The Effect of Sloping Land Conversion Program on Soil Erosion in Shaanxi Province, China: A Spatial Panel Approach

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Soil erosion is a land degradation process that may threaten the sustainability of ecosystem as well as cause severe social and economic problems. The studies on the effect of ecological restoration policies on soil erosion have been well documented, while the spatial relationships and spillover effects of the policies on soil erosion have been rarely scrutinized, though it is of great policy implications in soil erosion control. Based on the analysis of the spatio-temporal evolution of soil erosion in 107 counties of Shaanxi Province with Revised Universal Soil Loss Equation, this study employs a panel spatial Durbin model (SDM) with multi-source data for 107 counties from 2000 to 2015 to investigate the spatial effects of the Sloping Land Conversion Program (SLCP) on soil erosion control with investment data of SLCP. The results show that during 2000–2015, the average amount of soil erosion exhibited a significant downtrend contributed by the continuous investment of SLCP. The spatial economic results demonstrate that the own effect, as well as the spillover effect of investment on soil erosion control, is significant and positive. A 0.1 billion CNY increase in investment in a county will result in a reduction of the total soil erosion by 288.69 thousand t/a, of which 63% is contributed to the own direct effect on local soil erosion control and the 37% of it is contributed to the spillover effect on the neighbors. Moreover, rainfall has a significant and positive moderating effect on the mitigation effect of SLCP on soil erosion at county scale; the marginal contribution of investment of SLCP on soil erosion control in the county with less rainfall is greater than that with more rainfall. These findings contribute to further our understanding of the long-term effects of ecological restoration policies and transboundary ecological governance.

Keywords: soil erosion, Sloping Land Conversion Program, spillover effect, spatial panel model, RUSLE

INTRODUCTION

Soil erosion is a widespread form of land degradation that severely threatens the ecosystem services, especially the terrestrial ecosystems globally (Pimentel, 2006; Amundson et al., 2015). The total amount of soil erosion caused by land use changes in the world increased by 2.5% from 2001 to 2012 (Borrelli et al., 2017). Similarly, soil erosion has been one of the most urgent environmental problems in China, with an estimated 2–4 billion tons of silt released into the Yangtze River and the Yellow

River annually, of which 65% came from the sloping cropland (Bennett, 2008). This phenomenon was particularly obvious in the Loess Plateau, which was once regarded as the most heavily eroded area in the world (Wen and Deng, 2020). Therefore, there are many different forms of strategies including soil management (Cerdà et al., 2017), nature-based solutions (Keesstra et al., 2018), and landscape restoration programs (Kong et al., 2018) conducted to mitigate regional soil erosion around the world. Among them, the Sloping Land Conversion Program (SLCP) is a typical ecological restoration program initiated by the Chinese central government in 1999 with the stated environmental goals of reducing water and soil erosion (Bennett, 2008), also known as the Grain for Green Project in the form of payments for ecosystem services (PES). SLCP had encompassed more than 2000 counties in 25 provinces, benefiting over 41 million rural households and invested $55 billion to increase the forest cover, converting sloping cropland and degraded rangeland back to forest and grassland in the past 20 years (NFGA (National Forestry and Grassland Administration, 2018). Hence, it is significant to evaluate the effect of SLCP on soil erosion with such a huge investment for formulating scientific and reasonable soil erosion management policies and the sustainable development of regional ecosystems.

Revised Universal Soil Loss Equation (RUSLE) is by far one of the most widely applied soil erosion prediction models at a large regional scale around the world due to its simple form and parsimonious parameterization (Renard et al., 1997; Farhan and Nawaiseh, 2015). Besides, a variety of long-term satellite-derived remote sensing data and the development of the integrated geographic information system (GIS) have made it possible to assess the spatio-temporal characteristics of soil erosion with RUSLE at a regional scale more effectively and accurately (Vrieling, 2006; Poesen, 2018; Alewell et al., 2019). Some of the studies evaluated the dynamic spatio-temporal changes of soil erosion and indicated that the policies improved the ecosystem services by increasing vegetation cover and land use conversion (Xu et al., 2018). Although there are several environmental factors including topography, mean annual rainfall, land use and cover, and the soil conservation methods that have significant effects on soil erosion (Nearing, 1997; Zhao et al., 2022), land use still dominates the variation of soil loss and runoff, especially at the large regional scale (Zhao et al., 2022). Wen and Deng indicated that the change in land use and land cover induced by SLCP is the most critical factor that affects the soil erosion in the Loess Plateau after a literature review (Wen and Deng, 2020). The study in southern China's red soil hilly region indicated that the soil loss was largest for cropland, while grassland and natural shrub have less soil loss and lower sediment values (Chen et al., 2021). Satellite-derived observations used in the studies mentioned above can capture the objective changes of soil erosion at the regional scale, but it is difficult to demonstrate that these changes are only caused by SLCP due to the contributions from the other ecological projects such as National Forest Conservation Program and Soil and Water Conservation Program (Li et al., 2020). While this problem could be solved partly in technic with econometric methods in

which the missing variables are represented by the random error term, the research exploring the effect of ecological restoration policies on soil erosion as well as the impact of socio-economic factors with econometric methods is well documented (Rao et al., 2016; Li et al., 2020; Zhou et al., 2021). For instance, the increasing grain yield could mitigate soil erosion by diminishing the substantial demand for farmland and the excessive deprivation of ecological lands (Zhou et al., 2021); however, the area of forest and grassland converted from cropland or the vegetation cover (Kong et al., 2018; Zhou et al., 2021) was used to characterize the SCLP in many studies, which would lead to biases in the evaluation of policy effectiveness. To compensate for this deficiency, the investment of SLCP is used in this study to examine the effect of SLCP on soil erosion from the perspective of cost-effectiveness of investment, which is important for the sustainability and efficiency of the policy (Börner et al., 2017).
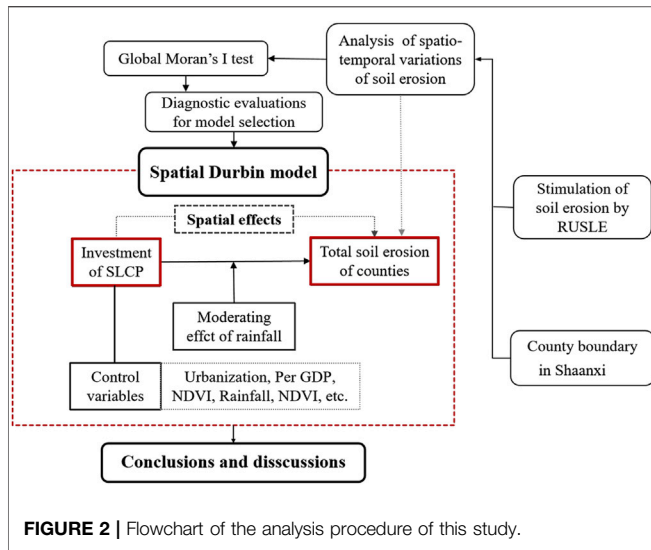
Soil erosion has a strong geographical dimension in the formation process whether at the watershed scale or at the regional scale (Ganasri and Ramesh, 2016; Rao et al., 2016); so, it tends to fall into dilemmas when evaluating the impact of the ecological restoration policy on soil erosion with administrative divisions. One of the dilemmas is that the ecological effects of SLCP such as mitigating soil erosion may not only remain in the implementation area but also diffuse into the neighboring area (Lin et al., 2020). Hence, we propose a hypothesis: the marginal effects of SLCP on soil erosion control may be the combination of mitigation effects of the local region with specific characteristics and spatial spillover effects of neighboring regions. However, regional policy and practice often completely ignore external beneficiaries like the adjacent administrative districts, which leave afforestation and management burdens on the local area when the spatial effects exist (Wolch et al., 2014). The classical econometric models are used in the studies mentioned above (Rao et al., 2016; Kong et al., 2018; Li et al., 2020) to examine the influencing factors of soil erosion in China with the omission of the spatial spillover effects of the afforestation, which could result in biased estimations and even undermine the scientific foundations (Jiang et al., 2020). Hence, it is necessary to examine the spillover effects of SLCP on soil erosion and separate the own and spatial spillover effects of afforestation at the regional scale with spatial econometric models for the effective transboundary ecological governance, which improves the cost-effectiveness of ecological governance and the sustainability of green development. Besides, the effect of rainfall on soil erosion is significant for all land use types (Zhao et al., 2022), and the rainfall has a significant threshold effect on the fiscal efficiency of SLCP (Liu and Yao, 2021). However, detailed mechanisms of the interaction role of rainfall and SLCP in soil erosion control are still unclear at the county scale.

