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Impact of natural and social factors on ecosystem services based on structural equation modeling

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Abstracts: Ecosystem service value (ESV) are closely related to physical geography and socioeconomic, however, the interactions between natural conditions and human activities with ESV remain unclear. In this study, spatial and temporal changes in LULC as well as three ecosystem services, carbon storage, habitat quality and water conservation, were analyzed from 2000 to 2020 in Hubei Province, China, using InVEST and other methods. Structural equation modeling (SEM) was used to explore the mechanisms by which anthropogenic and natural factors drive ESV. Structural equation modeling indicated that LULC change was the main factor affecting ESV (-0.59), and both meteorological and socioeconomic factors had greater indirect than direct effects on ESV. Understanding the driving mechanisms of natural and socioeconomic factors on ESV is useful for guiding and implementing effective land management policies.

1. Introduction

Ecosystem services (ES) are often defined as a collective term for the direct and indirect benefits that humans derive from the natural environment[1].It closely links ecosystems to human socioeconomic systems[2],which is essential for human socioeconomic development and sustainable ecosystem management[3,4]. Ecosystem service value (ESV) is a quantitative assessment of the potential service capacity of ecosystems and a medium for translating the concept of ecosystem services into realistic practical applications[5]. Numerous anthropogenic and natural causes have an impact on ES, and the relationships between them are complex and variable[6]. Previous studies have typically focused on one factor, often considering how land use change directly affects ESV [7-9]. For example, Wang and Dai (2020) found that land use change can strongly influence habitat quality and carbon storage in mountainous areas[10], and Youlton (2016) found that converting pastureland to sugarcane increased soil erosion and soil loss[11].In addition, the effects of some anthropogenic factors as well as other natural factors on ecosystem services still need to be further explored. Climate change affects ecosystem function and distribution by altering precipitation and temperature, and the ESV it provides will also change[12]. Rapidly increasing population densities and high rates of economic development have adversely affected ES[13]. Therefore, more focus should be placed on the relationship between socioeconomic and natural variables and ESV.

A more comprehensive approach is needed to fully understand the drivers of ecosystem services. Structural equation modeling (SEM) quantifies complex causal relationships between multiple factors simultaneously and elucidates the interaction paths between the direct and indirect effects of various factors, and this approach is very effective in solving system problems[14]. It has been used to evaluate the effects of tourism development on ecosystem services, both directly and indirectly [15].

There are a number of common methods for assessing ESV, InVEST Model is a widely used software to evaluate a wide range of ES models from a spatial perspective [1] . For example, The Songhua River Basin's water yield and soil retention were measured spatially and temporally by Yang (2021) using the InVEST model [16] .Hu (2023) found that carbon storage and habitat quality in the arid Loess Plateau of China showed similar spatial patterns[17].

Hubei Province is characterized by a dense population and a variety of landform types, with natural conditions and human activities combining to influence the development of the region. Therefore, this study attempts to analyze the potential mechanisms of natural change and socio-economic interactions on ESV by exploring the spatial and temporal variations of land use change and ESV at the provincial level in China, which can provide insights for managers and policy makers to prompt the green development of the society, as well as case references for other countries or regions to carry out the related studies.

2. Overview of the study area and data sources

2.1. Overview of the study area

As shown in Figure 1,The Hubei Province, located at 29°01′-33°6′N and 108°21′-116°07′E, Located in the center of China, having an approximate overall area of 185,900 km^2 , including 17 prefectural-level cities：Wuhan(WH), Huangshi(HS), Xiangyang(XY), Shiyan(SY), Jingzhou(JZ), Yichang(YC),Jingmen(JM), Ezhou(EZ), Xiaogan(XG), Huanggang(HG), Xianning(XN), Suizhou(SZ), Enshi(ES), Xiantao(XT), Qianjiang(QJ), Tianmen(TM,), Shennongjia Forestry Area(SNJ).Hubei Province is densely populated and highly urbanized, and the accelerating process of urbanization has led to the encroachment of large amounts of ecological land and arable land in order to achieve rapid expansion, putting greater pressure on the protection of healthy ecosystems.

