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Uncertainties of Two Methods in Selecting Priority Areas for Protecting Soil Conservation Service at Regional Scale

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Abstract: Soil conservation (SC) is an important ecosystem regulating service. At present, methods for SC mapping to identify priority areas are primarily based on empirical soil erosion models, such as the RUSLE (Revised Universal Soil Loss Equation) based model. However, the parameters of the empirical soil conservation model are based on long-term observations of field experiments at small spatial scales, which are very difficult to obtain and must be simplified when implementing these models at large spatial scales. Such simplification of model parameters may lead to uncertainty in quantifying SC at regional scale. In this study, we have analyzed a new method to map SC in Jiangxi Province of China based on the multiplication of multiple biophysical data. After comparing the spatial-temporal changes of SC from the RUSLE based model and those from the surrogate indicator based method in the study area, the similarities and differences of these methods for identifying SC priority areas were revealed. The result showed that the two methods similarly represented the effects of vegetation coverage and land use types on SC, however, they were significantly different in representing the spatial pattern of SC priority areas and its temporal change. Based on the comparisons, the advantages and drawbacks for both methods were made clear and suggestions were made for the suitable use of the two methods, which may benefit for the research and application of concerning the planning and assessment with SC as key criteria.

Keywords: ecosystem services mapping; ecosystem services conservation; RUSLE; ecological indicators; Jiangxi Province of China

1. Introduction

Spatial conservation prioritization is a form of conservation assessment that supports conservation planning and is the key technical phase within the systematic conservation planning process; it aims to answer questions about when, where, and how conservation goals can efficiently be achieved [1–3]. Traditionally, conservationists have focused on the conservation of biodiversity to make systematic conservation planning [4,5]. Recently, many conservationists have begun focusing on both the conservation of biodiversity and the sustainable provision of ecosystem services (ESs), which are the benefits that humans obtain from ecosystems that support the well-being of humans [6–9]. However, the goal of conserving both biodiversity and ESs is less likely to be achieved unless the target types of ESs have been spatially explicitly mapped [7,8,10,11]. Spatially explicit mapping of ESs is one of the critical methods of mainstreaming ESs into spatial conservation prioritization in systematic conservation planning that focuses on planning implementation and conservation monitoring [10,12,13]. In addition, spatially explicit mapping of priority areas for ESs is an essential step of incorporating ESs into policies and practices to ensure the continuous provision of ESs and associated benefits to humans [10,14–17].

The SC refers to the integrative capability of terrestrial ecosystems and their vegetation cover, root matrix, and soil biota to prevent soil damage from erosion/siltation [18], which is an important ecosystem regulating service [6]. The worldwide degradation of ecosystem SC exacerbates serious soil erosion problems [19] and has become a concern of stakeholders and decision-makers during the conservation planning process. Recently, the degradation of terrestrial ecosystem SC of China has resulted in serious soil erosion, which has become one of the most critical national ecological problems; in fact, nearly one-third of China's land area suffers from soil erosion, resulting in severe economic losses in China. Therefore, a robust method should be provided to mapping ecosystem SC in order to conserving ecosystem SC and release the damage of soil erosion. At present, methods for spatially explicit mapping of the SC of terrestrial ecosystems are primarily based on empirical soil erosion models, such as the RUSLE [17,20–22]. Based on the empirical models, the SC can be quantified by determining the difference between the actual soil loss of the landscape and the potential soil loss, which presumes no vegetation cover in an extremely degraded form of the landscape [21,23]. However, this hypothesis may yield a considerable overestimation of SC. More importantly, the parameters of the empirical soil conservation model are based on long-term observations of field experiments at small spatial scales, which are very difficult to obtain and must be simplified when implementing these models at large spatial scales. Such simplification of model parameters may lead to uncertainty in quantifying SC at large spatial scales [24]. Recently, Carreño et al. [25] formulated a simple biophysical method for estimating the effects of land use changes on the relative provision capability of ESs in Argentina. This method was improved by Barral et al. [26] to evaluate ESs related to land use planning in the southeast pampas of Argentina. Both methods utilized such biophysical data as biomass or NPP, water coverage, soil infiltration capacity, slope, temperature, precipitation, and altitude as formulating parameters. Because the availability of biomass (NPP as the indicator) and its stability over time, soil erodibility factor, and the slope of the land surface are the main factors of soil conservation in the face of erosion [25–29], a multiplication of these factors can be used as the biophysical-based surrogate indicator for mapping the SC of ecosystems [25,26,30,31].

The objective of this research is to compare the new biophysical-based surrogate indicator method and the traditional RUSLE-based method in quantifying SC using the Jiangxi Province in China as the case study area. The comparison aims to clarify the advantages and disadvantages of the two methods and thereby to contribute to the rational selection of suitable quantitative methods for SC assessment as support in the decision-making process associated with sustainable land use planning and ecosystem management.

2. Materials and Methods

2.1. Study Area

Jiangxi Province (113.57°~118.5°E, 24.5°~30.1°N) is located in the southeastern region of China; the capital is Nanchang (Figure 1). Jiangxi has an area of approximately 167,000 km^2 and around 46 million people (Census 2016). The mean altitude of Jiangxi is 249 m, while the maximum and minimum altitudes are 2150 m and 22 m below sea level, respectively. The topography of Jiangxi consists of higher mountain ranges in the southern areas and the marginal areas of the entire province, and small hills and lowlands in the central and northern parts of the province. The province has five large rivers. Gan River, Fu River, Xin River, Rao River, and Xiu River, which flow into Poyang Lake, the largest freshwater lake in China. Poyang Lake is located in the northern part of Jiangxi, which is also home to internationally important freshwater wetlands that serve as habitat for many endangered waterfowl species. Therefore, Jiangxi Province makes up the greatest part of the Poyang Lake basin, approximately 96.6% of whose area is located in the Jiangxi Province [32].