Shaanxi Province, in inland northwest China, a pilot and demonstration province for SLCP since 1999 due to serious soil erosion problems in the 20th century, is selected as the study area. Due to the rapid economic development and the large-scale implementation of SCLP, it provides an ideal sample to examine the effect of SLCP on soil erosion. In this study, we employed RUSLE to evaluate the spatio-temporal variations of

FIGURE 1 | Location of the study area.
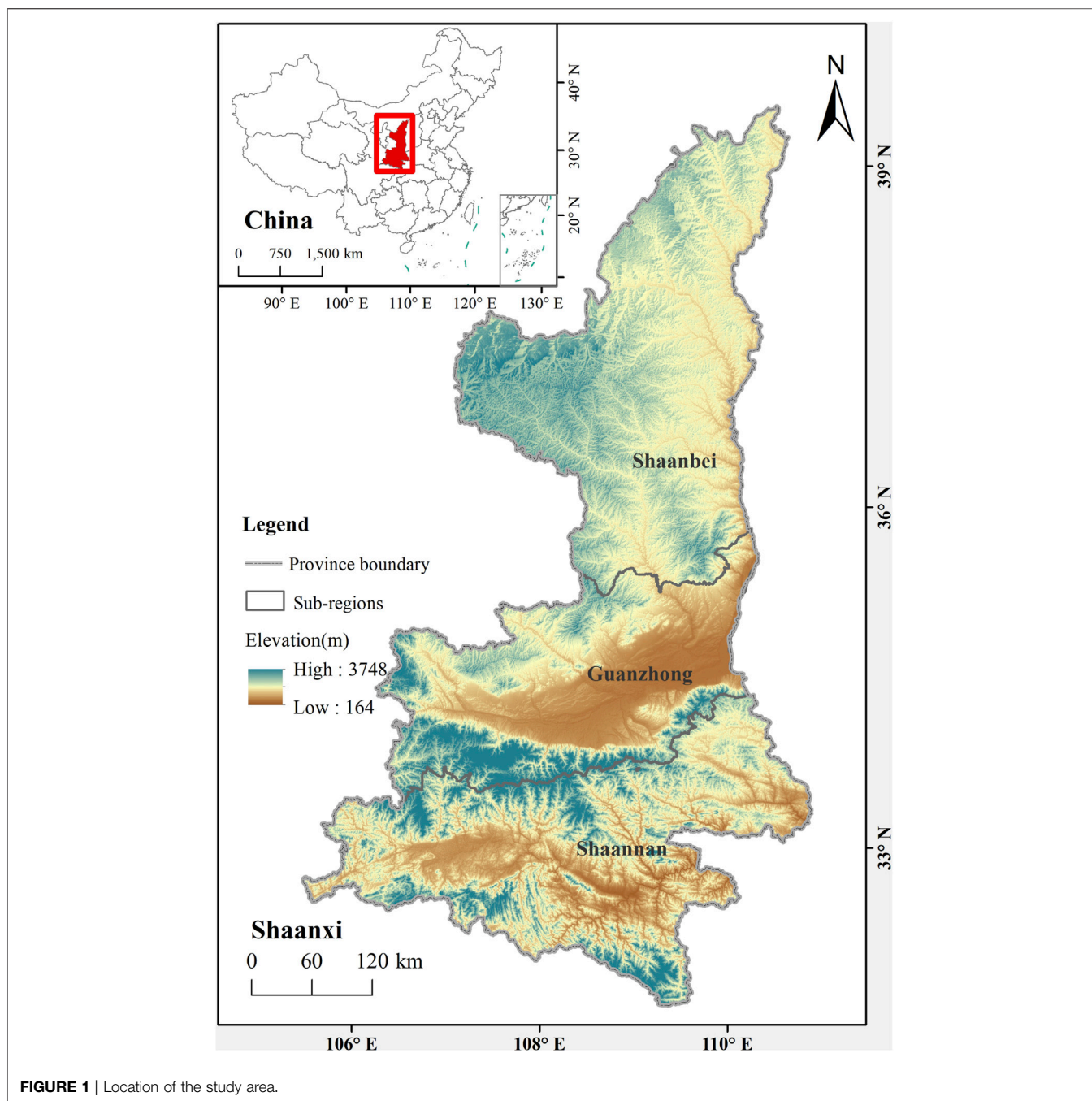
soil erosion over Shaanxi Province from 2000 to 2015 and then we construct a panel data set that spans yearly data on soil erosion estimated by RUSLE and investment data on SLCP as well as a range of natural and socio-economic variables for 107 counties in Shaanxi Province from 2000 to 2015. Different from most related studies, data that characterize SLCP are the investment of SLCP instead of the area of forest converted from cropland or other satellite-derived observations of vegetation cover. This shift from satellite-derived observations to investment data benefits improves the validity and reliability of the estimation of the marginal contribution of SLCP to soil erosion control. To fill up

the knowledge gap mentioned above, the study manages to make two major contributions to the literature with a spatial panel model framework proposed by us with both socio-economic and natural factors concerned. Based on the spatial panel models, we first derive the possibly unbiased estimates for the marginal contribution of SLCP to soil erosion control with the investment variable after accounting for the existence of spatially autocorrelated disturbances. Secondly, we construct first-time empirical evidence regarding the own and spillover effects of SLCP on soil erosion and the direct and indirect paths of how SLCP has a spillover effect on neighboring counties.

FIGURE 2 | Flowchart of the analysis procedure of this study.

MATERIALS AND METHODS

Study Area

Shaanxi Province is located in the inland northwest of China (**Figure 1**), which spans 105° 29′–111° 15′ E and 31° 42′ –39°35′ N with a total area of 20.58×10^4 km². There are obvious differences in climate and topography across this area, which divides this region into three sub-regions (Shaanbei, Guanzhong, Shannan). Shaanbei is the typical ecologically fragile area of the Loess Plateau. Guanzhong is a plain with a concentrated population and developed agriculture. Shannan is a mountain area with sufficient rainfall and dense vegetation.

SLCP started in Shaanxi Province as a pilot in 1999 to especially mitigate severe soil erosion in the 20th century, since 1999 the project has invested over 400 billion CNY for afforestation in this area, which improved the ecological environment—the statistical data from Shaanxi Forestry Bureau showed that the forest coverage increased from 30.92% in 1999 to 43.06% in 2015 and the sediment transport in the Loess Plateau decreased from 800 million tons in 2000 to nearly 400 million tons at present. Meanwhile, Shaanxi has experienced rapid urbanization and booming socio-economic development. During the period 2000–2015, Shaanxi's GDP and proportion of the urban population had increased from 180.40 billion CNY to 1789.88 billion CNY and 27.80–53.92%, respectively. Therefore, it is an ideal region to explore the effect of SLCP on soil erosion under the interaction of socio-economic factors, policy, and natural factors.

As shown in **Figure 2**, we present the analysis procedure of the study for readers' better understanding.

Revised Universal Soil Loss Equation

RUSLE is used to estimate the potential annual average soil erosion loss. In this study, all the input factors of RUSLE including rainfall, soil, topography, and land use and cover are transformed and calculated on ArcGIS10.5 software in GIS raster form (30 m resolution), with the annual soil erosion loss raster map produced by the tool of raster calculator on the GIS platform. The formula of RUSLE is as follows (Renard et al., 1997):

$$A = R*K*LS*C*P \tag{1}$$

where A is the estimated average annual soil loss (t·ha^{-1}·a^{-1}), R is the rainfall erosivity factor (MJ·mm·ha^{-1} h^{-1}·a^{-1}), K is the soil erodibility factor (t·h·MJ^{-1}·mm^{-1}), LS is the terrain (slope length and steepness) factor (dimensionless), C is the cover and management factor (dimensionless), and p is the conservation practice factor (dimensionless).

