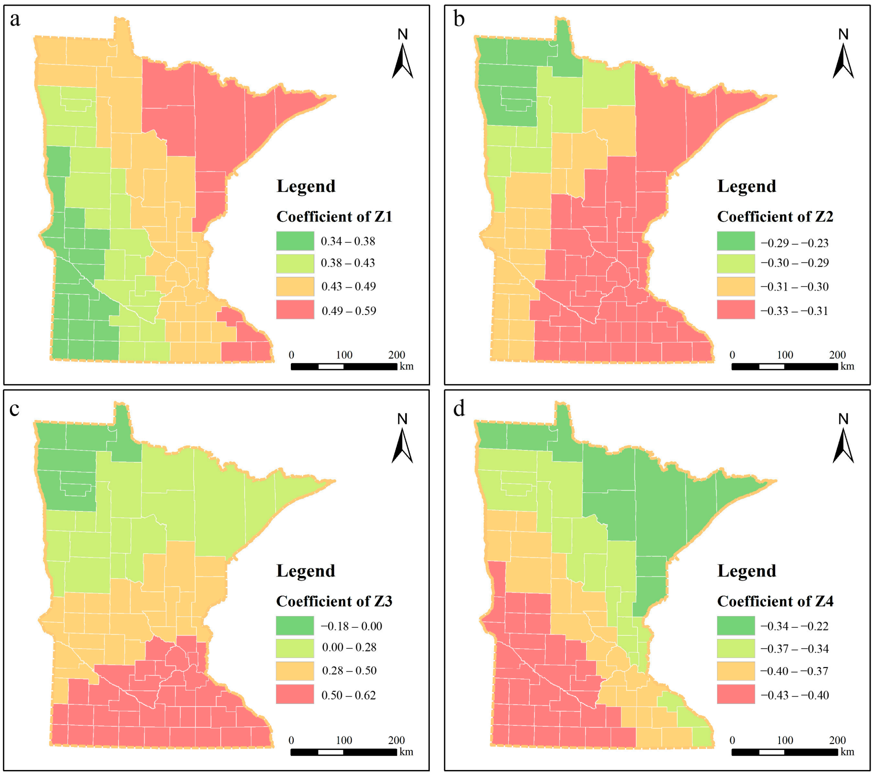

Figure 8. Spatial distribution of impact coefficients of CCD.

In the northwest corner, Z_3 showed a negative effect on the CCD. The landscape is primarily farmland and grassland. The CCD worsened as Z_3 increased, indicating that steeper terrain negatively impacted coordination. In the rest of the area, the effect was positive and increased from the northwest to the southeast (Figure 8c). In the southern region, as the slope increased, the CCD improved. This may indicate that, in the southern region, as the terrain becomes rugged, greater attention is given to conservation tillage and sustainable agriculture, along with soil conservation and agricultural productivity.

Both Z_2 and Z_4 exhibit negative impacts on CCD, with small spatial variation in their effect (Figure 8b,d). This indicates that the negative influence of economic growth on CCD is relatively stable and exhibits low spatial heterogeneity. The impact of Z_4 demonstrates a strip-like pattern, increasing from the northeast to the southwest. This indicates that the vegetation quality (as measured by the NDVI) negatively affects the coupling of food provision and soil conservation in Minnesota. The NDVI reflects the growth status and cover of vegetation, therefore, especially in the southwestern region, dominated by extensive farmland, an increase in crop cover may further diminish the coupling between food provision and soil conservation.

4. Discussion

Balancing the relationship between food supply services and soil conservation services is crucial for promoting sustainable agricultural development and the harmonious development of socio-ecological systems. From 1998 to 2018, Minnesota's food provisioning services showed a significant upward trend. The two drops occurred in 2008 and 2018. The global economic crisis of 2008 likely caused fluctuations in the price and demand for agricultural commodities, affecting farmers' planting decisions and input levels [88,89]. Additionally, natural anomalies have adversely impacted agricultural production. In 2018, summer temperatures exceeded 30-year averages in about 90% of Minnesota, and parts of the southwestern and central regions experienced heavy and consecutive rainstorms in June, July, and August [84]. Furthermore, Minnesota suffered a blizzard in April [85]. The spatial structure of soil conservation ecosystem services in Minnesota remained stable from 1998 to 2018, characterized by low values in the northeast and high values in the southwest. This distribution pattern aligns with the spatial distribution of farmland in the state. This study found that, over the past decade, the area of high-value regions in the southwest has expanded, including Otter Tail, Fillmore, Freeborn, Kandiyohi, Mower, and Stearns, indicating the significant effectiveness of related projects in Minnesota. Programs such as the Federal Conservation Reserve Program (CRP) encourage farmers to convert environmentally sensitive agricultural land to various conservation practices, including planting species that improve environmental health and quality [90]. The Minnesota Agricultural Water Quality Certification Program (MAWQCP) assists farmers in implementing conservation practices to protect water quality, with certified farms being recognized for their efforts and benefiting from improved soil health and potentially increased crop yields due to enhanced water management [91].

The large interannual fluctuations in total soil conservation over the 20-year period may be related to the heavy summer precipitation and flooding hazards frequently experienced in Minnesota [92–94]. Despite a significant increase in food production, soil conservation services remained stable over the 20-year period, although they experienced fluctuations from year to year. This indicates that Minnesota has made efforts to protect soil conservation alongside agricultural production. The increase in CCD values signifies a growing synergy between food provisioning and soil conservation services over the study period, reflecting Minnesota's efforts to reconcile these two critical areas [95]. Cover Crop Initiatives promote the use of cover crops to enhance soil structure, prevent erosion, and improve nutrient cycling, contributing to overall soil health [96]. The University of Minnesota Extension Services offers research-based guidance and education on the best practices for soil conservation and sustainable agriculture [97]. Minnesota's Buffer Law also requires perennial vegetation buffers along waterways to protect water resources and prevent soil erosion [98]. These efforts collectively aim to balance agricultural productivity with the preservation of soil health and environmental quality.

