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Article

Revisiting mid-long term ecosystem services projections: Integrating the interaction effects of future climate and land use changes

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ABSTRACT

Two of the most critical issues of sustainability are how future ecosystem services (ES) will change under natural and artificial stressors. To answer the above problems accurately with a quantitative manner and develop an intelligent and sustainable management of ecosystems, the projections of ES considering climate change under different Shared Socioeconomic Pathways (SSPs) are needed. However, current ES projection studies often lack quantitative methods to simulate ES dynamics, especially incapability to integrate the interactions between climate and land use changes on ES dynamics. To overcome these challenges, this study proposes a framework for ES simulation under climate and land use change stressors. The framework developed includes four modules: climatic attributes simulation, land use change simulation, scenario design, and ecosystem services simulation modules. Taking China as a case study, this study simulated the evolution of China's ES under the interactions between climate and land use change during the period of 2020–2100. The simulation results show that China's ES increases by 33%, 34%, 9%, and 60% under scenarios SSP1, SSP2, SSP3, and SSP5, respectively. Additionally, the overall growth rate of ES decreases by a gradually slowing rate from the mean at 1% during 2000–2020 to 0.5% during 2020–2100, respectively. Meanwhile, the ES in China shows significantly spatial variability based on simulation results. Shandong province yields the largest potential to be the key area with ES declining in the future. At ecosystem scale, increases in woodland ES are expected to dominate China's ES growth continuously. In the first four decades (2020–2060), development ways under SSP1 scenario are more helpful to promote increase in subtypes of ES, while in the last four decades (2060–2100), ES are expected to increase under SSP5 scenario. The key contributions of this study include tracking the causation and revealing the influencing mechanism of interactions of climate and land use change (rather than regional overlapping or single factor) on ES dynamics, and quantitatively simulating ES dynamics under the two integrated drivers. This study can be further extended to other cases and various scales to provide risk assessment for ecosystem services loss and detailed guidance for ecosystem conservation and management methodology with robustness and reliability in rapidly changeable environments, and critical analysis on the tradeoffs between social environmental investments and ecological welfare.

1. Introduction

Two primary issues are considered, related to sustainability: "How are ecosystems and their services going to change in the future?" and "How do human activities affect this path?" [1–4]. Therefore, the ecosystems and ecosystem services under different human development scenarios is in need for us to answer the above questions accurately and quantitatively [5–7]. At the same time, proper and intelligent management of ecosystem services requires understanding of their dynamics, whereas present practices are mainly based on static maps [8–10]. For example, forests management requires plans decades forward, in order to take ecosystem services like carbon sequestration and water and air purification together into account with the 70–100 years to harvest a tree for timber if necessary [11,12]. The global total growing stock of forests was 557 billion m^3 in 2020 [13], and it was estimated that terrestrial ecosystems release 10%–20% of global CO_2 into the air and capture

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around 30% annually [14]. However, the carbon storage capability of forest ecosystems is expected to decline as forest age generally [15,16] and climate change induced risks including increasing drought, temperature and forest fire [17]. This is a classic example of the need to consider the ecosystem service dynamics at long-term scale [18,19]. Some studies have emphasized the high level of short-term changes of three forest ES, including wood production, bilberry production and topsoil carbon storage, since nearly 85% of cold spots and 65% of hotspots of these services had converted into different conditions over a decade [20]. As a matter of fact, static ES maps may offer limited knowledge for assessment and management of multifunctional and dynamic ecosystems [20,21].

The description above is only valid for the prediction of a specific ecosystem service. Concerning the relationship between various different ecosystem services, the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES) indicated that harvest of materials including agricultural, aquicultural, and bioenergy production had increased since 1970, but 14 of 18 types of nature's contributions, largely regulating services and immaterial provisions, have decreased during the same period [22,23]. IPBES [23] also suggested that gains in material contributions have been growing at the cost of nature's sustainable capability and many other ecosystem services including air, water purification, as to the whole environments. Therefore, time scales need to be accounted for sustainable management of various ES, highlighting the significance of studying short, medium, and long terms of ES dynamics [9,20], considering the current changing speed of environment [24].

However, predicting ecosystem services dynamics at different time scales accurately and quantitatively is still difficult due to the lack of fully quantitative simulation methods, especially the method integrating the interactions of climate change and land use change, which are the two dominant drivers of variations in ecosystem services [23,25,26]. Specifically, IPBES [23] pointed out that the five direct and most influential drivers to changes in ecosystem services worldwide are land and sea use changes, climate change, direct exploitation of natural resources, biological invasion, and pollution, among which land use and climate changes are the two primary drivers [23,25]. Due to the complexity in dynamics, non-linear and inhomogeneous characteristics of these environmental pressures, in the future non-linear or abrupt changes of ecosystem services will likely occur both with and without warning signals [27–32]. As the result of this gap, critical question has been raised that whether can research improve the accuracy of the results when forecasting ecosystem services and enhancing detection of warning signs, especially under different scenarios of climate-land use changes [29]? Considerable and critical research will be needed to address the above question. Via the increase in the accuracy and reliability of projected ecosystem services, the sustainability and robustness of ecosystem management are expected to be improved significantly under the rapidly changing natural and artificial conditions. Meanwhile, achieving dual goals to protect biodiversity and sustain ES in the Post-2020 Global Biodiversity Framework proposed by the United Nations needs valid and resilient generalizations and projections on ES responding to multiple environmental changes and management [5,33].