The Rainfall Erosivity (R) Factor

The R reflects the power of soil separation and transportation caused by rainfall, which is the main driving force of soil erosion (Wischmeier and Smith, 1978). Based on the availability of data and the actual situation in the study area, this study calculates the R factor from **Eq. 2**, which is verified and applied by many similar studies in China (Yu and Rosewell, 1996; Zhang and Fu, 2003):

$$R = \alpha_1 P^{\beta_1} \tag{2}$$

where p is the average annual rainfall (mm), R is the average rainfall erosivity (MJ·mm·hm^{-2}·h^{-1}·a^{-1}) in many years, and α_1 ($\alpha_1 = 0.0668$) and β_1 ($\beta_1 = 1.6266$) are model parameters.

The Soil Erodibility (K) Factor

The soil erodibility (K) factor is an index that represents the sensitivity of soil texture to soil erosion, determined by the soil physical properties like soil texture, soil structure, organic content, and permeability (Wischmeier and Smith, 1978). The most common equation is as follows:

$$K = \left[2.1*10^{-4}m^{1.14}(12-OM)+3.25(S_c-2)+2.5(P_c-3)\right]/100 \tag{3}$$

$$M = N_1(100 - N_2) \tag{4}$$

where K (t·h·MJ^{-1}·mm^{-1}) represents soil erodibility, N_1 (0.002–0.100 mm) represents the percentage of silt (0.002–0.050 mm) plus very fine sand (0.050–0.100 mm), N_2 (<0.002 mm) is the percentage of clay fraction, OM is the soil organic matter content (%), S_c and P_c are the codes of soil structure and permeability. Provided by the National Earth System Science Data Center of China, the K factor used in this study is calculated by the above equations, which are modified by the experimental observation data of the runoff plot.

The Slope Length and Steepness (LS) Factor

Numerous soil erosion studies on slopes or watershed scales show that terrain factors are the direct factors that induce soil erosion, and the LS factor reflects the impact of terrain factors on soil erosion, and its value is between 0 and 1. The calculation of LS in this study is based on the DEM data, using the modified soil erosion model terrain factor calculation tool proposed by Fu et al. (2015) to generate the LS factor map of the study area. The formulas are as follows:

TABLE 1 | The p-value of cultivated land in different slope ranges.

Slope Range	0°~5°	5°~10°	10°~15°	15°~20°	20°~25°	>25°
p value	0.100	0.221	0.305	0.575	0.705	0.800

$$S = \begin{cases} 10.8sin\theta + 0.03, \theta < 5° \\ 16.8sin\theta - 0.5, 5° \leq \theta < 10° \\ 21.91sin\theta - 0.96, \theta \geq 10° \end{cases} \quad (5)$$

$$L_i = \frac{\lambda_{out}^{m+1} - \lambda_{in}^{m+1}}{(\lambda_{out} - \lambda_{in})22.13^m} \quad (6)$$

$$m = \begin{cases} 0.2, \theta < 0.5° \\ 0.3, 0.5 \leq \theta < 1.5° \\ 0.4, 1.5 \leq \theta < 3° \\ 0.5, \theta \geq 3° \end{cases} \quad (7)$$

where S is the slope gradient factor, θ is the slope of the grid cell (in degree), L_i is the slope length factor of the grid cell i, λ_{out} and λ_{in} are the slope lengths of the outlet and entrance of the grid, and m is the slope length index determined by slope θ.

The Cover Management (C) factor

In RUSLE, the C factor reflects the impact of vegetation coverage and management measures on soil erosion, considered to be the most sensitive factor affecting soil erosion, ranging from 0 to 1. Based on the related research (Zhou et al., 2006; Yan et al., 2020), this study calculates the C factor with the Normalized Difference Vegetation Index (NDVI) as follows:

$$C = \begin{cases} 1, f < 0.1 \\ 0.6508 - 0.3436 \lg f, 0.1 \leq f < 0.783 \\ 0, f > 0.783 \end{cases} \quad (8)$$

$$f = \frac{NDVI - NDVI_s}{NDVI_v - NDVI_s} \quad (9)$$

where C is the cover management factor, f is the vegetation coverage determined by $NDVI$, and $NDVI_s$ and $NDVI_v$ are the $NDVI$ values for pure bare soil grid cell and pure vegetation grid cell, respectively.

The Conservation Practice (P) Factor

The p factor reflects the impact of conservation practice in different land types on reducing the erosion potential of the runoff; the value of p ranges from 0 to 1.0 means areas where no soil erosion occurs and one means areas where no conservation practice has been taken. This study assigns p values to different land use types according to land use maps and slope gradients based on research in similar areas in China (Li and Zheng, 2012): the p values of built-up land, water land, unused land, forest land, and grassland are 0, 0, 1, 1, and 1, respectively. The value of cultivated land is assigned according to different slope grades as shown in **Table 1**.

In order to validate the model's regional applicability, we validated RUSLE with the soil erosion area in Shaanxi gathered from the First China Census for Water (Ministry of Water Resources of China (MWR), 2013). The validation results showed that our estimation of soil erosion area in Shaanxi was

consistent with the results of the census (the consistency of results reaches 85%). Besides, we further compared the total amount of soil erosion in Shaanbei between our results and the study using the high-precision terrace data (Liu et al., 2019), and the simulations of RUSLE were significantly similar to the corresponding results in the study (the consistency of results reaches 78%). Therefore, we could confirm that RUSLE and its parameters were reasonable for the simulation of soil erosion in the study area based on the two validations above.

Spatial Econometric Methods
Spatial Autocorrelation

In this study, the spatial autocorrelation of soil erosion of counties in Shaanxi is measured by Moran's I statistics, and then the spatial econometric analysis is employed to avoid biased and inconsistent estimation rather than the traditional econometric analysis (Anselin, 2013). Moran's I can be expressed as:

$$I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij} (Y_i - \bar{Y})(Y_j - \bar{Y})}{\sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij} \sum_{i=1}^{n} (Y_i - \bar{Y})^2} \quad (10)$$

where I is the value of Moran's I, which ranges from -1 to 1. A positive value of Moran's I indicates a positive spatial autocorrelation, a negative value implies a negative autocorrelation, and 0 means random spatial distribution. Y represents the variable of interest ($i \neq j$), and Y denotes the arithmetic mean of the variable of interest in all regions. W_{ij} is an element in the spatial weight's matrix W corresponding to the adjacent relationship or distance between samples. The most common rook spatial weight matrix is used to calculate Moran's I in this study.

Spatial Econometric Models

We specify a generic spatial panel model as follows:

$$TSE_{it} = \rho W TSE_{jt} + \alpha INV_{it} + \lambda_k X_{it} + c_i(optional) \\ + d_t(optional) + u_{it} \, With \, u_{it} = \delta W u_{jt} + v_{it}, v_{it} \sim (0, \sigma_i^2) \quad (11)$$

where TSE_{it} denotes the total weight of soil erosion in county i in year t, INV_{it} is the investment of SLCP in county i in year t, X_{it} is a vector of covariates, c_i presents the unobserved county fixed effects (FEs) accounting for all time-invariant space-fixed variables whose omission in a typical cross-sectional analysis could lead to biased estimation, d_t presents the unobserved time FEs accounting for all time-related effects whose omission could bias the estimates in time-series analysis, u_{it} is a composite error term, and v_{it} is an independently and identically distributed disturbance with zero mean and heteroscedastic variance. The (vectors of) parameters to be estimated in this model are ρ, α, λ_k, and δ. W is the spatial weight matrix, which is composed of the corresponding element W_{ij} (the squared inverse geographic distance between two counties i and j with row standardized as suggested). Besides, to ensure the robustness of the estimation results in this study, a queen contiguity spatial weight matrix is used as an alternative spatial matrix in the model, in which the elements W_{ij} equal one if there are common boundaries or points between county i and county j, 0 otherwise.

TABLE 2 | Results of the LM test, Hausman test, and LR test.