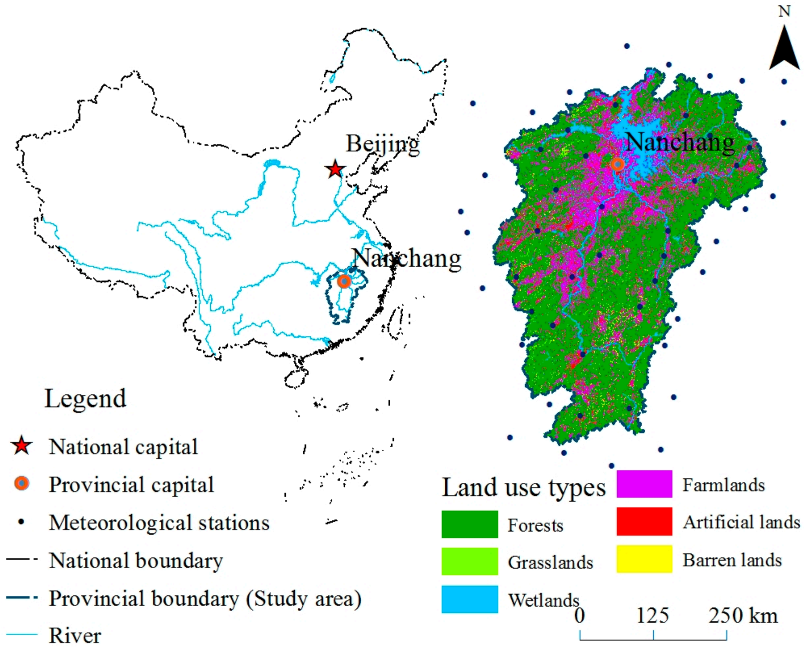

Figure 1. Location, meteorological stations, and land use types in Jiangxi Province, China.

The dominant land use type is forest, which accounts for 66% of Jiangxi's area, followed by 21% farmland, 6% artificially built-up land, 5% wetland, 2% grassland, and 1% barren land (Figure 1). Major soil types include red soil, weakly developed red soil, and brown soil [33]. The annual mean vegetation coverage of Jiangxi is approximately 65.55%, while the maximum value is 91.97%. The high values of vegetation coverage are mainly located in the mountainous areas, which have a relatively high altitude with relatively low human disturbance. The main climate type in Jiangxi is a subtropical monsoon climate, and the annual mean air temperature and precipitation amount to approximately 18 °C and 1700 mm, respectively. The annual mean air temperature increases from the southwestern to the northeastern region of Jiangxi. The precipitation increases from the northwestern to the southeastern region of Jiangxi [34]. Recently, identifying the hotspots for conserving biodiversity and ESs has been a great concern as population growth and economic development have continued to impose enormous pressures on Jiangxi Province's natural environment [35] (Figure 1).

2.2. Data Sources

The critical data of the soil conservation mapping methods were obtained as follows. The daily meteorological data (solar radiation, precipitation, and temperature) for the year 2000 and 2010 were retrieved from the China Meteorological Data Service Center [36].The 52 meteorological stations (Figure 1) within and around Jiangxi Province were used to produce the interpolation raster maps (250 m resolution) by using the Kriging method of the ArcGIS 10.2 software. The 250 m MODIS NDVI data were composites of 16-day NDVI maximum values and were acquired from the Level 1 and Atmosphere Archive and Distribution System (LAADS) [37].The land use data were interpreted from Landsat 5 TM of the 2000 and 2010 land cover map with 30-m thematic resolution. The vegetation coverage of the 2000 and 2010 used the dimidiate pixel model, which is a simplified linear spectral unmixing method to calculate the coverage of vegetation [38,39]. Topographical parameters were derived from STRM digital elevation data at a resolution of 90 m [40].The soil property data used in the RUSLE model came from the Chinese soil dataset [41]. All data were interpolated or resampled to a 250-m resolution before being input into the ES models for further analysis.

2.3. Soil Conservation Mapping Methods

2.3.1. RUSLE-Based Model for Mapping Soil Conservation

The annual soil erosion can be calculated by means of the RUSLE empirical model [27] as follows [34]:

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

$$R = \sum_{i=1}^{12} 1.735 \times 10^{\left(1.5 \times lg \frac{P_i^2}{P} - 0.8188\right)} \tag{2}$$

$$K = \left\{0.2 + 0.3e^{\left[-0.0256S_a\left(1-\frac{S_i}{100}\right)\right]}\right\}\left(\frac{S_i}{C_l+S_i}\right)^{0.3}\left\{1.0 - \frac{0.25C}{\left[C+e^{(3.72+2.95C)}\right]}\right\}\left\{1.0 - \frac{0.7\left(1-\frac{S_a}{100}\right)}{\left(1-\frac{S_a}{100}\right)+e^{\left(-5.51+22.91-\frac{S_a}{100}\right)}}\right\} \tag{3}$$

$$L = \left(\frac{\lambda}{22.13}\right)^m \begin{cases} m = 0.5 & \theta \geq 9 \\ m = 0.4 & 9 > \theta \geq 3 \\ m = 0.3 & 3 > \theta \geq 1 \\ m = 0.2 & 1 > \theta \end{cases} \tag{4}$$

$$S = \left(\frac{\sin\theta}{0.0896}\right)^{0.6} \tag{5}$$

where A describes the estimated average soil loss (t·hm^{-2}·year^{-1}); R is the rainfall erosivity factor calculated by means of the Wischmeier empirical formula [27]; P_i identifies the monthly precipitation (mm), and P refers to the annual total precipitation (mm); K is the soil erodibility factor, which was calculated using the EPIC (Erosion—Productivity Impact Calculator) equation [28]; S_a, S_i, C_l, and C encompass the percentage (%) of the sand, clay, silt, and organic matter of the soil, respectively; L is the slope length factor [27], and S is the slope steepness factor [42]; m describes a dimensionless constant dependent on the percent slope (θ); C is the crop and management factor; and P is the conservation practices factor. The values of C and P were the same as in Zhang et al. [34].

If both C and P are assigned a value of 1, then the calculated soil erosion is the potential soil erosion, which presumed the land to be bare or to have no vegetation protection. Therefore, the amount of soil retention can be estimated by the difference between the potential soil erosion and actual soil erosion. The SC model based on the empirical equation of RUSLE is as follows:

$$\mathrm{SC_{RUSLE}} = R \times K \times L \times S \times (1 - C \times P) \tag{6}$$

where $\mathrm{SC_{RUSLE}}$ is the annual amount of soil conserved (t·hm^{-2}·year^{-1}), and the other parameters were calculated in the same fashion as in Equation (1).