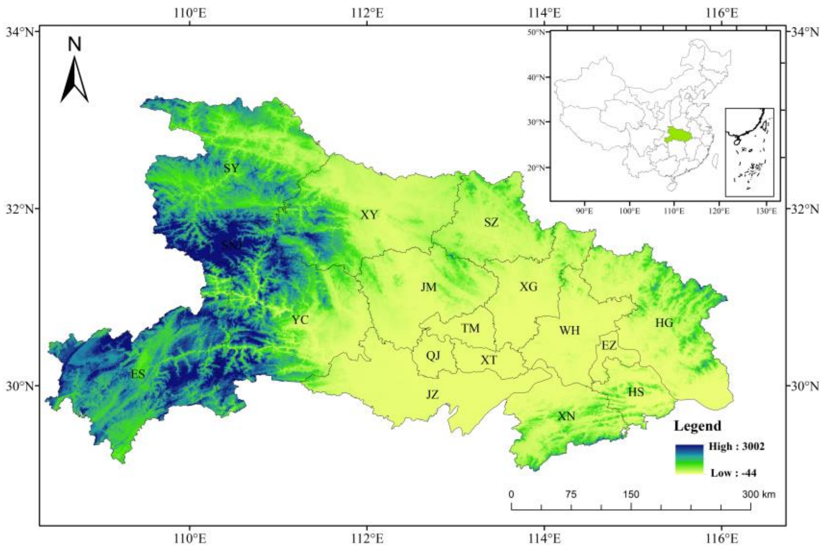

Figure 1: The geographical location of Hubei Province, China(The map is based on the standard map with review number GS (2020) 4619 downloaded from the website of the Standard Map Service of the Ministry of Natural Resources of China, with no modifications to the base map.).

2.2. Data sources

Table 1: The data sources for different parameters in the models.

Parameters	Database sources
Land use	Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences (RESDC)(http://www.resdc.cn)
Precipitation data	The National Earth System Science Data Center (http://www.geodata.cn/)
Evapotranspiration data	The National Earth System Science Data Center (http://www.geodata.cn/)
Administrative area data	The National Earth System Science Data Center (http://www.geodata.cn/)
Data on soil characteristics	Harmonized World Soil Database (HWSD)(http://webarchive.iiasa.ac.at/)
Annual average temperature	The National Earth System Science Data Center (http://www.geodata.cn/)
Population density	WorldPop (https://data.worldpop.org/)
Road network density	National Catalogue Services for Geographic Information(https://www.webmap.cn)
Gross domestic product (GDP).	Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences (RESDC) (http://www.resdc.cn)
DEM data	The Geospatial Data Cloud(https://www.gscloud.cn/)

The data sources for the different parameters in the model are shown in Table 1. All of the information utilized to appliance PLS-SEM came from open datasets (see Table 1), slope and topographic relief were obtained using a Global Digital Elevation Model (GDEM) with a resolution of 30 m.

3. Methods

3.1. Calculation of ES based on InVEST

Various land types have various carbon density values, therefore altering regional land types will result in changes to carbon storage. The formula is as follows:

$$C_{total} = C_{above} + C_{below} + C_{soil} + C_{dead} \tag{1}$$

Where C_{total} is the total ecosystem Carbon storage, C_{above} is the ecosystem aboveground Carbon storage, C_{below} is the ecosystem belowground Carbon storage, C_{soil} is the ecosystem soil Carbon storage, and C_{dead} is the ecosystem dead organic matter Carbon storage. The carbon pool table of the InVEST carbon module mainly refers to the relevant literature[18,19].

The habitat quality module reflects the ability of protected species to endure and procreate within an area, showing alterations in biodiversity[20] . (Formula 2) was taken from the user guide for InVEST:

$$Q_{xj} = H_j \left(1 - \left(\frac{D_{xj}^z}{D_{xj}^z + k^z} \right) \right) \tag{2}$$

Where D_{xj} is the total threat level in grid cell x with j th land cover; z is a scaling factor that is set to 2.5 by default in the model; k is the half-saturation constant and is set to half of the size of the landscape grid resolution. H_j is the habitat score assigned to j th land cover, and its value ranges from 0 to 1.

The difference between precipitation and actual evapotranspiration on each grid is defined as the water production of the grid, and the sum of water production of each grid unit on the sub-basin is calculated. The calculation method is as follows:

$$Y_{xj} = P_x \times \left(1 - \frac{AET_{xj}}{P_x} \right) \tag{3}$$

where Y_{xj} is the annual water yield in grid cell x with land use j (mm); P_x is the annual precipitation of grid cell x (mm); and AET_{xj} is the annual evapotranspiration (mm).