Tests	Statistic	p-value
LM: no lag	14.209	0.000
Robust LM: no lag	20.319	0.000
LM: no error	128.161	0.000
Robust LM: no error	6.271	0.012
Hausman test with SDM: FE vs. RE	5685.610	0.000
LR test: SDM vs. SLM	38.020	0.000
LR test: SDM vs. SEM	2.980	0.084
LR test: Spatial and time-period fixed vs. Time-period fixed Spatial fixed	1653.160	0.000
LR test: Spatial and time-period fixed vs. Spatial fixed	39.670	0.000

Besides, two interaction terms are added, respectively, to the following new type of soil erosion model:

$$
\begin{aligned}
TSE_{it} = &\rho WTSE_{jt} + \alpha INV_{it} \\
&+ \left(\beta_1 RAIN_{it}*INV_{it} \text{ or } \beta_2 NDVI_{it}*INV_{it} \right) + \lambda_k X_{it} + u_{it}
\end{aligned}
\tag{12}
$$

where $(RAIN_{it} * INV_{it})$ and $(RAIN_{it} * NDVI_{it})$ are the interaction terms, while the coefficients β_1 and β_2 for the terms indicate how rainfall moderates the effect of INV and $NDVI$ on soil erosion. The marginal effects of INV and $NDVI$ on soil erosion control are as follows:

$$
\frac{d(TSE_{it})}{d(INV_{it})} = \lambda_1 + \beta_1 RAIN_{it} \frac{d(TSE_{it})}{d(NDVI_{it})} = \lambda_1 + \beta_2 RAIN_{it}
\tag{13}
$$

It is difficult to interpret the effect of investment of SLCP on soil erosion by its coefficient estimates (α) when explained variable lag exists. It is obvious that changes in investment in any county will affect the soil erosion in the county as well as the soil erosion in neighboring regions through the spatial lag effect. Therefore, partial differentiation needs to be used to decompose the model results to obtain direct and indirect effects if the coefficient ρ is not 0 (Lesage and Pace, 2010). The direct effect (own effect) refers to the average value of the explanatory variable's influence on the explained variable in the local county, and the indirect effect refers to the average value of the explanatory variable's influence on the explained variable in the neighboring counties, that is, the spatial spillover effect. The total effect is the sum of the two items. Hence, the generic spatial panel model can be transformed as follows to get the direct and indirect effects:

$$
TSE_{it} = \left(1 - \rho W\right)^{-1} \left(\alpha INV_{it} + \lambda_k X_{it} + c_i + d_t + u_{it}\right)
\tag{14}
$$

Let $Z_{it} = \alpha INV_{it} + \lambda_k X_{it}$, $A_i = (1 - \rho W)^{-1}$, A_d be a matrix with diagonal elements of A_i on its diagonal, and all other elements be 0. The own effects are:

$$
A_d Z_{it}
\tag{15}
$$

and the spillover effects are:

$$
(A_i - A_d) Z_{it}
\tag{16}
$$

Diagnostic Evaluations for Model Selection

Generally, there are several commonly used spatial econometric models: (17) spatial lag mode (SLM), (18) spatial error model (SEM), and (19) spatial Durbin model (SDM) (Hao & Liu, 2016). Their basic form can be written as:

$$
\text{SLM: } Y = \alpha + \rho WY + X\beta + \varepsilon
\tag{17}
$$

$$
\text{SEM: } Y = \alpha + X\beta + \varepsilon \, \varepsilon = \lambda W\varepsilon + \mu, \mu \sim \left(0, \sigma^2\right)
\tag{18}
$$

$$
\text{SDM: } Y = \alpha + \rho WY + X\beta + WX\gamma + \varepsilon
\tag{19}
$$

where Y denotes the dependent variables, X is a matrix of explanatory variables α is a constant term, ρ, β, λ, and ε are the estimated parameters of variables, W is a random error term, W is the spatial weight matrix, and μ is a normally distributed error term.

In this study, we choose SDM with spatial and time-period FEs to conduct the spatial econometric analysis after conducting the diagnostic evaluations like the likelihood ratio (LR), Lagrange multiplier (LM) test, and Hausman test (Khezri et al., 2021).

As shown in **Table 2**, the LM test's null hypothesis is dismissed, and this can affirm the SLM and SEM. The Hausman test is used to explore which effects to choose in the model: FEs or random effects (REs), and the result indicates that the presence of FEs is verified at a 1% significance level in the SDM. In order to figure out whether the SDM can be simplified as the SLM or SEM, LR tests are conducted. The results show that the SDM cannot be simplified as the SLM; either the SEM or the SDM is the basis model to explore the effects of SLCP on soil erosion. Then, LR tests are conducted to examine the possibility of the spatial FEs and the time-period FEs in the model, and the results reject all the null hypothesis; the spatial and time-period FEs are chosen to continue with the estimation process.

Data Definitions and Sources
Variable Design

Explained variables are the average soil erosion modulus (SE) and the total soil erosion (TSE) in the county. The calculation result of the integration of RUSLE and GIS is a raster map of the soil erosion modulus, and SE is the average soil erosion modulus of the county obtained by the regional statistical function of the ArcGIS10.5 platform. The total soil erosion represents the total weight of soil erosion in the county, with the area of the region taken into consideration. What's more, SE is used as the alternative explained variable to enhance the robustness of the model.

Explanatory variable is the total investment (INV) of SLCP. The initial and fundamental goal of SLCP is to alleviate soil erosion by afforestation; so, this study chooses the INV as the

**TABLE 3 |** Variable design and descriptive statistics (in 2015).

Name	Design and data description	Unit	Mean	Std	Min	Max
SE	Annual average soil erosion modulus	t/(ha·a)	264.119	268.768	0.000	1077.499
TSE	Total weight of soil erosion	10^4 t/a	12.538	9.748	0.000	40.620
INV	Total investment in the county of SLCP	$CNY10^8$	2.834	3.085	0.000	17.855
RAIN	Annual average rainfall	mm	638.946	178.748	332.181	1130.060
URBR	The ratio of the built-up land to the total land	%	9.000	19.000	0.100	100.000
IS	The ratio of the gross industrial product to the gross domestic product	%	42.700	17.000	7.300	91.700
PGDP	Per capita GDP	$CNY10^4$	4.348	2.879	1.491	16.747
CROP	Total production of wheat, corn, and rice	10^4 t	11.456	9.331	0.000	37.237
RPI	Rural per capita annual income	$CNY 10^4$	0.918	0.298	0.000	1.982
NDVI	Annual average NDVI	Dimensionless	0.831	0.124	0.451	0.958

explanatory variable to verify the effects of SLCP on soil erosion, especially with the spatial spillover effect of variables. Since rainfall has an extremely important impact on soil erosion, this study chooses rainfall (*RAIN*) as the natural factor to test the regulating effects in the prevention and mitigation of soil erosion by SLCP.

According to the previous studies (Kong et al., 2018), we account for socio-economic factors on soil erosion by including the following variables as control variables: the urbanization rate (*URBR*) is the proportion of the built-up land of the total land, the industrial structure (*IS*) is the ratio of the gross industrial product to the gross domestic product as an indicator for industrialization, the GDP per capita (*PGDP*) represents the change of economic condition, grain production (*CROP*) is the total production of wheat, corn, and rice, and the rural per capita annual income (*RPI*) is the index reflecting the condition of the rural economic development. In addition, reflecting the growth status of vegetation with significant impact on soil erosion, the Normalized Vegetation Index (*NDVI*) is selected as the natural control variable accounting for regional natural resource endowments.