However, current projection studies mainly focus on the effect of one single factor at a time, i.e. climate change or land use change on ecosystem services dynamics. For instance, Watson et al. [34] forecasted worldwide ES values loss in climate class transitions caused by climate change (single factor) under scenarios of Representative Concentration Pathways (RCPs) including RCP2.6, PCR4.5, RCP6.0 and RCP8.5. The results suggested that, by 2050, 20%−30% of global ES value are in a Köppen-Geiger climate class (KGCC, five main categories including tropical, temperate, desert, continental and polar climates) change under both RCP 2.6 and 8.5 scenarios [34]. Their prediction method for the influences from climate change on ES is to overlap the worldwide KGCC change map at time series with global ES value (expressed in US dollar units) map in 2005 to get where and how much ES would be lost under different scenarios. However, this simulation method presented static ecosystem services map in 2005 rather than the simulating mid- and long-term ES dynamics with the corresponding climate change. It highlights that this regional overlapping method cannot fully capture the influencing mechanism of climate change on variations in ES. Another projection study predicted the impact of land use change (single driver) on ES in the US from 2001 to 2051 under two possible economic scenarios [28]. Land use change was predicted using an econometric model to generate a land-use transfer probability matrix during 2001–2051. However, this projection method does not capture spatial processes, for example, land use change of one plot might affect land use types of neighboring plots. The projected land use types include: farmland, grazing land, forest, urban and range, ignoring aquatic ecosystems, which are significant parts of regional ecosystem services. Meanwhile, the study's conclusion is weakened as changes among land use have been represented without the variations in land use intensity in this econometric model [28]. Furthermore, the study overlaid national land use data and soil carbon map of US county to investigate the average soil carbon storage of each land use type per hectare, and then evaluated the influences of land use change on soil carbon storage dynamics. As a result, the influence mechanism of land use change on ES variations is not fully clarified by this method.

Therefore, the challenges of current studies on ES projection included: (1) The detailed dynamics of how ES responses to natural and artificial factors remained unclear. Particularly, the lack of projections of ES dynamics response to multiple factors would neglect the causality mechanisms responsible for changes in ES and may hamper progress in developing conservation targets and sustainability goals; (2) Insufficient understanding upon the interactive dynamic between climate and land use changes on ES projection; (3) Relatively low projection accuracy of spatial distribution of land use was expected to add bias and error to projected ES results. To overcome these challenges, this study proposes a framework for ES simulation considering the dynamics of climate and land use change interactions. Moreover, it may reveal how climate change and land use change mutually influence each other, and couple their interactions to ES dynamics through different development ways, also improving the accuracy of spatial simulation of land use change. As a result, a novel guiding tool for ecosystem conservation and management with full consideration of climate change impacts and land use variabilities could be provided by this study.

2. Methods

2.1. Case study

In the background of global ES declining, several studies reported China's ES improvement since year 2000. For instance, Chen et al. [35] indicated that China and India dominated worldwide greenness trend during 2000–2017 through land use management. Ouyang et al. [36] stated that China's ES such as food production, carbon sequestration, water and soil retention, sandstorm prevention and flood mitigation improved in the period 2000–2010 from investments in ecological restoration programs. Yang et al. [37] claimed that China's ES increased 19% during 2000–2020, and ecosystem areas growth contributed 55% to the improvement. China has promised to reach CO_2 emissions peak by 2030 and strive for carbon neutrality before 2060. To achieve these goals, China is implementing a series of climate mitigation strategies, such as adjusting industrial structures, optimizing energy structure, controlling non-carbon dioxide gas emissions, enhancing ecosystems carbon sink capacity, promoting coordination effect of carbon and pollution reduction and so on, as listed in 2022 Annual Report of China's policies and actions to respond to climate change [38]. Meanwhile, China has implemented series of ecological restoration programs like Natural Forest Conservation Program (NFCP) and the Sloping Land Conversion Program (SLCP), etc. These are expected to have significant effects on its land use changes. Therefore, to explore the future short, mid- and long

Table 1
Data sources in this study.

Data types		Year	Sources
Natural factors	Precipitation Solar radiation Wind	2020–2100	CMIP6 database: https://esgf-node.llnl.gov/search/cmip6/
	NPP	2020[a]	United States Geological Survey (https://lpdaac.usgs.gov/products/mod17a3hgfv061/)
	Evapotranspiration	2020[a]	Aerospace Information Research Institute, Chinese Academy of Sciences (https://data.casearth.cn/sdo/detail/653b6024819aec42f0fefcd3); [39]
	Elevation	N/A	Resource and Environment Science and Data Center, Chinese Academy of Sciences (https://www.resdc.cn/data.aspx?DATAID=123)
	NDVI	2019[a]	Resource and Environment Science and Data Center, Chinese Academy of Sciences (https://www.resdc.cn/data.aspx?DATAID=257)
Land use change		2015	Resource and Environment Science and Data Center, Chinese Academy of Sciences (https://www.resdc.cn/DOI/DOI.aspx?DOIID=54)
		2020–2100	Simulated by this study and detailed in Supplementary section S2
Socio-economic factors	GDP	2020–2100	IIASA (https://tntcat.iiasa.ac.at/SspDb/dsd?Action=htmlpage&page=citation)
	Population	2020–2100	IIASA (https://tntcat.iiasa.ac.at/SspDb/dsd?Action=htmlpage&page=citation)
	Cognition degree driver τ	2020–2100	Simulated based on GDP and population data and the specific processes and results can be found in Supplementary section S3.