3.2. Driving factor analysis based on SEM

Based on previous relevant studies[11, 13, 17, 21], a structural equation model was constructed to explore the interaction of ESV with anthropogenic and natural factors. The four latent variables in the model were LULC, meteorological environment (MET), geological characteristics (GEO), and economic growth (ECO). The explicit variables for LULC were cultivated land and built-up land. Mean annual temperature and total annual precipitation were used to represent the latent variable MET. Slope, topographic relief, and dem were chosen to represent the latent variable GEO. Explicit variables such as gross domestic product (GDP), population density, and road network density were used to represent the latent variable ECO. Considering the computational efficiency and analytical validity, the entire basin was covered with small cells of 7km x 7km, and any grid with less than 80% of the study area was removed, a total of 4980 grids were built[5] .The spatial data of LULC, natural factors, and anthropogenic factors were extracted into the small cells and then exported.

Due to the non-positive distribution of variable data, partial least squares structural equation modelling (PLS-SEM) is chosen [22] . To confirm that the SEM results are accurate, the commonly used tests mainly include: the reliability test, the validity test, the model fit validity test and the path validity test. The reliability test mainly adopts Cronbach's alpha (CA greater than 0.7) and Composite reliability (CR greater than 0.7) as the measurement indexes[23] . The validity test mainly includes discriminant validity and convergent validity. Discriminant validity is often assessed using the square root of the AVE value, which is higher than the latent variable's correlation coefficient; convergent validity is usually judged by the AVE value, and its critical value is 0.5[24].The model fit validity test is judged by R^2, and when R^2 is greater than 0.67, the model has a better explanatory power [25] . Bootstrapping algorithm was used to test the significance of PLS-SEM model.

4. Results

4.1. Spatial and temporal characteristics of LUCC

From 2000 to 2020, alterations in land types in the Hubei province include an increase in water bodies and building land and reductions in other types of land, especially the transformation of cultivated land and forest land to building land (Figure 2). Among these changes, the areas of cultivated land and forest land converted to building land were 2145 km^2 and 574 km^2, accounting for 1.2% and 0.3% of the total area, with the conversion of cultivated land to building land accounting for the largest proportion of the transformation of the entire land type. The land area of building land in Hubei Province increased by 2613.86 km^2, an increase of 51.2%, which can be seen that the urbanization process of Hubei Province is remarkable. The area of cultivated land decreased by 2746.78 km^2, a notable decline during the study period. Cultivated land was mainly transformed into forest land, water bodies and building land, and the proportion of the transformed land was 0.8%, 0.6% and 1.2% respectively. The transformation of Cultivated land into building land is mainly concentrated in most areas in Hubei Province's eastern regions, with Wuhan City as the center and radiating to the surrounding cities, and the transformation of Cultivated land into water bodies is mainly concentrated in Xiantao City and Jingzhou City.

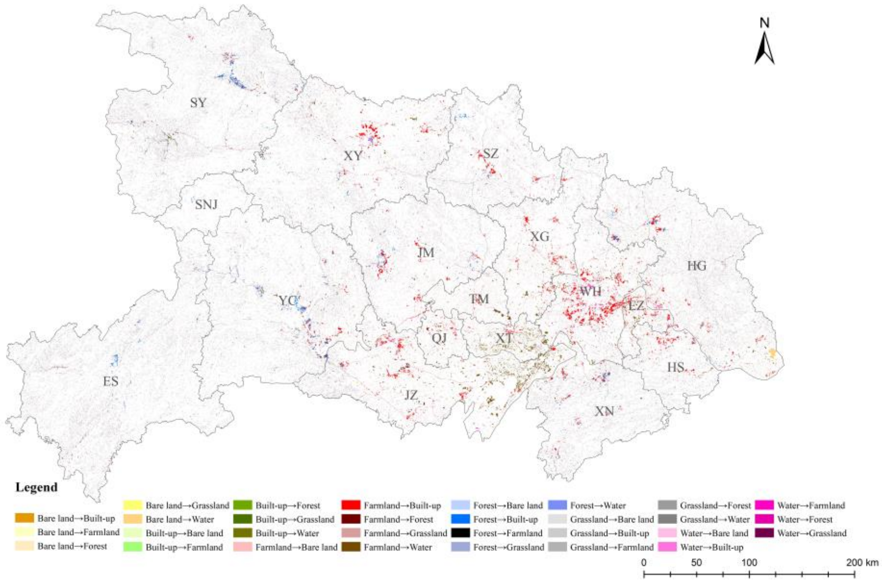

Figure 2: Proportion and dynamic degree of land use in basin from 2000 to 2020.