Data Source

There are 107 counties in Shaanxi as samples on the cross-sectional dimension of the panel data set used in the spatial econometric analysis in this study, and the time period is from 2000 to 2015 with 5 years gap in its time dimension with multiple sources of sample data. Soil erosion data are obtained from the result of RUSLE. The investment data of counties in Shaanxi come from the Central South Investigation and Planning Institute of State Forestry and Grassland Administration; the detailed calculation of these data is shown in the study of Liu et al. (Liu and Yao, 2021). The raster data of rainfall with a resolution of 1 km are from the Resources and Environmental Sciences Data Center of the Chinese Academy of Sciences (http://www.resdc.cn/). Land use and cover data with a resolution of 30 m are from the Resources and Environmental Sciences Data Center of the Chinese Academy of Sciences (http://www.resdc.cn/). The accuracy of land use classification is 94.3% with field verification and error correction (Liu et al., 2010). The soil erodibility factor raster data with a resolution of 30 m are from the National Earth System Science Data Center of China
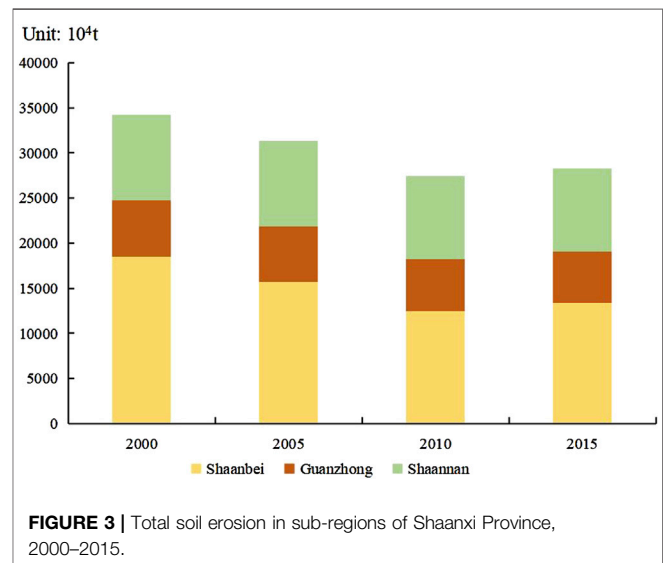

FIGURE 3 | Total soil erosion in sub-regions of Shaanxi Province, 2000–2015.

(http://www.geodata.cn/). Administrative boundaries of the counties are obtained from the national 1:1,000,000 database of China Geographic Information Monitoring Platform (http://www.dsac.cn/). The digital elevation model (DEM) data are SRTM data with a resolution of 30 m (http://www.resdc.cn/). The NDVI data are derived from the Chinese Geospatial Data Cloud (http://www.gscloud.cn/) with a resolution of 500 m. The socio-economic data such as GDP, population, and grain yield are all from the "Shaanxi Regional Statistical Yearbook." The spatial data used in this study are uniformly resampled at a resolution of 30 m with the same spatial coordinate system (Krasovsky_1940_Albers). The design of each variable and the descriptive statistical analysis are reported in **Table 3**.

RESULTS

Spatio-Temporal Characteristics of Soil Erosion

The temporal variations and the spatial distribution of soil erosion over Shaanxi from 2000 to 2015 are shown in **Figure 3** and **Figure 4**. As shown in **Figure 3**, the total

FIGURE 4 | Spatial pattern of changes in soil erosion in Shaanxi: 2000–2015.
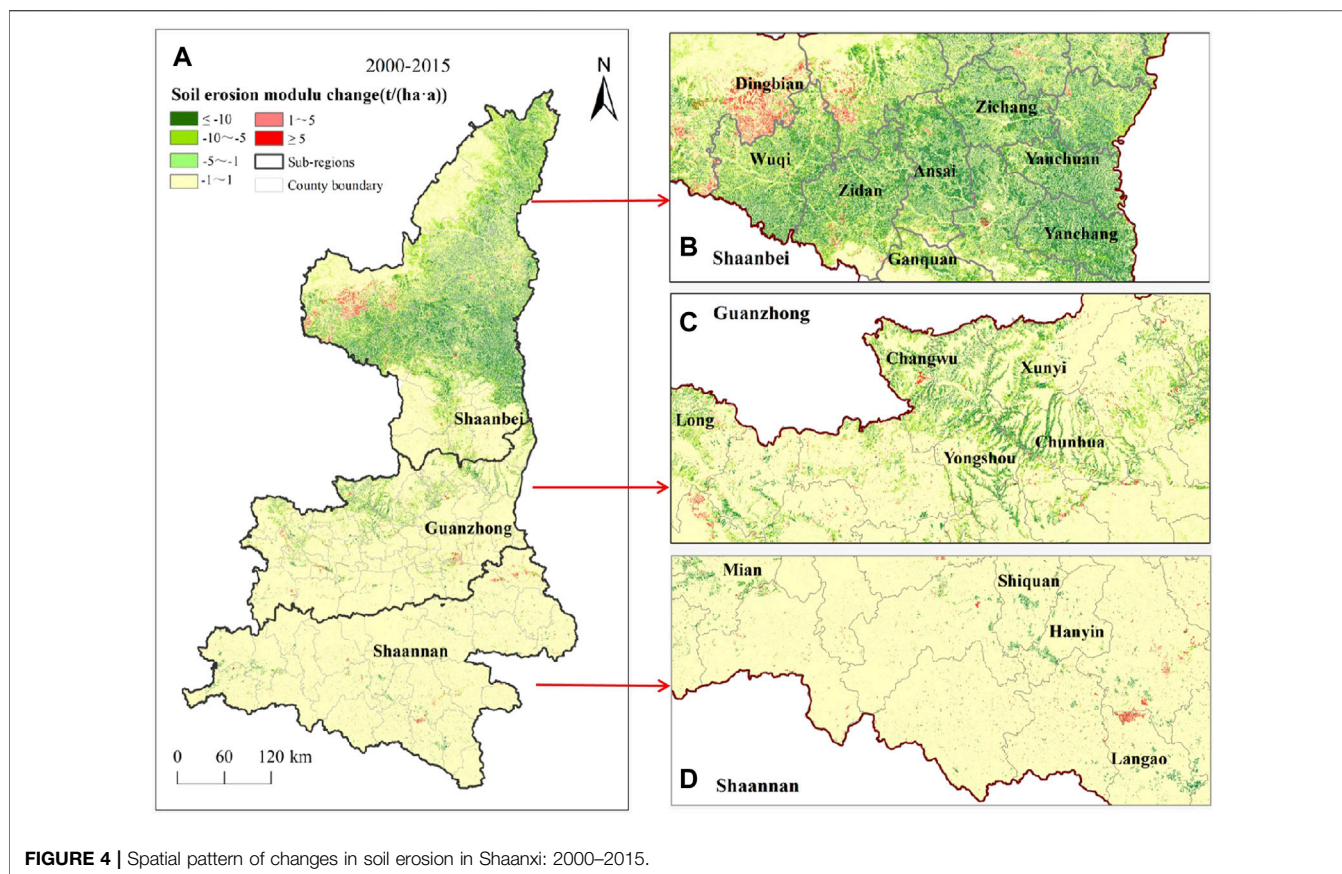
amount of the soil erosion in Shaanxi showed a downward trend from 2000 to 2015. Specifically, the total amount of soil erosion in 2000 was 341.66 million t, of which the largest proportion in Shaanbei was 54.21%, exceeding the sum of the proportions of Guanzhong and Shannan. It decreased to 282.61 million t in 2015, indicating that 17.29% of the soil erosion (341.66 million t in 2000) was mitigated over the 15-year period. And Shaanbei contributed 87.14% to this total mitigation (a reduction of 51.47 million t of soil erosion). Besides, we visualized the spatial distribution of soil erosion changes over Shaanxi from 2000 to 2015, as shown in **Figure 3**. The soil erosion in Shaanbei was more serious than in other sub-regions; however, the decrease in soil erosion in Shaanbei was also the most significant. Especially in Yan'an City, the soil erosion modulus of most counties was basically reduced by more than 5 t/ha/a. The soil erosion modulus was even reduced by more than 10 t/(ha·a) in some specific areas with a dark green color in **Figure 3**. It is obvious that soil erosion had been effectively controlled during the period of SLCP, which is also consistent with similar studies (Liu, et al., 2019). At the same time, the soil erosion modulus of Changwu County, Xunyi County, Chunhua County, and Long County in the northern part of Guanzhong also decreased significantly, while the soil erosion reductions in Shannan were mainly scattered in some areas such as Langao County, Mian County, and Shiquan County. Besides, the spatial distribution of the total investment of SLCP in Shaanxi from

2000 to 2015 is visualized for a more intuitive understanding of the relationship between the total investment of SLCP and soil erosion changes at the county scale (**Figure 5**).

As shown in **Figure 5**, counties in Shaanbei like Ansai, Zhidan, Wuqi, and Zichang were the key area of SLCP, which got more investment than other counties, ranging from 0.87 to 1.79 billion CNY. This also coincided with the good performance in mitigating soil erosion in these counties. The investment of Shannan counties like Zhenba, Ningqiang, and Ziyang also reached a high level, more than 0.51 billion CNY, while most counties in Guanzhong had less investment in SLCP than other regions, and the decline of soil erosion modulus in these areas was not obvious either.