Note: N/A means the data provision institution did not present the year of the data and due to the relatively small change in elevation, this study uses the current Digital Elevation Model (DEM) data from the Resource and Environment Science and Data Center, Chinese Academy of Sciences. a means these variables cannot be find in Ec-Earth3 as well as they are not so significant drivers of changes in ecosystem services, thus the data in 2019 or 2020 are used in this study. Except for the above drivers of ecosystem services dynamics, data source of other variables can be found in the ecosystem services accounting method in supplementary section S1.

terms dynamics of China's ES in the context of global rapid changing environments and local efforts to improve ecosystem services, this study selects China as a case study to simulate its ecosystem services dynamics under future continuous climate change and rapid land use change interactions, to provide references for application of the proposed framework and guidance for ecosystem management and conservation under rapid changing environments.

2.2. Data sources

Ecosystem services (ES) simulation is based on the existing ES accounting method proposed by the authors' previous studies (detailed in Supplementary section S1). It can be found from the ES accounting methods that dozens of parameters are used to calculate ES and their responding data sources can be also found in Supplementary section S1. Due to the unavailability of all the simulated variables and according to the attribution analysis results of changes in ES [37], this study mainly selects the simulated data of the three key drivers of ES dynamics, including natural drivers R (including precipitation, wind, and solar radiation), human drivers S (land use change), and cognition degree driver τ. Natural drivers are obtained from CMIP6 dataset (Table 1). China's land use cover data in 2015 was used as the initial land use data. Human drivers S (land use change) in the future is simulated by the DLUCP model in this study and the specific results are detailed in Supplementary section S2. Cognition degree driver τ is simulated based on GDP and population, and the specific calculation process and results are detailed in Supplementary section S3. The specific data sources can be found in Table 1.

2.3. Framework for ES simulation under climate-land use change interactions

Yang et al. [37] performed an attribution analysis of ES dynamics and found that three main factors drive changes in ES: natural drivers R (such as precipitation, wind, solar radiation, etc.), human drivers S (land use change), and cognition degree driver τ (regional total health expenditure per capita). The more the health expense reflects the more attention paid to health care, thereby the greater significance degree of human-being attention to ES improvement. Hence τ is viewed as cognition degree driver). To reveal the influence mechanism of climate-land use change on ES variations, this study selects climatic and land use change drivers based on the attribution analysis of ES dynamics [37], constituting the modules for climatic attributes and land use changes simulation. To link the interactive effects of these two drivers, we select different development ways such as scenario design modules (Table S3), then achieving ES simulation under climate-land use change interactions. The simulated climate change, land use change, and socio-economic data under different scenarios are the input for ecosystem services accounting method (ecosystem services simulation module). Therefore, the framework for ES simulation includes four modules, as shown in Fig. 1: climatic attributes simulation module, land use change simulation module, scenario design module, and ecosystem services simulation module.

2.3.1. Climatic attributes simulation module

Yang et al. [37] identified climatic drivers of ecosystem services dynamics including solar, radiation precipitation, wind speed, evapotranspiration (ET), etc. We have therefore extracted the needed climatic factors data by simulating ES from CMIP6 database (Fig. 1). Extraction constraints are present for several aspects, namely, the extraction activity: Scenario MIP; the source ID: EC-Earth3; the organization ID: EC-Earth-Consortium; the test IDs: SSP126, SSP245, SSP370, SSP585. The number of models simulate variables under SSP460 is less, which cannot meet the simulation need in this study. Meanwhile, SSP126, SSP245, SSP370, SSP585 are enough to simulate future potential scenarios with low, moderate, moderate to high, and high emission pathways, which will not affect the ranges of simulation results. Therefore, this study selects SSP126, SSP245, SSP370, SSP585 as scenarios. As concerns the variables: precipitation (pr), wind speed (sfcWind), solar radiation (rss), etc.

The EC-Earth3 model has been selected because it offers a better simulation performance for climate in East Asia. In fact, the simulated climate average and standard deviation distribution of summer precipitation in East Asia - during the historical period- are basically consistent with observation results, with spatial correlation coefficients of simulation and observation reaching 0.93 and 0.95, respectively ($P < 0.01$) [40]. Moreover, this model properly captures the features of larger rainfall and variabilities in Eastern and Southern China, as well as the aridity and the lower rainfall values in Western China [40]. Based on the shapefiles of the case area boundary, NCAR Command Language (NCL) and Climate Data Operators (CDO) are used to extract (extraction by mask) and calculate the annual average value of the simulated raw data (.nc format) for climatic factor data in the case area. We have selected climate factors data for five years in the period from 2020 to 2100 since