Based on the impact coefficients of CCD, soil quality ranks higher than foundational topography, vegetation quality, and socio-economic factors. This indicates that soil quality is the most critical factor in balancing food provisioning and soil conservation ecosystem services. High-quality soil, rich in organic matter and nutrients, promotes crop growth and increases yield. Additionally, robust root systems can promote soil stability and enhance erosion resistance. This insight suggests that policymakers and stakeholders should prioritize sustainable agricultural practices like crop rotation, cover cropping, and reducing fertilizer use to improve soil quality and fertility. These practices are crucial for ensuring the long-term coordination between food supply and soil conservation. Compared to the existing research that analyzes the impact mechanisms of multiple socio-economic indicators on the coupled coordination relationship between population, food, and soil [16], this study uniquely incorporates natural environmental factors. It innovatively shows that natural elements have a greater impact on CCD than socio-economic indicators. This underscores the importance of respecting the natural baseline in human interventions, prioritizing actions that impact natural resources, especially soil quality.

The coefficient for the topographic factor exhibited significant spatial heterogeneity, reflecting the importance of topographic elements in soil erosion [93]. In Minnesota, various initiatives protect soil in rugged terrains while ensuring food production. Contour farming reduces soil erosion and water runoff by plowing along land contours, maintaining soil integrity and water retention. Terracing creates flat planting areas on steep slopes, conserving soil and enhancing water management and yields. Agroforestry integrates native trees and shrubs into landscapes to stabilize the soil, reduce erosion, and boost biodiversity. Vegetation quality negatively impacts CCD, especially in the southwestern agricultural areas, highlighting that excessive cultivation worsens soil erosion in farmlands and reinforcing the traditional view that agriculture exacerbates soil erosion.

Minnesota-specific research on the trade-offs between food provision and soil conservation can guide sustainable agricultural practices in regions facing similar challenges. Areas experiencing rapid agricultural intensification and land degradation can explore pathways that integrate efficient agricultural land use with ecosystem protection. This includes focusing on the trade-offs between food provision and soil conservation as two critical ecosystem services and implementing sustainable agricultural practices [99]. Conservation agriculture (CA), characterized by minimal soil disturbance, diversified crop rotations, and organic soil cover maintenance, has proven effective in regions like sub-Saharan Africa [100] and the Indo-Gangetic Plain in South Asia [101]. These practices enhance ecosystem services and ensure food security through interconnected approaches. Additionally, implementing terracing measures in mountainous and plateau regions can better balance food supply and soil conservation services [102]. Achieving equilibrium between agricultural productivity and soil health is essential for sustainable agricultural practices.

There are some limitations to this study. First, this study strictly selects the influencing factors; however, due to data limitations and the lack of time series, some indicators, such as agricultural technological advancement, are not included. Therefore, future research should further strengthen the selection of indicators. In addition, our study employs statistical models (Mann–Kendall, PCA, and GWR) to enhance the clarity and comprehensibility. However, these models are subject to potential biases and uncertainties, such as the strong linearity assumption in PCA and the necessity of selecting an optimal spatial weighting function in GWR. Therefore, future research needs to explore more suitable modeling approaches. Although this study is limited to the use of data up until 2018, we believe that it remains representative, as it encompasses all counties in Minnesota, a major agricultural state, and extends the time frame to 20 years. In the future, we will focus on collecting the latest data and more reliable indicators to assess the coupling coordination between agricultural provision and soil ecosystems, as well as to continue exploring the balance between agricultural activities and the ecological environment.

5. Conclusions

This study integrated multiple remote sensing data sources to assess food provision services and soil conservation services in Minnesota from 1998 to 2018 and analyzed the spatial and temporal changes. We explored the balance of the two services using the CCDM and examined the influence mechanism of CCD. The results indicate the following conclusions: (1) The total amount of food provision services in Minnesota exhibited a continuous upward trend from 1998 to 2018, but significant drops occurred in 2008 and 2018; (2) Soil conservation services have no significant upward trend and fluctuate significantly from year to year; (3) The CCD for food provision and soil conservation services shows a rising trend, indicating an improving balance and coordinated development of the agricultural social subsystem and ecological subsystem; (4) Regarding the influence mechanism, climate–soil indicators > topography indicators > vegetation quality indicators > socio-economic indicators. The first two principal components exhibit a mainly positive influence, while the latter two show a negative influence. This indicates that natural environmental factors have a greater impact on the CCD than socio-economic conditions; (5) Spatially, climate–soil indicators, socio-economic indicators, and vegetation quality indicators exhibit less spatial heterogeneity. Topography is the principal spatial driving factor. The changes in the influence effects of each principal component show a more pronounced banded distribution.

This study successfully quantitatively assessed Minnesota's food provision and soil conservation services, as well as their developmental balance. The findings have important implications for sustainable agricultural development. This study has provided a foundation for balancing ecosystem services. Future research could differentiate between the relationships of food supply and soil conservation in precision agriculture versus traditional agriculture, allowing for a more in-depth investigation.

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alization, D.S.; supervision, D.S.; project administration, Y.L.; funding acquisition, D.S. All authors have read and agreed to the published version of the manuscript.

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