To test whether the distributions of soil erosion in Shaanxi counties exist, we conducted Moran's I statistics on the ArcGIS (**Table 4**). As shown in **Table 4**, Moran's I values are all positive in the study period and are basically greater than 0.6 at a 1% significance level, indicating that there is a strong positive spatial autocorrelation, which means that soil erosion in counties appears to be spatially dependent. Hence, it is necessary to use the spatial econometric methods in the next analysis.

Results of Spatial Econometric Models

The main results of estimating the factors influencing soil erosion with **Eq. 11** are reported in **Table 5**. Besides, we also report results on estimations of non-spatial economic models adapted from **Eq.**
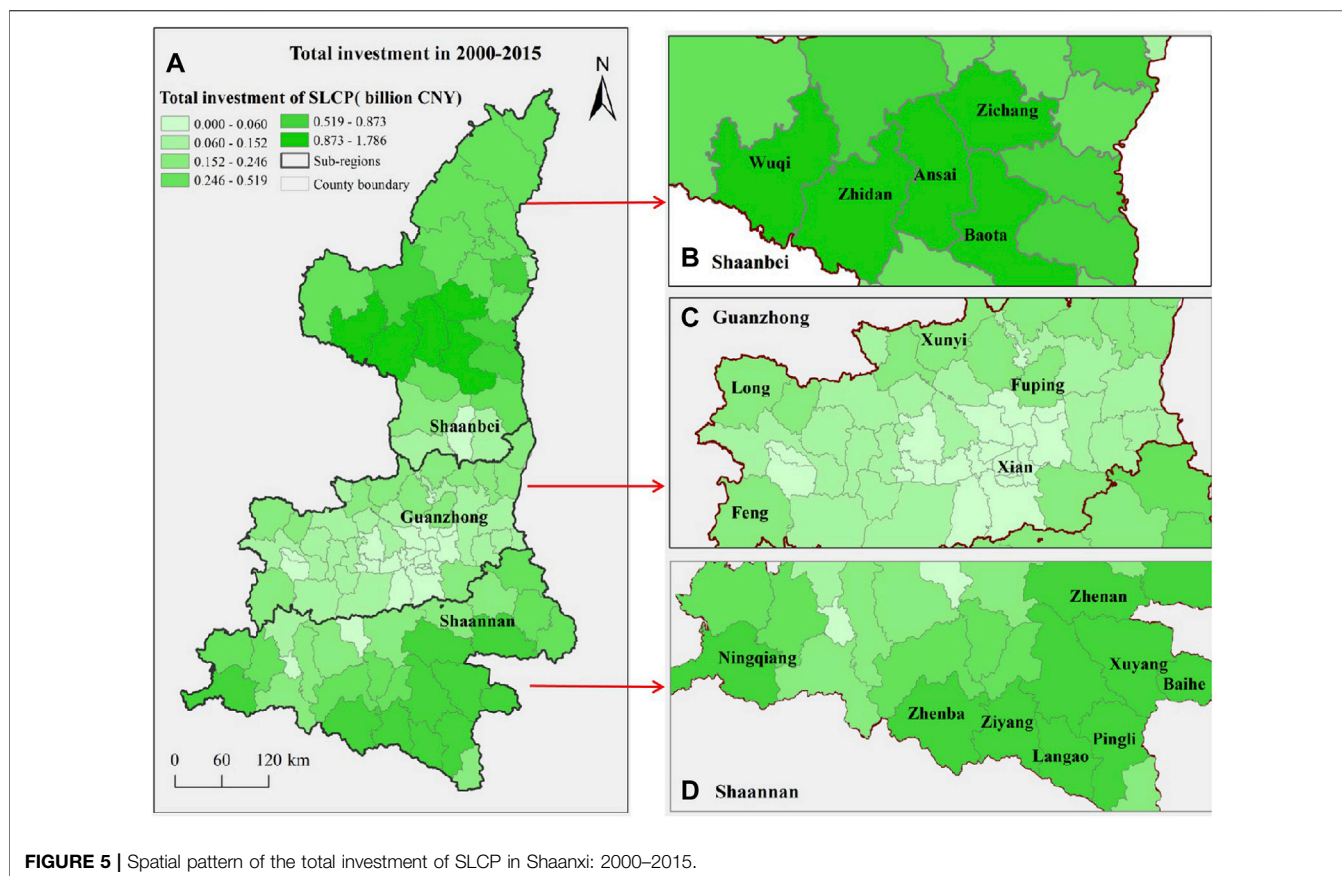
FIGURE 5 | Spatial pattern of the total investment of SLCP in Shaanxi: 2000–2015.

TABLE 4 | Moran's *I* test results for soil erosion in Shaanxi, 2000–2015.

	Moran's *I*	Z-value	*p*-value
2000	0.6912	11.0024	0.0000
2005	0.6221	10.6368	0.0000
2010	0.6142	9.7784	0.0000
2015	0.6313	10.0474	0.0000

11 with conventional panel FEs and pooled OLS. As shown in **Table 5**, most of the model variables have a significant effect on soil erosion except for *RAIN* and *IS*; these results confirm our hypothesis that the heterogeneity in the investment of SLCP (*INV*), socio-economic, and natural characteristics can systematically explain differences in soil erosion. A highly positive significant coefficient for the spatial lag parameter of soil erosion (*W*Y*) indicates that a county's total weight of soil erosion (*TSE*) is systematically affected by its geographical neighbors' soil erosion status and the spatial spillover effect of soil erosion is significant; hence, there is an indirect spillover effect of *INV* in a county on *TSE* of its adjacent counties through the transboundary spillover of soil erosion. The coefficient of the investment of SLCP indicates a negative link between the investment of SLCP and soil erosion at a 1% significance level, which means that the increase of a county's investment of SLCP will significantly reduce the *TSE* in that area. While the coefficient

of *INV* (−23.256) in the panel fixed estimator is also significant but the absolute value of it is larger than that in SDM, which indicates the panel fixed model would overestimate the effect of *INV* on *TSE* with spatial effects ignored. The coefficient of *INV* is significantly negative in the pooled OLS, which contradicts our hypothesis that SLCP has alleviated soil erosion, so the pooled OLS is not suitable for carrying out the regression estimation in this study. As shown in the table, we used *SE* as the alternative explained variable to enhance the robustness of the SDM model (column 3 of **Table 5**), and the estimation results show consistent conclusion with the estimation in column 2 of **Table 5**.

The coefficient estimation for the spatial lag of *INV* is found to have a significant but positive impact on *TSE*, but it is difficult to interpret the effect of variables based on the coefficient estimate when the dependent variable lag exists because the coefficient is part of the recursive computation of marginal effects just as **Equation 14** shows. Hence, we report the own and spillover effects as well as the average total impacts for the SDM in **Table 6**[1].

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[1]Due to the magnitude of spatial effects, it depends critically on the spatial weight matrix W, which is defined a priori; we also report the estimation results of SDM with a queen contiguity matrix (provided in **Appendix Table A1** in the Appendix), which did not lead to a qualitative change on the estimates for the own, spillover, and total effects.

TABLE 5 | Estimation results of the model specified in **Eq. 11** with different specifications: panel SDM, panel FE, and pooled OLS.