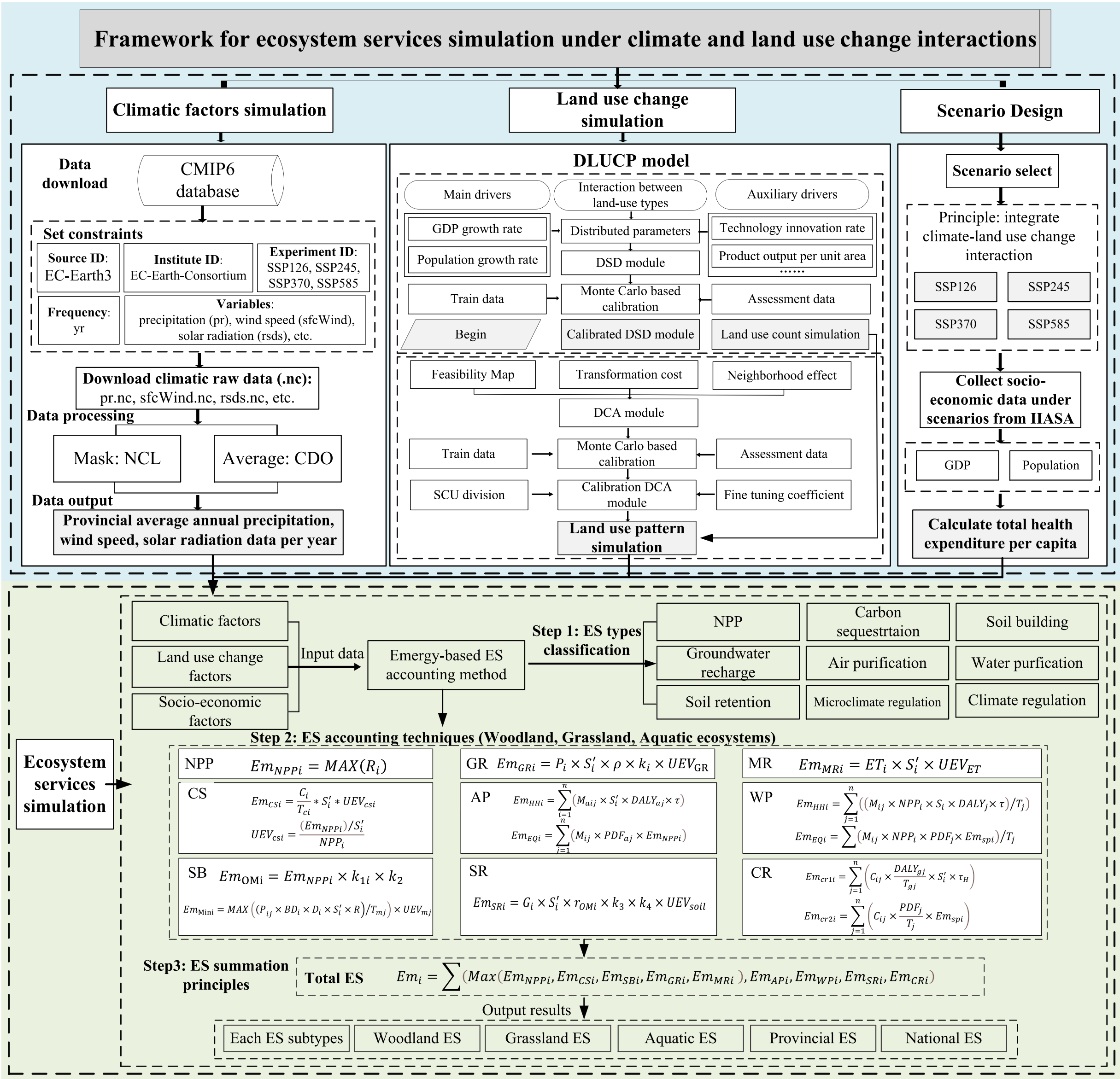

Fig. 1. Framework for ecosystem services simulation under climate and land use change interactions.

this is the time step used by the International Institute for Applied Systems Analysis (IIASA) projects national GDP and population from 2020 to 2100 under SSPs [41].

2.3.2. Land use changes simulation module

Substantial models have been applied to simulate spatiotemporal land use change [42–46], such as linear extrapolation method, Markov Chain model, and system dynamics (SD) model for land use amount simulation [47,48], as well as the Conversion of Land Use and its Effects (CLUE) series model (including CLUE, CLUE-S, and Dyna-CLUE) and Cellular Automata (CA) model for spatial distribution simulation [49,50]. Among them, distributed models have been applied to simulate spatial heterogeneity of environmental factors at large-scale [51,52], because related divers vary in different subareas, resulting in various land use change trends and patterns [53]. Based on the distributed model, Wang et al. [46] developed the Distributed Land-Use Change Prediction (DLUCP) model to better present the spatial heterogeneity of land use change in various subregions. The average kappa coefficients (representing the agreement level between frequencies of two datasets collected under two different situations, with values ≤ 1, increasing with the agreement level) for the conventional distributed models and DLUCP model were both satisfactory, with values of 0.91, 0.92, and 0.93 for the conventional method, the DLUCP model with provincial spatial calculation units (SCUs), and the DLUCP model with municipal SCUs, respectively. Yet, the DLUCP model improves the kappa coefficients in the majority of SCUs, with kappa coefficients higher than for the conventional method in up to 74% of SCUs. Therefore, DLUCP model can improve the simulation accuracy of spatial pattern of land use change, so this study selects DLUCP model to simulate future land use change (see middle of Fig. 1). The detailed description of the DLUCP model can be found in Wang et al. [46].

2.3.3. Scenario design module

To link the interactions between climate change and land use change, we select different socio-economic development scenarios. This study applies the key experiment scenarios of the Scenario Model Intercomparison Project (Scenario MIP) from the 6th World Climate Research Programme (CMIP6), i.e. Shared Socioeconomic Pathways (SSPs), including SSP126, SSP245, SSP370 and SSP585 as the scenarios in this study [54] (right of Fig. 1), since these scenarios are a matrix combina-