2.3.2. The Surrogate Indicator Method for Mapping Soil Conservation Service

The biophysical-based surrogate indicator method for mapping SC can be calculated by Equation (7):

$$\mathrm{SC_{SUR}} = NPP \times (1 - VC_{npp}) \times (1 - K) \times (1 - F_{slo}) \tag{7}$$

where $\mathrm{SC_{SUR}}$ refers to the capability of the SC of the ecosystem, NPP is the sum of the annual net primary production of vegetation, VC_{npp} describes the standard deviation of the NPP within a year, and K is the soil erodibility factor, which was calculated by means of the EPIC equation (Equation (3)). F_{slo} refers to the slope of the land surface, which can be calculated using Arcgis10.2 software. The parameters of VC_{npp}, K, and F_{slo} were standardized between zero and one by the maximum and minimum value of their values. Lü et al. [30] and Zhang et al. [31], using the modeling framework of this NPP based surrogate indicator, incorporated the K factor into the model, mapped the SC of ecosystems, characterized the spatio-temporal variations of SC in China, and revealed the representation of critical natural capital in China. The above-mentioned works showed the usability and reliability of the NPP based surrogate indicator for mapping SC well.

The terrestrial Carnegie Ames-Stanford Approach (CASA) was used to estimate the NPP of vegetation. The CASA model advocates determining the NPP of vegetation as the product of the modulated absorbed photosynthetically active radiation (APAR) and the light use efficiency (ε) factor [43]:

$$NPP(x,t) = APAR(x,t) \times \varepsilon(x,t) \quad (8)$$

where $NPP(x, t)$ describes the net primary production of location x at time t, $APAR$ refers to the canopy-absorbed incident solar radiation ($MJ \cdot m^{-2}$), and the parameter ε is the light use efficiency ($g \cdot C \cdot MJ^{-1}$). Land cover, NDVI, and climate data are needed for the CASA model. The annual total NPP ($g \cdot C \cdot m^{-2} \cdot year^{-1}$) is the sum of the NPP during the twelve months within a year [34].

3. Results

3.1. Spatial Patterns of SC

After mapping the SC of Jiangxi Province using the two methods provided in the paper, the spatial patterns of SC were revealed (Figure 2). The results indicated that the spatial patterns of SC maps which using the SC_{SUR} method are heterogeneous and the high SC areas are scattered in regions of high altitude and with a high fractional vegetation cover. The spatial patterns of SC are similar in 2000 and 2010. The high values of SC maps using the SC_{RUSLE} method were located in the southern and northeastern region of the mountain areas of Jiangxi in 2000, and then moved to the middle-eastern and northeastern region of the mountain areas of Jiangxi in 2010. The variation in the spatial patterns using the SC_{RUSLE} method is significantly impacted by the variation in the annual rainfall erosivity factor for Jiangxi. The mean values of SC quantifying by means of the biophysical surrogate indicator (SC_{SUR}) method were 381.43 in 2000, and 385.72 in 2010, while the mean values of SC modeled by the RUSLE-based method are 351.69 $t \cdot hm^{-2} \cdot year^{-1}$ in 2000, and 579.92 $t \cdot hm^{-2} \cdot year^{-1}$ in 2010. The minimum values of the results of the two methods are zero, while the maximum values of the two methods increased from the 2000 to 2010.

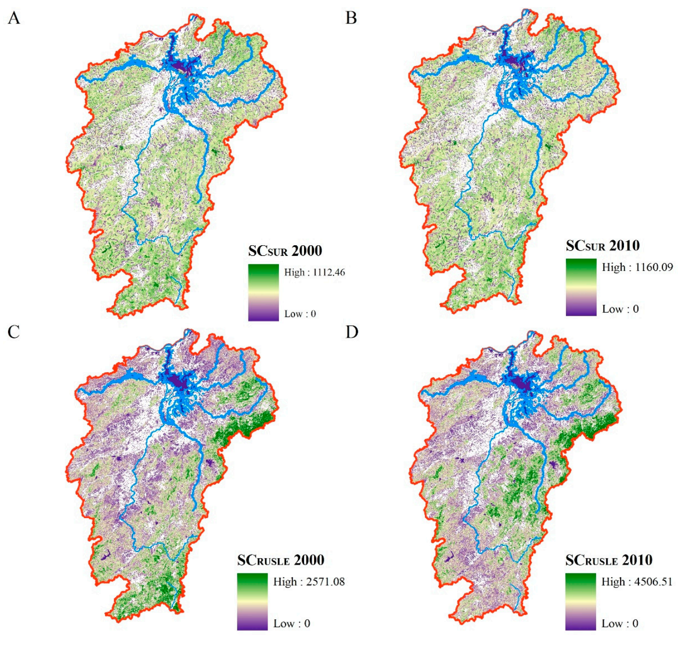

Figure 2. Spatial patterns of the surrogated soil conservation model (SC_{SUR}) (**A**,**B**) and RUSLE-based soil conservation model (SC_{RUSLE}) (**C**,**D**) in 2000 and 2010. The results of SC_{SUR} have no units, while the units of the results of SC_{RUSLE} are $t \cdot hm^{-2}$ $year^{-1}$.

3.2. SC Variations under Different Land Use Types, Fractional Vegetation Covers and Land Surface Slopes

After comparing the differences in the two SC methods in each land use type in 2000 and 2010, the results indicated that variations in the results of the SC_{SUR} model tend to be smaller than the variations of the results of the SC_{RUSEL} model among different land use types (Figure 3). The mean capacities of SC of the SC_{SUR} and SC_{RUSLE} model in each land use type are ranked as follows: forest > grassland > barren land > wetland (Figure 3). The relationship between the results of the two SC methods under different vegetation coverages was analyzed using ArcGIS 10.2 software. The results showed that the values of SC mapped by both the SC_{SUR} and SC_{RUSLE} methods increase with the increase in fractional vegetation covers (Figure 4). The values of SC mapped by the SC_{RUSLE} model increase with the increase in slope; however, the values of SC mapped by the SC_{SUR} method decreases with the increase in land surface slopes (Figure 4).