	Panel SDM		Panel FE	Pooled OLS
	(1) TSE	(2) SE		
INV	−17.387***	−0.284***	−23.256***	59.690***
	(1.130)	(0.031)	(4.552)	(5.376)
RAIN	−0.010	−0.001	−0.055	0.425***
	(0.019)	(0.001)	(0.039)	(0.062)
CROP	1.222**	0.108***	−0.050	−0.845
	(0.424)	(0.030)	(1.130)	(0.891)
IS	5.250	0.452**	16.598	151.340**
	(4.882)	(0.187)	(20.362)	(69.259)
PGDP	−1.548**	0.079***	−2.748	4.818
	(0.669)	(0.016)	(3.284)	(6.232)
RPI	−14.489***	−0.576**	51.261**	−80.860**
	(2.919)	(0.180)	(17.128)	(31.018)
NDVI	−14.489***	−13.650***	−293.235**	−1316.133***
	(2.919)	(2.573)	(92.022)	(121.170)
URBR	−231.531***	-8.557***	−122.562	−611.960***
	(30.286)	(1.232)	(176.032)	(51.743)
Constant			573.155***	958.545***
			(58.140)	(83.626)
W*Y	0.713***	0.699***		
	(0.028)	(0.042)		
W*INV	9.072***	0.013		
	(0.564)	(0.017)		
σ^2	441.866***	0.667***		
	(39.891)	(0.119)		
R-squared (within)	0.445	0.525	0.597	0.616

*Robust estimators are reported for the SDM, FE, and pooled OLS. Standard errors in parentheses. ***p < 0.01, **p < 0.05, and *p < 0.1.*

The own effect of *INV* on *TSE* is significant and negative, indicating that a county's expected conditional mean of *TSE* would be reduced by 183.15 thousand t/a if the investment of SLCP in this county increases 0.1 billion CNY compared with other conditions remaining unchanged. In addition, the coefficient estimate for the spillover effects of *INV* is also negative and significant

at the 1% level, which means the reduction of *TSE* in a county can be attributed to the afforestation of SLCP in its neighbors even if there is no spatial spillover effect dependence in *TSE*. Specifically, the conditional mean of *TSE* in a county would have depreciated by 105.54 thousand t/a less on average if the investment of SLCP in all other counties each increases 0.1 billion CNY. The total effect of *INV* in a county *i* represents the overall effect on *TSE* of county *i* from changing *TSE* by the same amount across all 107 counties. Every 0.1 billion CNY increase in the investment of SLCP in every county would, on average, imply a 288.69 thousand t/a lower in *TSE*.

In line with our expectations, the impact of *NDVI* on *TSE* is found to be negative and significant, indicating that the increase in vegetation coverage will slow down the soil erosion in the area. Hence, SLCP can prevent soil erosion by increasing vegetation coverage. Besides, the spillover effect of *NDVI* on *TSE* is also significant at the 1% level, which implies that the ecological effects of vegetation can benefit the neighboring areas through transboundary ways. However, we find a negative but insignificant effect of *RAIN* on *TSE* in all models mentioned in **Table 5**, which is contrary to RUSLE (**Eq. 1**), in which the rainfall has a positive and significant effect on soil erosion. This difference could be explained by the fact that the changes in rainfall are not significant for specific regions, especially in SDM with county FEs (while a significant and positive effect of *RAIN* on *TSE* is found in the pooled OLS specification).

The own effect of urbanization on *TSE* is negative and significant, indicating that urbanization has a positive effect on soil erosion prevention; indeed, other socio-economic factors like *RPI* and *PGDP* also have negative and significant coefficient estimates in the model, which means that the development of the regional economy will benefit the ecological environment, especially for the soil erosion. Besides, the coefficient of *CROP* indicates a positive link between *CROP* and *TSE*, implying that although high-intensity farming activities will increase food production, the disturbance to soil will also aggravate soil erosion. We argue that the estimation results of *TSE* are

TABLE 6 | Estimation results of different effects in the SDM.

	Own effects		Spillover effects		Total effects	
	(1) TSE	(2) SE	(3) TSE	(4) SE	(5) TSE	(6) SE
INV	−18.315***	−0.336***	−10.554***	−0.578***	−28.869***	−0.913***
	(1.185)	(0.032)	(0.756)	(0.138)	(1.609)	(0.145)
RAIN	−0.014	−0.002	−0.031	−0.005	−0.045	−0.007
	(0.032)	(0.021)	(0.065)	(0.039)	(0.096)	(0.060)
CROP	1.529***	0.134***	2.967**	0.242***	4.496**	0.375***
	(0.540)	(0.034)	(1.286)	(0.079)	(1.813)	(0.107)
IS	5.846	0.554**	10.746	1.023*	16.592	1.577**
	(5.533)	(0.226)	(10.337)	(0.525)	(15.822)	(0.734)
PGDP	−1.890**	0.097**	−3.501***	0.176**	−5.391***	0.273**
	(0.753)	(0.042)	(1.301)	(0.089)	(2.032)	(0.128)
RPI	−17.783***	−0.708***	−33.870***	−1.254***	−51.653***	−1.962***
	(3.567)	(0.198)	(8.673)	(0.343)	(11.932)	(0.508)
NDVI	−283.601***	−16.596***	−534.928***	−29.506***	−818.529***	−46.102***
	(33.332)	(2.514)	(73.367)	(4.440)	(96.352)	(5.511)
URBR	−177.994***	−10.193***	−332.651***	−18.222***	−510.645***	−28.415***
	(22.414)	(1.302)	(16.621)	(2.988)	(32.786)	(3.445)

*Standard errors in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.*

TABLE 7 | The estimation results of model specified in **Eq. 12**.

	(1) TSE	(2) SE	(3) TSE	(4) SE
INV	−27.417***	-0.604***	−17.598***	−0.290***
	(3.461)	(0.102)	(1.256)	(0.035)
RAIN	0.020***	0.000	−0.271***	−0.008***
	(0.006)	(0.000)	(0.052)	(0.002)
CROP	1.862***	0.132***	1.763***	0.124***
	(0.380)	(0.031)	(0.453)	(0.031)
IS	7.323	0.484*	4.787	0.428**
	(4.548)	(0.260)	(5.195)	(0.201)
PGDP	−1.024**	0.112***	−0.937*	0.101***
	(0.484)	(0.029)	(0.531)	(0.021)
RPI	−9.845***	−0.425**	−9.768***	−0.450**
	(3.057)	(0.170)	(3.575)	(0.203)
NDVI	−209.052***	−13.316***	−363.495***	−17.405***
	(22.937)	(2.442)	(50.067)	(3.107)
URBR	−137.133***	−8.415***	−114.673***	−7.744***
	(18.574)	(1.107)	(21.939)	(1.210)
RAIN * INV	0.018***	0.001***		
	(0.004)	(0.000)		
RAIN * NDVI			0.314***	0.009***
			(0.049)	(0.002)

robust according to the estimation results of the alternative explained variable (*SE*) [as shown in columns (2), (4), and (6) of **Table 6**].

To check whether the *RAIN* moderates the effect of *INV* and *NDVI* on soil erosion, we report the estimation results with two interaction terms added in SDM in **Table 7**. The result of a positive coefficient on the interaction term between rainfall and investment of SLCP indicates that there is a negative moderating effect of *RAIN* on the alleviating effect of SLCP on soil erosion. As the *RAIN* increases, in magnitude, the marginal alleviating effect of *INV* on soil erosion decreases. Specifically, the increase in rainfall will increase the rainfall erosivity, thereby aggravating regional soil erosion, and the mitigation effect of *INV* on soil erosion will decrease. We also find that *RAIN* has a negative and significant moderating effect on the alleviating effect of *NDVI* on soil erosion, which means with the increase in rainfall, the role of *NDVI* in preventing soil erosion will be weakened. To sum up, the marginal contribution of the investment of SLCP is smaller in the area with more rainfall, like counties in Shannan than those in Shaanbei. The estimation results of the model with *SE* as the alternative explained variable indicate the robustness of our conclusion [as shown in columns (2) and (4) in **Table 7**].

DISCUSSION

Marginal Contribution of SLCP to Soil Erosion Control and the Transboundary Path

The crucial role of SLCP in mitigating soil erosion has been widely recognized worldwide (Borrelli et al., 2017; Chen et al., 2021), but what cannot be ignored is to explore how soil erosion is controlled by SLCP from the perspective of marginal cost and income for the sustainability of the policy. In this study, we use the data of investment of SLCP to characterize the intensity of policy

implementation and some indirect observation indicators like vegetation cover or the area of land use change (Rao et al., 2016; Zhou et al., 2021), which can maximally strip out the marginal contribution of the investment of SLCP to soil erosion with a specific SDM. It is of critical relevance for policymakers to figure out the cost-effectiveness of the investment on soil erosion control and make the next decision with reference to the result. Indeed, in research design, we draw upon the study by Kong et al. (2018), who explored the relationships among SLCP, the soil conservation service, and the socio-economic factors using structural equation modeling (SEM) with a cross section of 779 counties. However, their estimation result bias may arise from county heterogeneity. It is widely recognized that soil erosion is local by nature, influenced by both geographical and socio-economic factors (Ganasri and Ramesh, 2016; Rao et al., 2016), which makes it difficult to properly capture by the analysis of cross-sectional data. Hence, the spatial SDM with FEs proposed in this study is conducted to derive possibly unbiased estimates of the investment of SCLP in soil erosion control.