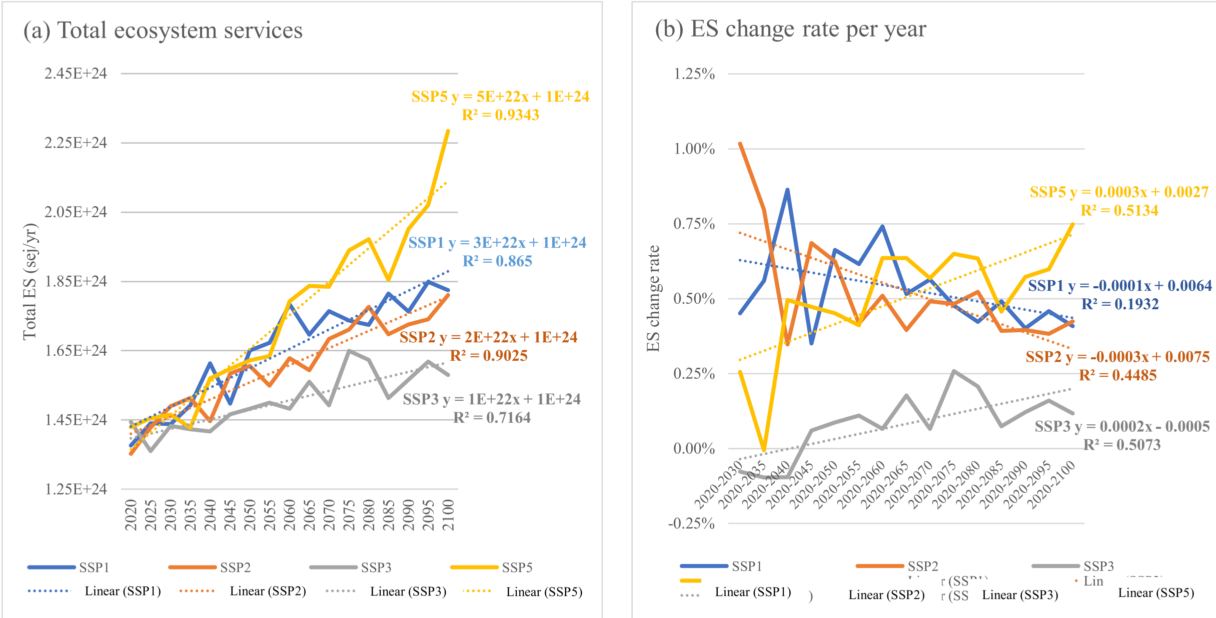

Fig. 2. Simulated future trend of total China's ecosystem services and change rate per year during the period 2020–2100.

tion of SSPs and Representative Concentration Pathways (RCPs). Each row of the matrix can be regarded as the consequences of different climate change under different development ways; each column can be regarded as the corresponding socio-economic development status under different climate change scenarios [41,55]. The structure indicates how SSP126, SSP245, SSP370 and SSP585 scenarios can reveal the links between the socio-economic development ways and climate change challenges, aligning various projections and settings on economy, population and energy-consuming among the three groups, i.e. Integrated Assessment Model (IAM), climate model and impacts and adaptation or vulnerability research. At the same time, a comprehensive analysis is addressed of climate change influences, vulnerability, and mitigation, also providing scientific support and policy guidance for climate change risk assessment [41,56]. These scenarios can therefore affectively address the coupling of climate and land use changes. Indeed, SSPs and RCPs represent the organic integration of future possible socioeconomic development states and climate change scenarios. Under various scenarios, the adoption of different economic development ways or social and environmental policies will drive the land use change (indeed, population and GDP are the two major driving forces for urban expansion), so as to realize the organic coupling of climate and land use changes under different scenarios [57].

SSP126, SSP245, SSP370 and SSP585 can be made representing *Sustainability, Middle of the road, Regional rivalry* and *Fossil-fueled development* ways respectively, and their specific descriptions can be found in Table S3. In addition, the cognition degree driver τ is calculated based on regional total health costs per capita [37], which can be estimated by the rate of local total health costs to its local GDP multiplied by local simulated GDP allocated by the projected national GDP under different scenarios provided by IIASA.

2.3.4. Ecosystem services simulation

Ecosystem services quantification and simulation (bottom of Fig. 1) is based on the emergy accounting method, where emergy is defined as the available energy used directly and indirectly to produce a service or a product, with units of solar equivalent joule, sej [58]. Emergy-based ES accounting method has been proposed by various studies ([59–62]). By using simulated climate change, land use change and total health expenditure per capita data as input for the ES accounting method (step 2 at the bottom of Fig. 1), we can then calculate ES for each subtype (NPP, carbon sequestration, soil building, groundwater recharge, air and water purification, soil retention, microclimate regulation, climate regulation, see step 1 at the bottom of Fig. 1) and each ecosystem (woodland, grassland or aquatic), and obtain provincial and national total ES based on the total ES summation principle (step 3 at the bottom of Fig. 1) as detailed in Yang et al. [37]. Through these steps, we can therefore achieve ecosystem services simulation under climate-land use change interactions.

3. Results

3.1. Trends of future aggregated ecosystem services

Fig. 2 shows the trend of China's total ES as simulated until the 2100. Results shows that simulated ecosystem services increase from 2020 to 2100, with respective increase values of 4.49E+23, 4.58E+23, 1.35E+23, 8.55E+23 sej, and net increase of 33%, 34%, 9%, and 60% under SSP1, SSP2, SSP3, and SSP5, respectively. Yet, the overall growth rate of ecosystem services slows down, at an annual increase rate of around 0.5% (Fig. 2b) comparing with the annual increase rate of China's ecosystem services at around 1% during 2000–2020 [37]. Particularly, the growth rate in the first decades is the highest among the simulation period. Simulation outputs shows that the annual ES increase rate under SSP1 during 2020–2070 is aggregately simulated higher than 0.5%, while the yearly increase would be below 0.5% from 2020 to 2100, ranging from 0.4% to 0.49%. One possible reason is because the transferring rates from farmland to forest for the Grain to Green Project tend to slow down as time goes and are partially controlled by the conservation of permanently protected farmland. Hence the increase rate of woodland areas may decline leading to the overall decrease in the growth rate of total ES. As a result, the promotional effect on ES of land use change driven by the Grain to Green Project improvement tends to be smaller, reflecting the potential conflicts between ensuring food security and improving ecosystem services.