4.2. ESV based on InVEST calculations

Figure 3 shows the spatial distribution of water yield, habitat quality and carbon storage in 2000 and 2020. It can be seen that water yield service are unevenly distributed spatially. In general, WY is higher in the southern part of Hubei Province and lower in the northwestern part, with a general increasing trend from north to south. From 2000 to 2020, the WY in the northwestern and southwestern parts of the province show a decreasing trend year by year, while the total WY value is increasing year by year, mainly due to the increasing WY in the eastern part of the province, and the east-west gap is increasing year by year, as can be seen from the figure 3. The areas with the lowest water yields correspond to the rivers, higher water yields correspond to the distribution of arable land. Habitat quality in the central and eastern parts of Hubei Province is relatively low, and the corresponding land types are farmland and building site, while habitat quality in the western part of the province is relatively high, and the corresponding land application type is forested land. The distribution pattern of this ecosystem service and the land use type in this area show high consistency, which indicates that there is a correlation between this ecosystem service and the land use type. The spatial distribution of habitat quality has basically not changed much during the past 20 years, but a decline in habitat quality can be observed in a few areas in the west. Carbon storage in the cultivated land portion of central Hubei Province were relatively low compared to those in the forested land in the east and west, with the lowest values corresponding to the land use types of river watersheds and construction land, and similar to the habitat quality, the location of the ecosystem service showed a high degree of consistency with the local land use types. There is little change in carbon storage between years, but an improvement in the values of the low carbon storage areas in the center can be observed, i.e., a recovery in carbon storage in 2020 in the locations of river waters and built-up land.