There are many studies exploring the factors affecting soil erosion at the regional scale (Alewell, et al., 2019; Zhou et al., 2021; Zhao et al., 2022), but the results of this article demonstrate that the spatial spillover effect of soil erosion is significant at the county scale, which has so far been overlooked by the literature mentioned above. It is significant to figure out how soil erosion in one region affects soil erosion in the neighboring regions for the effective transboundary ecological governance. According to the results of the panel SDM in this study, the spillover effect, as well as the own effect of investment in SLCP, is significant and positive on soil erosion control, which means soil erosion control in a county benefits not only from SLCP locally but also from the greening efforts of SLCP in its neighbors, and a joint effort in all counties has a much larger marginal effect on soil erosion control than unilateral ecological restoration effort in one county. Obviously, the separation of own from spillover impacts of SLCP on soil erosion provides solid evidence of the necessity of promoting "beneficiary pay" taxes and afforestation subsidies (Schomers and Matzdorf, 2013) in transboundary ecological governance, especially when it comes to this case that the soil erosion of a county has been mitigated by the green intervention efforts of SLCP in its neighboring counties without investing in these efforts by itself. Therefore, we argue that a well-functioning transboundary soil conservation system with collaborative green efforts from all stakeholders in the region is much more crucial and effective than the efforts only focusing on the local interests.

Impact of Socio-Economic and Natural Factors on Soil Erosion Control

Previous studies have highlighted the positive and significant link between urbanization and soil erosion control (Wang et al., 2020; Kong et al., 2018), which is consistent with our estimate results in **Table 5**. Due to rural–urban migration and the land use change in urbanization, the negative impacts of population on environmental degradation will be mitigated by alleviating the extent of disturbance to soils from farming (Grau and Aide, 2007; Deshingkar 2012), ultimately facilitating the mitigation of soil erosion. However, urbanization might aggravate other ecological problems like water pollution, carbon emission, and air pollution (Peng et al.,

2017; Ke et al., 2020); so, it is necessary to balance ecosystem protection and urbanization. In addition, we also found that the economic growth, as well as the growth of rural per capita income, has a significant and positive effect on soil erosion control. The underlying reason may be that the growth of the economy provides enough funds for the government to take action on soil erosion control (Wang et al., 2020), while the growth of the rural economy will stimulate the farmers to depend less on the vulnerable ecosystem and adopt environment friendly farming methods to avoid damage to the environment. These results emphasized that policymakers should attach importance to the social and economic effects and the related interactions on ecosystem services and functions besides the direct goal of the ecological restoration to achieve a win–win situation for ecology and economy.

The rainfall has a significant impact on the cost-effectiveness of the investment in SLCP; for instance, Liu and Yao (Liu and Yao, 2021) pointed out that there is a distinct threshold effect of rainfall on the ecological effects (characterized by NDVI), while from the perspective of soil erosion control, rainfall has a significant moderating effect on the alleviating effect of investment of SLCP on soil erosion. The complexity of the interaction mechanisms lies in the different roles of rainfall in the process of soil erosion. On the one hand, the rainfall benefits the growth of plants, and then the increased vegetation cover will mitigate soil erosion (Chen et al., 2019). On the other hand, the rainfall also increases the erosivity of the soil, especially in Shaanbei and the typical arid and semi-arid areas in the Loess Plateau (Zhou et al., 2006). The results in our specific SDM indicate that the rainfall will weaken the effect of the investment of SLCP on soil erosion control at the county scale. Moreover, when the investment of SLCP is the same, the county with lower rainfall has a greater marginal contribution to soil erosion control than that with higher rainfall. Indeed, the investment of SLCP for soil erosion control should give priority to counties with intense soil erosion and lower rainfall considering its non-negligible direct spillover effects of soil erosion to neighbors and a much greater marginal effect of SLCP on soil erosion control. Therefore, it is necessary to scientifically identify the complex impact mechanism of climatic conditions on ecosystem services to improve the effectiveness and sustainability of ecological restoration policies.

Limitations of This Research

Admittedly, the green interventions of SLCP have a considerable contribution to soil erosion control, while the scale effect of the distribution of soil erosion and its evolution over time may exist due to the spatial heterogeneity within the region. In this study, to ensure the consistency of all multi-source data, we have to use the soil erosion data at the county scale in a spatial panel model framework, which may neglect the scale effect. Indeed, the small watersheds usually have the same physical–geographical features like climatic type, rainfall pattern, soil type, and vegetation (Chen et al., 2019); hence, further research could take our findings as a basic point to investigate the possibilities of integrating county-level statistics and watershed data. Besides, we only examined the effectiveness of SLCP on soil erosion; a question open to further investigation is how to comprehensively evaluate the efficiency of investment in ecological restoration projects with the existence of trade-offs and synergy among various ecosystem services.

CONCLUSION

In this study, we evaluated the effect of SLCP on soil erosion based on the specific spatial panel approach after the diagnostic evaluations in the selection process using the data of investment of SLCP. The conclusions were as follows: (1) the erosion intensity in Shaanxi province, especially in Shaanbei, exhibited a significant decreasing trend from 2000 to 2015 contributed by the continuous and comprehensive investment of SLCP. (2) The spatial econometric results demonstrate evidence of positive and economically meaningful effects of the investment of SLCP on soil erosion control, both locally and spatially in the study area. On the one hand, the investment in a county has a significant own effect on the soil erosion control locally. A 0.1 billion CNY increase in the investment in the county will diminish the expected conditional mean of *TSE* of it by 183.15 thousand t/a, with other conditions remaining unchanged. On the other hand, the soil erosion will be mitigated by the green efforts of SLCP from the neighboring counties due to the significant spillover effect of investment of SLCP on the soil erosion control and the spatial lag of soil erosion. (3) We confirm the moderating effect of rainfall on the mitigation effect of SLCP on soil erosion empirically at the county scale. The county with less rainfall performs better in soil erosion control with the same investment than that with more rainfall. These results indicate that it is necessary to establish a transboundary collaborative ecological governance system based on the long-term monitoring of both natural and socio-economic factors for improving the effectiveness of ecological restoration policy and the sustainability of the ecosystem.

DATA AVAILABILITY STATEMENT

The original contributions presented in this study are included in the article/supplementary material; further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

YX: conceptualization, methodology, writing—original draft, and software; LW: writing—reviewing and editing and visualization; RA: writing—reviewing and editing and validation; XL: writing—reviewing and editing; YL: writing—reviewing; YLo: writing—reviewing and editing, conceptualization, and supervision; SY: conceptualization; and YLn: software and writing—reviewing.

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APPENDIX A

TABLE A1 | Estimation results of an SDM with a contiguity matrix.

	Own effects	Spillover effects	Total effects	Main coef
INV	−23.472***	−5.600*	−29.072***	−23.087***
	(1.849)	(2.890)	(3.125)	(1.857)
RAIN	0.004	0.003	0.007	0.006
	(0.043)	(0.066)	(0.108)	(0.023)
CROP	0.596	0.954	1.550	0.505
	(0.395)	(0.690)	(1.077)	(0.333)
IS	1.062	1.711	2.774	0.799
	(7.157)	(11.254)	(18.368)	(6.417)
PGDP	−3.291***	−5.063**	−8.354***	−2.905***
	(1.181)	(1.984)	(3.103)	(1.063)
RPI	−20.776***	−32.189***	−52.965***	−18.175***
	(3.620)	(8.208)	(11.361)	(3.018)
NDVI	−275.111***	−423.278***	−698.389***	−242.171***
	(29.786)	(75.551)	(95.443)	(27.967)
URBR	−187.773***	−286.892***	−474.665***	−165.857***
	(24.272)	(43.460)	(58.867)	(23.312)
W*TSE				0.651***
				(0.023)
W*INV				12.987***
				(1.227)
σ^2				551.308***
				(48.844)
R-squared (within)				0.443