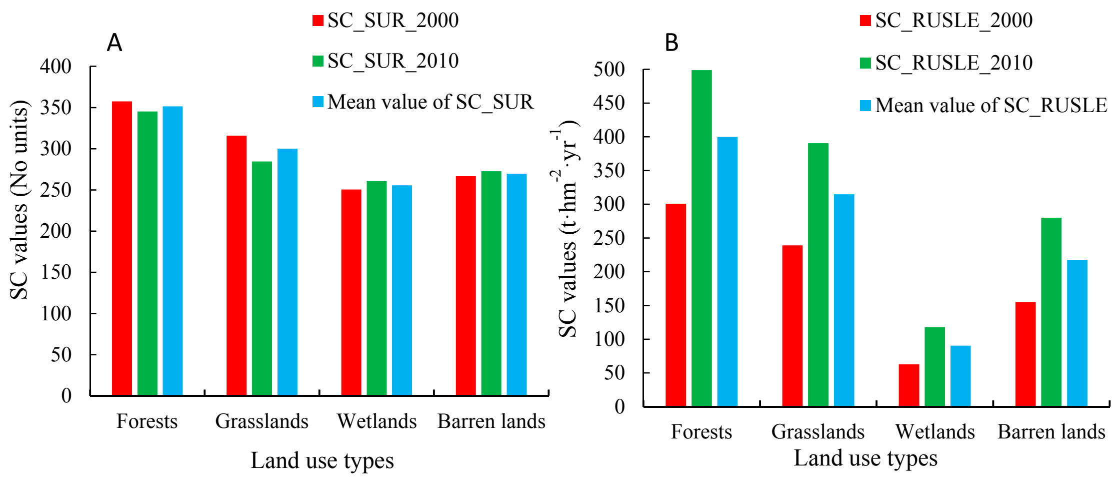

Figure 3. Variations of the surrogated soil conservation model ($SC_{\_SUR}$) (**A**) and RUSLE-based soil conservation model ($SC_{\_RUSLE}$) (**B**) for different land use types in the year 2000 and 2010.

3.3. Distance Distributions from Artificial Land, Farmland, and Wetland

The spatial patterns of the distance distribution from artificial land, farmland, and wetland of the two SC models were analyzed using ArcGIS 10.2 software, which was based on the raster land use maps for 2000 and 2010. The results showed that the high values of SC mapped by the SC_{SUR} method were located near artificial land and farmland, while the high values of SC mapped by means of the SC_{RUSLE} model were located relatively far from artificial land and farmland. High values of SC mapped by the SC_{SUR} model were located near wetlands, while the high values of SC mapped by the SC_{RUSLE} model were located relatively far from wetlands (Figure 4).

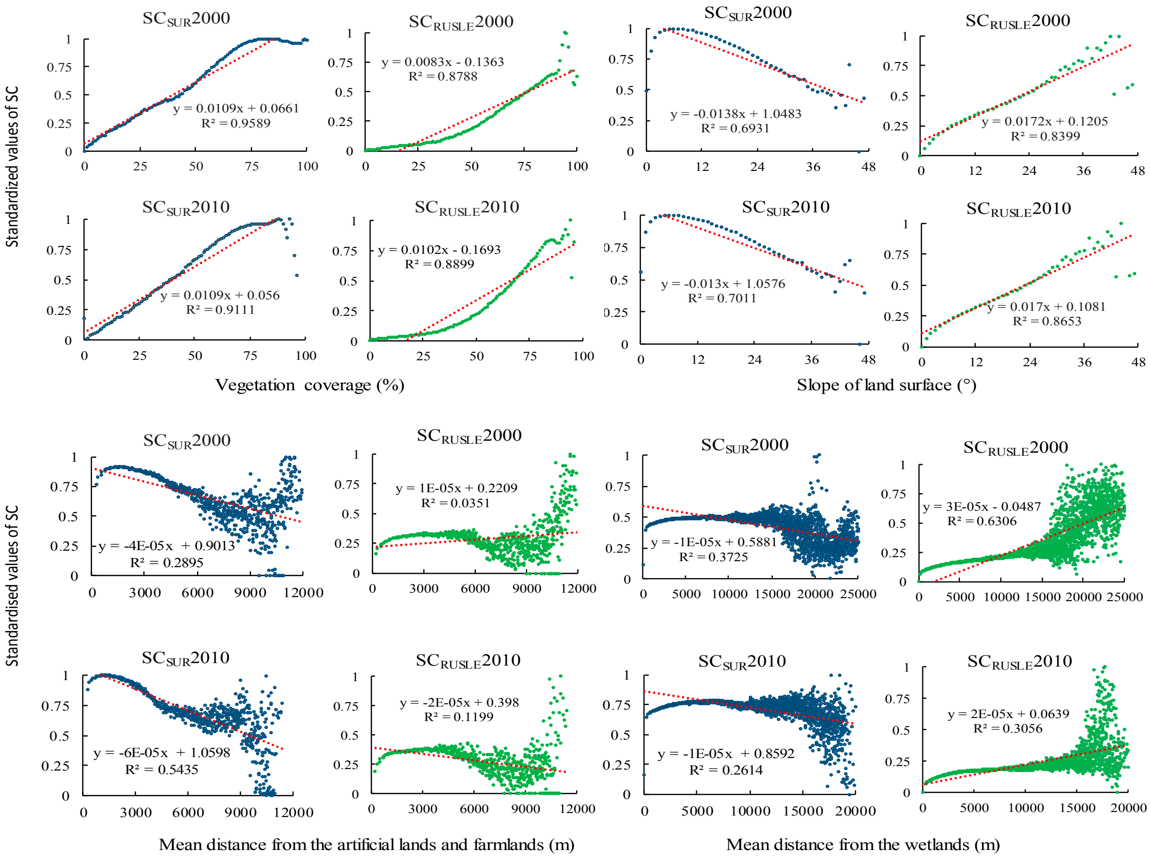

Figure 4. Variations in soil conservation service (SC) based on different mapping methods under different vegetation coverage and land surface slopes and due to different distances from the artificial lands, farmlands, and wetlands in 2000 and 2010. Both the linear equations are through the significance level of 0.05 of the *t*-test.