3.2. Characteristics of changes in future ecosystem services at different scales

3.2.1. Provincial scale

Although China's ES is expected to increase on temporal scale, not all provinces exhibit ES increase trend on spatial scale (Fig. 3). Except

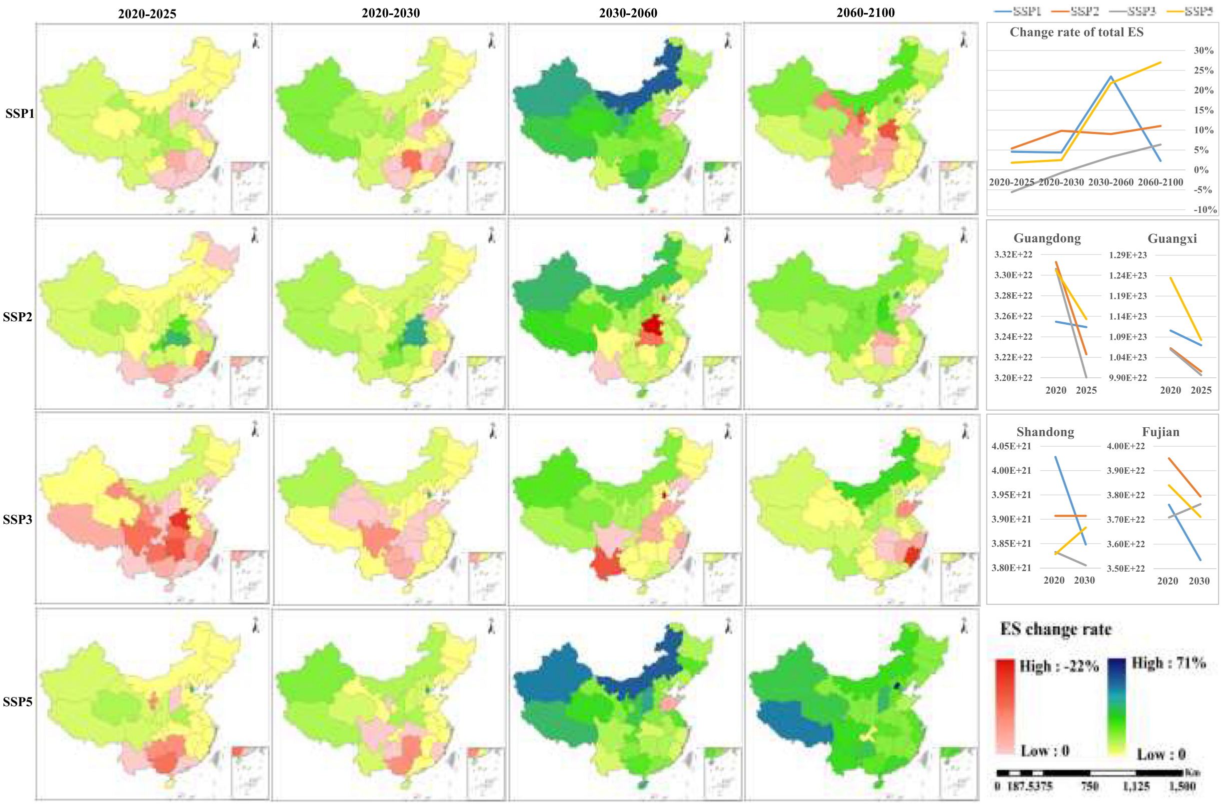

Fig. 3. Provincial changes in simulated future ecosystem services under different scenarios (The deeper red and blue colors suggest the higher decrease and increase rate of ecosystem services, respectively). These maps are generated based on the standard map GS(2024)0650.

for SSP3, ecosystem services are expected to increase mainly concentrated in China's Central and Western provinces from 2020 to 2025. While the decrease trend of ES is mainly exhibited in some Eastern and Southern coastal provinces at the same time period. Simulation results shows that the ES in one third of provinces are expected to decrease under SSP1, SSP2, and SSP5 while the other two thirds of provinces would decline in their ES under SSP3. Specifically, the ecosystem services of Hunan, Shanxi, Guangxi, Shandong, Fujian, Jiangxi, Hebei, Jiangsu, and Guangdong provinces are expected to decrease by 5.51%, 3.44%, 3.24%, 2.12%, 1.43%, 0.93%, 0.53%, 0.33%, and 0.16% under SSP1, respectively. The rest 21 provinces show significant ES increase with the highest growth ratio in Tianjin (34.52%), followed by Gansu (13.61%) and Ningxia (13.35%), whose increase rate are significantly lower than that of Tianjin. While, the region with less significant increase is primarily located in Northeast three provinces (Liaoning 0.12%, Heilongjiang 1.94%, Jilin 2.31%), Guizhou (0.13%), Zhejiang (0.57%), etc. The ES in 9 provinces are expected to decline, including Fujian (−8.47%), Guangxi (−5.33%), Beijing (−3.10%), Guangdong (−2.71%), Hainan (−1.52%), Yunnan (−1.08%), Heilongjiang (−0.87%), Tianjin (−0.71%), and Jiangsu (−0.26%) under SSP2. While the rest 22 provinces show significant ES increase with the highest growth rate in Hubei (39.17%), followed by Henan (24.58%) and Chongqing (21.50%). The areas with lower increase are concentrated in China's North provinces, including Jilin (0.36%), Gansu (0.46%), Shandong (0.76%), Liaoning (1.26%), and Hebei (1.78%). ES in 8 provinces (Southwest provinces in China) are expected to decrease, including Guangxi (−12.27%), Guizhou (−8.61%), Ningxia (−7.94%), Hunan (−7.02%), Yunnan (−2.85%), Beijing (−1.79%), Guangdong (−1.43%), and Shanxi (−0.30%) under SSP5. While China's Western provinces mostly exhibit higher ES increase than the Central and Eastern regions, with the highest increase in Tianjin (36.46%), followed by Henan (10.54%), Qinghai (10.30%), Shaanxi (9.58%), and Gansu (9.11%). ES in two-third of China's provinces are expected to decline, which are largely located in Central and Southern China with the highest decrease rate in Henan (−16.25%), Hunan (−14.95%), Guizhou (−12.11%), Sichuan (−11.75%), and Hubei (−10.95%), respectively under SSP3. Hence, it can be concluded from Fig. 3 (the second line chart) that no matter what types of scenarios, ecosystem services in Guangdong and Guangxi provinces are expected to decline from 2020 to 2025. Therefore, considerable attentions are needed to be paid to the ecosystems conservation and restoration in these two provinces.