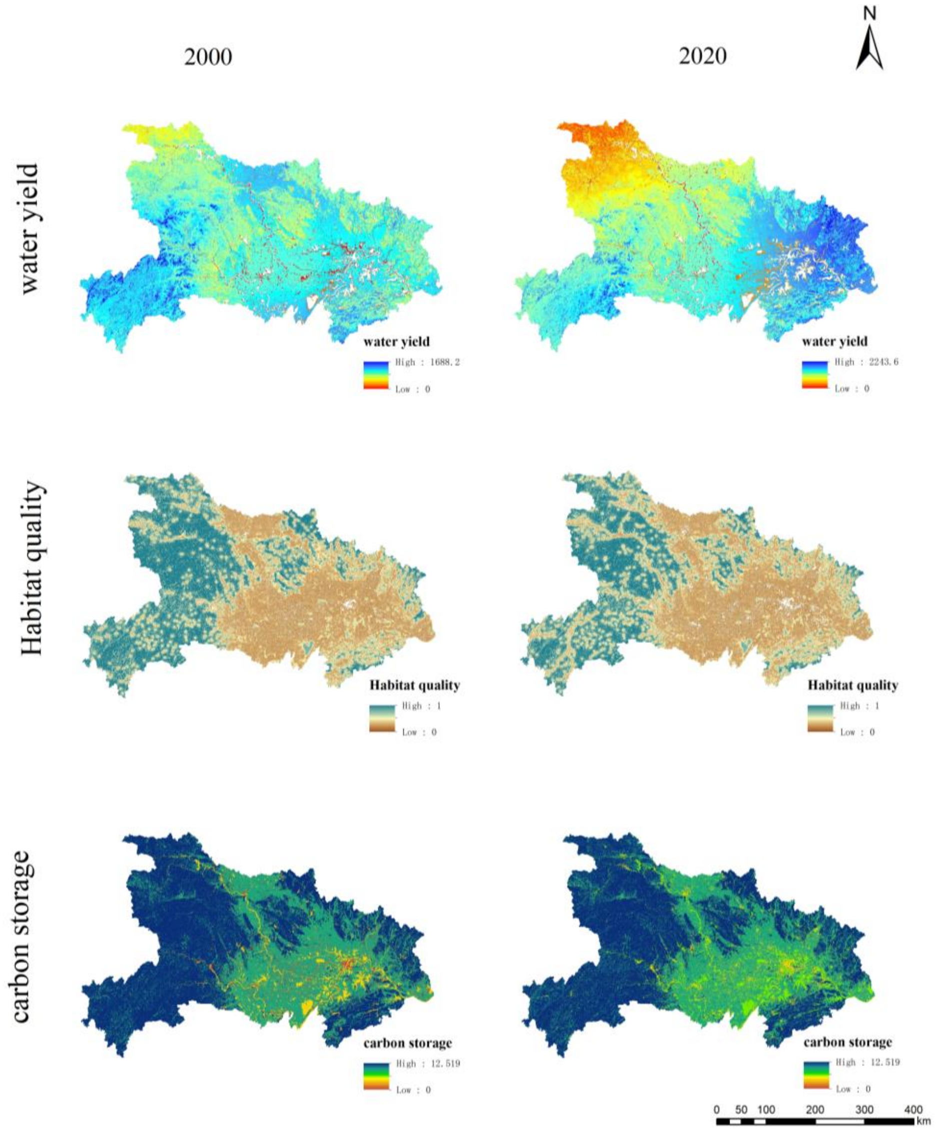

Figure 3: Spatial distribution of ecosystem services from 2000 to 2020.

4.3. Drivers of ESV

Several indicators confirm that the quality of the measurements and structural modeling in PLS-SEM meets the criteria. The alpha of all latent variables, excluding MET, was basically greater than 0.7, achieving high reliability. MET was less than 0.7, failing the test, suggesting that the measurement variable of total annual precipitation in MET needed to be censored, but it was theoretically retained because previous studies in the literature proved that total annual precipitation is an important indicator[12]. Except for MET, every latent variable had CR values more than 0.7. Both the model's reliability and correlation tests were successful, demonstrating the high reliability of the chosen data. The AVE of all latent variables is greater than 0.5, and the square root of the AVE value is greater than the correlation coefficient between the latent variables, which indicates that the discriminant and convergent validity test values of all latent variables are passed, suggesting that the constructed model has strong structural validity. All of the PLS-SEM model's R^2 values are higher than 0.7, so the constructed model has a strong explanatory power. Bootstrapping algorithm was used to test the significance of the constructed PLS-SEM model, and there were noteworthy overall and indirect effects. ($p<0.05$)

In the structural equation modeling, the strength and direction of the effects of different factors on ESV were investigated. As shown in figure 4, The LULC factor dominated the direct negative effect on ESV (-0.589). GEO showed a direct positive effect on ESV (0.387) but an indirect negative effect through LULC and MET. MET had a greater indirect negative effect on ESV than a direct negative effect. ECO has a throughput coefficient of -0.014, indicating that ECO has a direct negative effect on ESV, but ECO also has an indirect positive effect on ESV through meteorological and LULC factors.

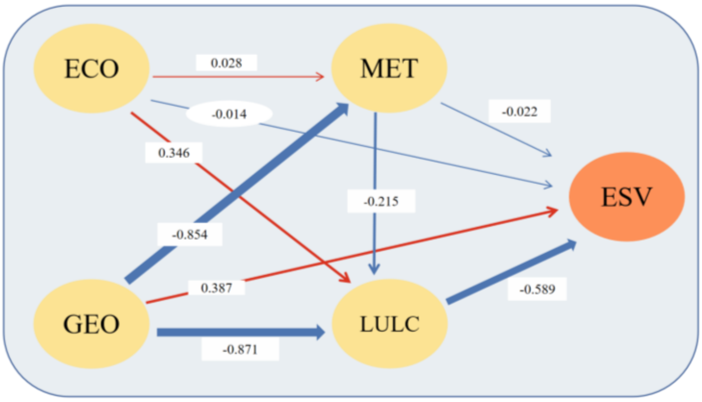

Figure 4: The partial least squares structural equation model for the effects of different factors on ESV in 2020.

5. Conclusion

The Hubei Province has urbanized significantly over the study period, Habitat quality and carbon storage services revealed similar geographical distributions in relation to the distribution of land use. In addition, both a dominating and a direct detrimental impact on ESV were caused by LULC. Topographic variables positively impact ESV directly, and meteorological factors have a direct negative effect on ESV, and show more indirect negative effects than direct effects through LULC. Socio-economic factors can show a positive contribution to ESV through interaction with natural factors. The study suggests that the application of logical and scientific land management principles has a crucial role in improving ESV, and in addition. The interaction of natural and socio-economic factors on ES needs to be further explored.

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