4. Discussion

4.1. Characteristics of Using the Two SC Methods in Practice

The spatial patterns of SC mapped by means of the SC_{SUR} and SC_{RUSLE} methods have certain similarities and differences when used in practice (Table 1). In selecting the appropriate method for mapping SC, decision makers need to consider the different purposes of the task in question, as well as the similarities and differences in the spatial patterns and temporal variations of the priority areas that may arise from using these methods. Because the values of SC of the two mapping methods both increase with increasing of the vegetation coverage, the priority areas for SC selected by the two models will be located in the area in which the fractional vegetation cover is relatively high. Moreover, both mapping methods resulted in higher values of SC in forest and grassland than the other two land use types, which can lead to greater attention given these land uses safeguard the SC capacity of the landscape. Because the values of SC modeled by the SC_{SUR} method decrease with the increasing slope of the land surface while the values of SC modeled by the SC_{RUSLE} method increase with the increase in the slope of the land surface, the priority areas for SC selected by these two methods may differ markedly. Similarly, the priority areas identified by the SC_{RUSLE} model for conserving SC are more likely to be located in precipitous regions than those identified using the SC_{SUR} method.

Table 1. Comparison of the two methods for mapping soil conservation service in the Jiangxi Province.

Variables	SC_{SUR}	SC_{RUSLE}
Land use types	Mean values of the SC of each land use types are: forests > grasslands > barren lands > wetlands	Mean values of the SC of each land use types are: forests > grassland > barren lands > wetlands
Slope	Decreases with the increase in land surface slope	Increases with increasing land surface slope
Vegetation coverage	Increases with the increasing of the vegetation coverage	Increases with increasing of the vegetation coverage
Distance from artificial land and farmland	Close	Far
Distance from wetland	Close	Far

Given that the distribution of the high values of the SC_{SUR} model are closer to artificial land and farmland than those of the SC_{RUSLE} model, the efficiency of conservation actions in the priority areas of SC identified by the SC_{SUR} model will be higher than that of the SC_{RUSLE} model. In the anthropic zones, disturbance and impacts from human activities on the natural ecosystems were very high; thus, the degradation of the SC was usually more severe in these areas. In contrast, in remote areas, the disturbance of human activities was relatively limited, the cost of building conservation areas to protect the SC will be considerably lower than in nearer anthropic locations. Nevertheless, the SC of the entire region may continue to degrade because the degraded areas of SC are located near anthropic zones, such as croplands and grazing grassland.

Therefore, the two mapping methods have a similar utility in discerning the influence of different land use types and vegetation coverage on the SC, whereas, there are large differences in the representation of the spatial distribution of SC. The slope factor, the rainfall erosivity factor, and the SC_{RUSLE} method as a whole reflect the soil erosion risk [44,45] but not necessarily the ground truth soil conservation capacity of ecosystems. Research based on field observations has revealed important characteristics of the relative ranking stability of different terrestrial ecosystem types on the soil conservation capability in both dry [46–48] and humid environments [49]. These ground truth observations under various environmental conditions support the relatively stable pattern of the ecosystems SC (Figure 2A,B) but defy the significant regional spatiotemporal variability of the SC capability (Figure 2C,D). Indeed, the spatial dimension of SC is crucial to land use planning and ecosystem management applications with practical soil erosion and nutrient loss control as key targets. In this sense, SC_{SUR} seems to perform better than SC_{RUSLE}.

4.2. Enlightenment after the Comparison of the Two SC Methods

As humans have already served as an important driving force of various biogeochemical processes on the earth surface, contemporary soil erosion by water can be largely impacted by the interactions between ecosystems and human society under the control of broad environmental regimes (e.g., climate and geomorphology) [50]. Therefore, contemporary soil erosion by water is the final representation of the complex mix from natural erosion and human-accelerated erosion. Humans can never destroy natural erosion or tolerable soil erosion [51]. However, humans' significant contribution to accelerating and decelerating soil erosion is well documented at various spatiotemporal scales and in various geographical locations [52–55]. Consequently, one of the key tasks of soil conservation is to avoid human-accelerated erosion [53]. Research also suggests that human-accelerated erosion tends to spread from human disturbance centers to remote areas [56]. The above observations seem to support findings from the SC_{SUR} approach in this research that suggest that the soil conservation service of natural ecosystems is usually higher near anthropogenic land use and wetlands (Figure 4). These may also explain the widespread use of various kinds of vegetated buffer strips to reduce fluxes of eroding soil and associated chemicals from hill slopes into water bodies in mitigating on-site land degradation and off-site water pollution [57–59]. However, the conservation values of ecosystems near anthropogenically used lands and wetlands will be largely neglected if solely dependent on the results from the SC_{RUSLE} approach (Figure 4).

The SC_{RUSLE} method can calculate the specific amounts of soil that are conserved in a region, although the accuracy of these amounts of SC cannot be validated because of the absence of suitable observed data on ESs provisioning [60] and the exaggeration of model assumptions, which supposed no vegetation cover in an extremely degraded landscape [21,23,34,61]. In addition, the main limitations of RUSLE-based model are that it requires data at affine spatial scales, the using of this model in the broad spatial scales needs to simplification of the model parameters [62], which may hamper the accuracy and the usability of SC_{RUSLE} in practical applications.

The SC_{SUR} method differs from the SC_{RUSLE} method in that the former is based on the causal relationships between the SC and multiple environmental variables, and the results of the SC_{SUR} method only reveal the relative rankings of the provisioning capability of ecosystems on SC in a region. The SC_{SUR} method incorporates the parameters of NPP into the model, and the NPP is modeled by the remote-sensing data of NDVI and a series of environmental variables. Therefore, the SC_{SUR} method can explicitly relate spatially to the realistic spatial patterns and temporal variations of SC as an important service of ecosystems [16,30,31,63]. These characteristics can meet the needs of policy-making related to soil conservation and ecosystem management, such as the assessment of SC variation caused by changes in land use and the priority setting of conservation planning.