From 2020 to 2030, it is simulated that ecosystem services in 9, 2, 11, and 7 provinces are expected to decrease under SSP1, SSP2, SSP3, and SSP5, respectively. Particularly under SSP1, the provinces with increasing ES are mainly concentrated in Middle and Western China, with the largest ES growth rate in Tianjin at 39.08%, followed by Tibet (16.83%), Xinjiang (16.55%), and Shaanxi (14.89%); while the decreased provinces are mostly located in Central and Southern regions, including Hunan (−12.20%), Fujian (−6.01%), Shandong (−4.46%), Guizhou (−3.99%), Guangxi (−3.30%), Ningxia (−1.65%), Jiangxi (−1.27%), Henan (−1.01%), and Zhejiang (−0.04%). Just 2 provinces are expected to face the challenges of ES decrease, including Fujian (−3.94%) and Shandong (−0.63%) under SSP2. The rest 29 provinces exhibit an ES increasing trend with the highest growth mainly located in Central China, including Hubei (44.63%), Henan (41.82%), Chongqing (23.60%), and Guizhou (17.33%), followed by Western areas, including Xinjiang (13.46%), Shaanxi (12.47%), and Tibet (11.51%). The ES decrease exhibits a V-shape distribution in China with the largest ES reduction on Southwest provinces, including Sichuan (−8.24%), Guangxi (−4.85%), and Guizhou (−4.83%) under SSP3. Under SSP1, Tianjin is still expected to exhibit the largest ES increase rate at 37.18 %, followed by Northern provinces including Xinjiang (10.85%), Inner Mongolia (8.56%) and other. As to SSP5, the risk of ES declining is mainly concentrated in China's Southern (in particular Southwest)

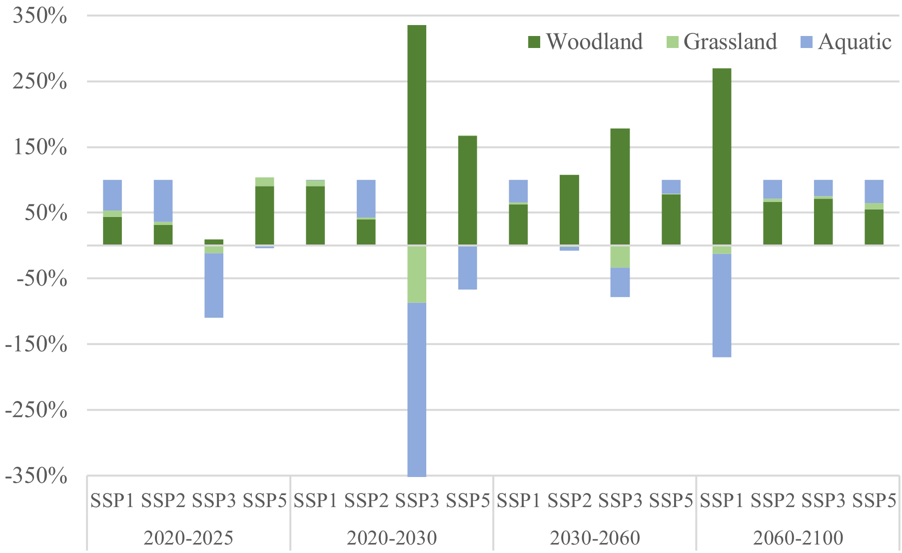

Fig. 4. Contribution of different ecosystems to changes in China's total ES.

regions, including Guangxi (−8.25%), Hunan (−7.65%), Fujian (−3.35%), Guizhou (−3.19%), Ningxia (−1.63%), Hubei (−1.30%), and Sichuan (−0.82%). Similar to other SSPs, Tianjin is expected to still exhibit the largest ES growth rate (42.40%), followed by Northern and Western provinces including Xinjiang (19.13%), Tibet (13.24%), and Inner Mongolia (11.68%). Thus, Fujian (SSP1, SSP2, SSP5) and Shandong (SSP1, SSP2, SSP3) are expect to face challenges of ES decrease during the next decade (the third line chart in Fig. 3) since their ES would decline under all three scenarios simulation results.