5. Conclusions

Spatially explicit mapping of ESs is the critical method of incorporating ESs into decision-making associated with land use and ecological conservation planning. Traditionally, empirical soil erosion models are usually used to map SC. However, the soundness of these models is largely taken for granted with little verification. Therefore, selecting suitable quantifying methods for SC mapping, especially at a large spatial scale, remains challenging but promising to facilitate conservation decision making and actions. This paper compared a newly formulated biophysical-based surrogate indicator method and a traditional RUSLE based method in SC mapping. Findings suggest that the biophysical indicator method can effectively rank terrestrial ecosystems in terms of their capability to provide SC services at a large spatial scale. The mapping results conform to both findings based on field observations in various environmental settings and the general implementation of soil conservation practices. Therefore, the biophysical indicator method is suitable for large-scale SC mapping meant to support efforts related to soil conservation planning and conservation effectiveness evaluation, despite being much simpler than the traditional empirical models, such as RUSLE. The RUSLE based model is similar to the biophysical indicator method in reflecting different ecosystem (or land cover) types in SC capability ranking. However, the results related to SC spatial patterns are problematic due to lack of support from published literature on soil conservation monitoring and practical applications. This problem may be largely rooted in its very extreme and unrealistic assumption when RUSLE is borrowed to map the SC of ecosystems. In fact, RUSLE has been used and verified globally in soil loss assessment and its environmental risks. However, this support does not necessarily guarantee its usability as a sound SC mapping tool. On the contrary, findings of the present research recommend great caution when using RUSLE to map the SC service of ecosystems, as shown in this paper and the published literature, especially regarding the spatial pattern of SC and its temporal change. Therefore, the newly formulated simple biophysical-based surrogate indicator method is by no means worse at mapping the rankings and spatiotemporal variations of SC in terrestrial environments, and this research revealed the advantages of this new method of SC mapping for soil conservation planning and conservation performance assessment, especially at large spatial scales.

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References

1. Wilson, K.A.; Underwood, E.C.; Morrison, S.A.; Klausmeyer, K.R.; Murdoch, W.W.; Reyers, B.; Wardell-Johnson, G.; Marquet, P.A.; Rundel, P.W.; McBride, M.F.; et al. Conserving biodiversity efficiently: What to do, where, and when. *PLoS Biol.* **2007**, *5*, 12. [CrossRef] [PubMed]
2. Ferrier, S.; Wintle, B.A. Quantitative approaches to spatial conservation prioritization: Matching the solution to the need. In *Spatial Conservation Prioritization: Quantitative Methods & Computational Tools*; Moilanen, A., Wilson, K.A., Possingham, H.P., Eds.; Oxford University Press: Oxford, UK, 2009; pp. 1–13.
3. Lehtomäki, J.; Moilanen, A. Methods and workflow for spatial conservation prioritization using Zonation. *Environ. Model. Softw.* **2013**, *47*, 128–137. [CrossRef]
4. Brooks, T.M.; Mittermeier, R.A.; da Fonseca, G.A.; Gerlach, J.; Hoffmann, M.; Lamoreux, J.F.; Mittermeier, C.G.; Pilgrim, J.D.; Rodrigues, A.S. Global biodiversity conservation priorities. *Science* **2006**, *313*, 58–61. [CrossRef] [PubMed]
5. Paviolo, A.; di Blanco, Y.E.; de Angelo, C.D.; di Bitetti, M.S. Protection affects the abundance and activity patterns of pumas in the Atlantic Forest. *J. Mammal.* **2009**, *90*, 926–934. [CrossRef]
6. Millennium Ecosystem Assessment. *Ecosystems and Human Well-Being: Synthesis*; World Resources Institute: Washington, DC, USA, 2005.
7. Egoh, B.; Rouget, M.; Reyers, B.; Knight, A.T.; Cowling, R.M.; van Jaarsveld, A.S.; Welz, A. Integrating ecosystem services into conservation assessments: A review. *Ecol. Econ.* **2007**, *63*, 714–721. [CrossRef]
8. Goldman, R.L.; Tallis, H. A critical analysis of ecosystem services as a tool in conservation projects. *Ann. N. Y. Acad. Sci.* **2009**, *1162*, 63–78. [CrossRef] [PubMed]
9. Polasky, S.; Johnson, K.; Keeler, B.; Kovacs, K.; Nelson, E.; Pennington, D.; Plantinga, A.J.; Withey, J. Are investments to promote biodiversity conservation and ecosystem services aligned? *Oxf. Rev. Econ. Policy* **2012**, *28*, 139–163. [CrossRef]
10. Cowling, R.M.; Egoh, B.; Knight, A.T.; O'Farrell, P.J.; Reyers, B.; Rouget, M.; Roux, D.R.; Welz, A.S. An operational model for mainstreaming ecosystem services for implementation. *Proc. Natl. Acad. Sci. USA* **2008**, *105*, 9483–9488. [CrossRef] [PubMed]
11. Luck, G.W.; Chan, K.M.; Klien, C.J. Identifying spatial priorities for protecting ecosystem services. *F1000Research* **2012**, *1*. [CrossRef] [PubMed]
12. Schulp, C.J.; Alkemade, R. Consequences of Uncertainty in Global-Scale Land Cover Maps for Mapping Ecosystem Functions: An Analysis of Pollination Efficiency. *Remote Sens.* **2011**, *3*, 2057–2075. [CrossRef]
13. Kukkala, A.S.; Moilanen, A. Core concepts of spatial prioritisation in systematic conservation planning. *Biol. Rev.* **2013**, *88*, 443–464. [CrossRef] [PubMed]
14. Daily, G.C.; Matson, P.A. Ecosystem services: From theory to implementation. *Proc. Natl. Acad. Sci. USA* **2008**, *105*, 9455–9456. [CrossRef] [PubMed]
15. Bateman, I.J.; Harwood, A.R.; Mace, G.M.; Watson, R.T.; Abson, D.J.; Andrews, B.; Termansen, M. Bringing ecosystem services into economic decision-making: Land use in the United Kingdom. *Science* **2013**, *341*, 45–50. [CrossRef] [PubMed]
16. Zurlini, G.; Petrosillo, I.; Aretano, R.; Castorini, I.; D'Arpa, S.; De Marco, A.; Pasimeni, M.R.; Semeraro, T.; Zaccarelli, N. Key fundamental aspects for mapping and assessing ecosystem services: Predictability of ecosystem service providers at scales from local to global. *Annali di Botanica (Roma)* **2014**, *4*, 53–63.
17. Xu, W.H.; Xiao, Y.; Zhang, J.J.; Yang, W.; Zhang, L.; Hull, V.; Wang, Z.; Zheng, H.; Liu, J.G.; Polasky, S.; et al. Strengthening protected areas for biodiversity and ecosystem services in china. *Proc. Natl. Acad. Sci. USA* **2017**, *114*, 1601. [CrossRef] [PubMed]

18. De Groot, R.S.; Wilson, M.A.; Boumans, R.M.J. A typology for the classification, description and valuation of ecosystem functions, goods and services. *Ecol. Econ.* **2002**, *41*, 393–408. [CrossRef]
19. Yang, D.; Kanae, S.; Oki, T.; Koike, T.; Musiake, K. Global potential soil erosion with reference to land use and climate changes. *Hydrol. Process.* **2003**, *17*, 2913–2928. [CrossRef]
20. Nelson, E.; Mendoza, G.; Regetz, J.; Polasky, S.; Tallis, H.; Cameron, D.R.; Chan, K.M.A.; Daily, G.C.; Goldstein, J.; Kareiva, P.M.; et al. Modeling multiple ecosystem services, biodiversity conservation, commodity production, and tradeoffs at landscape scales. *Front. Ecol. Environ.* **2009**, *7*, 4–11. [CrossRef]
21. Su, C.H.; Fu, B.J. Evolution of ecosystem services in the Chinese Loess Plateau under climatic and land use changes. *Glob. Planet. Chang.* **2013**, *101*, 119–128. [CrossRef]
22. Guerra, C.A.; Pinto-Correia, T.; Metzger, M.J. Mapping Soil Erosion Prevention Using an Ecosystem Service Modeling Framework for Integrated Land Management and Policy. *Ecosystems* **2014**, *17*, 878–889. [CrossRef]
23. Fu, B.J.; Liu, Y.H.; Lü, Y.H.; He, C.S.; Zeng, Y.; Wu, B.F. Assessing the soil erosion control service of ecosystems change in the Loess Plateau of China. *Ecol. Complex* **2011**, *8*, 284–293. [CrossRef]
24. Andrew, M.E.; Wulder, M.A.; Nelson, T.A.; Coops, N.C. Spatial data, analysis approaches, and information needs for spatial ecosystem service assessments: A review. *GIScience Remote Sens.* **2015**, *52*, 344–373. [CrossRef]
25. Carreño, L.; Frank, F.C.; Viglizzo, E.F. Tradeoffs between economic and ecosystem services in Argentina during 50 years of land-use change. *Agric. Ecosyst. Environ.* **2012**, *154*, 68–77. [CrossRef]
26. Barral, M.P.; Oscar, M.N. Land-use planning based on ecosystem service assessment: A case study in the Southeast Pampas of Argentina. *Agric. Ecosyst. Environ.* **2012**, *154*, 34–43. [CrossRef]
27. Wischmeier, W.H.; Smith, D.D. Predicting rainfall erosion losses: A guide to conservation planning. In *Agriculture Handbook No. 537*; US Department of Agriculture (USDA): Washington, DC, USA, 1978; pp. 5–8.
28. Sharpley, A.N.; Williams, J.R. EPIC-erosion/productivity impact calculator: 1. Model documentation. *Tech. Bull. U. S. Dep. Agric.* **1990**, *1*, 235.
29. Sidle, R.C.; Ziegler, A.D.; Negishi, J.N.; Nik, A.R.; Siew, R.; Turkelboom, F. Erosion processes in steep terrain: Truths, myths and uncertainties related to forest management in Southeast Asia. *For. Ecol. Manag.* **2006**, *224*, 199–225. [CrossRef]
30. Lü, Y.H.; Zhang, L.W.; Zeng, Y.; Fu, B.J.; Whitham, C.; Liu, S.G.; Wu, B.F. Representation of critical natural capital in China. *Conserv. Biol.* **2017**, *31*, 894–902. [CrossRef] [PubMed]
31. Zhang, L.W.; Lü, Y.H.; Fu, B.J.; Dong, Z.B.; Zeng, Y.; Wu, B.F. Mapping ecosystem services for China's ecoregions with a biophysical surrogate approach. *Landsc. Urban Plan.* **2017**, *161*, 22–31. [CrossRef]
32. Yu, J.; Zheng, B.; Liu, Y.; Liu, C. Evaluation of soil loss and transportation load of adsorption N and P in Poyang Lake watershed. *Acta Ecol. Sin.* **2011**, *31*, 3980–3989. (In Chinese)
33. Ding, Q.F.; Wang, J.B.; Qi, S.H.; Ye, H.; Huang, M.; Xu, Y.T.; Ying, T.Y.; Tao, J. Spatial patterns of vegetation net primary productivity in Jiangxi Province of China in relation to climate factors. *Chin. J. Ecol.* **2013**, *32*, 726–732. (In Chinese)
34. Zhang, L.W.; Fu, B.; Fu, B.J.; Lü, Y.H.; Zeng, Y. Balancing multiple ecosystem services in conservation priority setting. *Landsc. Ecol.* **2015**, *30*, 535–546. [CrossRef]
35. He, Y.; Che, T.; Wang, Y. Ecological Footprint and Endogenous Economic Growth in the Poyang Lake Area in China Based on Empirical Analysis of Panel Data Model. *J. Resour. Ecol.* **2012**, *3*, 367–372.
36. China Meteorological Data Service Center, Dataset of Monthly Values of Climate. National Meteorological Information Center, Beijing, China. 2008. Available online: http://data.cma.cn/data/cdcdetail/dataCode/SURF_CLI_CHN_MUL_MON.html/ (accessed on 4 September 2017).
37. LAADS. EOSDIS Distributed Active Archive Centers. 2000. Available online: https://earthdata.nasa.gov/about/daacs/daac-laads/ (accessed on 4 September 2017).
38. Ivits, E.; Cherlet, M.; Sommer, S.; Mehl, W. Addressing the complexity in nonlinear evolution of vegetation phenological change with time-series of remote sensing images. *Ecol. Indic.* **2013**, *26*, 49–60. [CrossRef]
39. Lü, Y.H.; Zhang, L.W.; Feng, X.M.; Zeng, Y.; Fu, B.J.; Yao, X.L.; Li, J.R.; Wu, B.F. Recent ecological transitions in China: Greening, browning, and influential factors. *Sci. Rep.* **2015**, *5*, 8732. [CrossRef] [PubMed]
40. SRTM 90m Digital Elevation Data. The CGIAR Consortium for Spatial Information. 2003. Available online: http://srtm.csi.cgiar.org/ (accessed on 4 September 2017).
41. Chinese soil dataset. China Soil Map Based Harmonized World Soil Database (v1.1). 2009. Available online: http://westdc.westgis.ac.cn/data/611f7d50-b419-4d14-b4dd-4a944b141175/ (accessed on 4 September 2017).

42. Zhou, Q.; Liu, X. *Digital Topography Analysis*; Science Press: Beijing, China, 2006; pp. 79–132. (In Chinese)
43. Potter, C.S.; Randerson, J.T.; Field, C.B.; Matson, P.A.; Vitousek, P.M.; Mooney, H.S.; Klosster, S.A. Terrestrial ecosystem production: A process model based on global satellite and surface data. *Glob. Biogeochem. Cycles* **1993**, *7*, 811–841. [CrossRef]
44. Delgado, M.E.M.; Canters, F. Modeling the impacts of agroforestry systems on the spatial patterns of soil erosion risk in three catchments of Claveria, the Philippines. *Agrofor. Syst.* **2012**, *85*, 411–432. [CrossRef]
45. Meusburger, K.; Steel, A.; Panagos, P.; Montanarella, L.; Alewell, C. Spatial and temporal variability of rainfall erosivity factor for Switzerland. *Hydrol. Earth Syst. Sci.* **2012**, *16*, 167–177. [CrossRef]
46. Zuazo, V.H.D.; Pleguezuelo, C.R.R. Soil-erosion and runoff prevention by plant covers. A review. *Agron. Sustain. Dev.* **2008**, *28*, 65–86. [CrossRef]
47. Wei, W.; Chen, L.D.; Fu, B.J.; Lü, Y.H.; Gong, J. Responses of water erosion to rainfall extremes and vegetation types in a loess semiarid hilly area, NW China. *Hydrol. Process.* **2009**, *23*, 1780–1791. [CrossRef]
48. Taye, G.; Poesen, J.; Wesemael, B.V.; Vanmaercke, M.; Teka, D.; Deckers, J.; Goosse, T.; Maetens, W.; Nyssen, J.; Hallet, V.; et al. Effects of land use, slope gradient, and soil and water conservation structures on runoff and soil loss in semi-arid Northern Ethiopia. *Phys. Geogr.* **2013**, *34*, 236–259.
49. Huang, Z.G.; Ouyang, Z.Y.; Li, F.R.; Zheng, H.; Wang, X.K. Response of runoff and soil loss to reforestation and rainfall type in red soil region of southern China. *J. Environ. Sci.* **2010**, *22*, 1765–1773. [CrossRef]
50. Lü, Y.H.; Fu, B.J.; Wei, W.; Yu, X.B. Major ecosystems in China: Dynamics and challenges for sustainable management. *Environ. Manag.* **2011**, *48*, 13–27. [CrossRef] [PubMed]
51. Verheijen, F.G.A.; Jones, R.J.A.; Rickson, R.J.; Smith, C.J. Tolerable versus actual soil erosion rates in Europe. *Earth Sci. Rev.* **2009**, *94*, 23–38. [CrossRef]
52. Wei, J.; He, X.B.; Bao, Y.H. Anthropogenic impacts on suspended sediment load in the Upper Yangtze River. *Reg. Environ. Chang.* **2011**, *11*, 857–868. [CrossRef]
53. Maetens, W.; Poesen, J.; Vanmaercke, M. How effective are soil conservation techniques in reducing plot runoff and soil loss in Europe and the Mediterranean? *Earth Sci. Rev.* **2012**, *115*, 21–36. [CrossRef]
54. Bichet, V.; Gauthier, E.; Massa, C.; Perren, B.; Richard, H.; Petit, C.; Mathieu, O. The history and impacts of farming activities in south Greenland: An insight from lake deposits. *Polar Rec.* **2013**, *49*, 210–220.
55. Bhandari, K.P.; Aryal, J.; Darnsawasdi, R. A geospatial approach to assessing soil erosion in a watershed by integrating socio-economic determinants and the RUSLE model. *Nat. Hazards* **2015**, *75*, 321–342. [CrossRef]
56. Haring, V.; Clemens, G.; Sauer, D.; Stahr, K. Human-Induced Soil Fertility Decline in a Mountain Region in Northern Vietnam. *Die Erde* **2010**, *141*, 235–255.
57. Gumiere, S.J.; Bissonnais, Y.L.; Raclot, D.; Cheviron, B. Vegetated filter effects on sedimentological connectivity of agricultural catchments in erosion modelling: A review. *Earth Surf. Process. Landf.* **2011**, *36*, 3–19. [CrossRef]
58. Stutter, M.I.; Chardon, W.J.; Kronvang, B. Riparian buffer strips as a multifunctional management tool in agricultural landscapes: Introduction to the special collection. *J. Environ. Qual.* **2012**, *41*, 297–303. [CrossRef] [PubMed]
59. Gaspar, L.; Navas, A.; Machin, J.; Walling, D.E. Using Pb-210(ex) measurements to quantify soil redistribution along two complex toposequences in Mediterranean agroecosystems, northern Spain. *Soil Tillage Res.* **2013**, *130*, 81–90. [CrossRef]
60. Schulp, C.J.E.; Burkhard, B.; Maes, J.; Van Vliet, J.; Verburg, P.H. Uncertainties in Ecosystem Service Maps: A Comparison on the European Scale. *PLoS ONE* **2014**, *9*, e109643. [CrossRef] [PubMed]
61. Yan, H.M.; Zhan, J.Y.; Liu, B.; Yuan, Y.W. Model Estimation of Water Use Efficiency for Soil Conservation in the Lower Heihe River Basin, Northwest China during 2000–2008. *Sustainability* **2014**, *6*, 6250–6266. [CrossRef]
62. Boardman, J. Soil erosion science: Reflections on the limitations of current approaches. *Catena* **2006**, *68*, 73–86. [CrossRef]
63. Costanza, R.; Fisher, B.; Mulder, K.; Liu, S.; Christopher, T. Biodiversity and ecosystem services: A multi-scale empirical study of the relationship between species richness and net primary production. *Ecol. Econ.* **2007**, *61*, 478–491. [CrossRef]