Fig. 3 also shows that till 2030 and beyond, the ES in most provinces are expected to increase with the growth rate aggregately larger than that of the 2020–2025 period. Conversely, China's ES increasing rates will slow down in the following years which is shown by the lightening for whatever scenarios of blue and green colors representing ES increase. Nevertheless, Shandong province is still the key region facing the risk of ES decrease during 2030–2060 as shown in Fig. 3 for SSP1, SSP3, and SSP5 scenarios, with the projected reduction rate at 1.82%, 6.36% and 4.15%, respectively. Hubei, Hunan, and Shandong provinces will face potential challenges of ES reduction, suggesting that these three regions should draw more attention to their ecosystem management and conservation. Generally, Shandong province has the largest potential to be the key area of decline in ecosystem services in the future scenarios during 2020–2030, 2030–2060 and 2060–2100 periods, demonstrating its different ES decrease degree. This conclusion is consistent with a previous study showing that Shandong province is the core region with ES declining during 2000–2020 [37].

3.2.2. Ecosystem scales

Fig. 4 shows the contribution of different ecosystems to China's total ES dynamics. On aggregate, woodland ES increase is expected to positively contribute to China's ES improvement, while ES decrease mainly comes from grassland and aquatic ecosystems during 2020–2100. Specifically, Fig. 4 also shows that aquatic ecosystem primarily accounts for China's ES increase in 2020–2025 while woodland dominates the ES growth in the remaining 75 years (2025–2100). Particularly, in woodland, grassland and aquatic ES are responsible for changes of 44%, 10% and 47% under SSP1, 31%, 5% and 64% under SSP2, 9%, −12% and −97% under SSP3, 91%, 13% and −4% in China's ES improvement from 2020 to 2025. During 2020–2030, the contribution of woodland ES growth to China's total ES improvement is increasing significantly at the rate of 91%, 40%, 336%, and 167% under SSP1, SSP2, SSP3, and SSP5, respectively. During both 2030–2060 and 2060–2100, woodland ecosystem services increases are expected to continuously dominate in China's ES growth, with the contribution percentage of 63%, 108%, 178% and 78% in 2030–2060 and 270%, 67%, 72% and 55% in 2060–2100 under SSP1, SSP2, SSP3 and SSP5, respectively.

3.2.3. Ecosystem services types scale

We further investigate the change rate of specific ES types in China under different scenarios and the results can be found in Table 2. Table 2 shows that air and water purification and climate regulation services have larger increase rates than other services in general which might relate to the development of economy, the higher health medical expense per capita, the more attention paid to the effects of ES increase on human health improvement, the stronger effects of ES in reducing damage to human health from air and water pollutions and greenhouse gases. Net primary productivity (NPP), carbon sequestration, soil building, groundwater recharge, hydropower generation (just including nature's contributions, like precipitation, elevation difference), microclimate regulation and soil retention have relatively stable increases. Specifically, during 2020–2100, growth rate of ES under SSP5 is larger than of the other three scenarios. Except for air and water purification and climate regulation, groundwater recharge is simulated to have the largest increase rate at 53%, followed by NPP (36%), Hydropower Generation (35%), carbon sequestration (29%), soil building (23%), soil retention (16%) while microclimate regulation could exhibit 1 % decrease. The change rates of these seven ES under SSP1 and SSP2 are very close with the exception of groundwater recharge and hydropower generation. Ecosystem services has lower change rate under SSP3, especially NPP, hydropower generation, microclimate regulation services, simulated to decrease by 1%, 5% and 2%, respectively.

During 2020–2025, ES have larger growth rate under SSP1 and SSP2, while lower increase rate or even decrease of these services are expected to become under SSP5 and SSP3. Air and water purification and climate regulation services are simulated to have around 30% increase rate, whereas hydropower generation is projected to have larger increase ratio, with the value of 6% and 10% under SSP1 and SSP2, respectively. This increased ratio is followed by NPP (5%, 3%), carbon sequestration (5%, 2%), groundwater recharge (3%, 6%), soil building (2%, 2%), soil retention (1%, 1%).

During 2020–2030, in addition to air and water purification and climate regulation services, ES under SSP2 have higher increase rate than for the other scenarios, followed by SSP1, while ecosystem services under SSP3 and SSP5 will mostly face decrease trends. Specifically, under SSP2, apart from air and water purification and climate regulation services, the largest growth ratio is hydropower generation (16%), followed

Table 2
Change rate of specific ecosystem service types under different scenarios.

Year	Scenarios	Ecosystem services types									
		NPP	CS	SB	GR	AP	WP	HG	MR	SR	CR
2020–2025	SSP1	5%	5%	2%	3%	39%	31%	6%	0%	1%	37%
	SSP2	3%	2%	2%	6%	32%	25%	10%	0%	1%	31%
	SSP3	−9%	−7%	−4%	−14%	27%	22%	−14%	0%	1%	27%
	SSP5	0%	0%	0%	−3%	44%	36%	0%	0%	1%	43%
2020–2030	SSP1	3%	2%	2%	1%	87%	64%	0%	−1%	3%	82%
	SSP2	7%	6%	4%	14%	65%	45%	16%	−1%	2%	60%
	SSP3	−5%	−4%	−1%	−6%	52%	37%	−6%	−1%	2%	48%
	SSP5	−2%	−2%	0%	−4%	105%	79%	−4%	−1%	3%	100%
2030–2060	SSP1	20%	21%	13%	21%	155%	96%	22%	0%	9%	132%
	SSP2	4%	3%	5%	2%	115%	61%	−1%	−1%	8%	95%
	SSP3	−6%	−8%	−1%	1%	56%	18%	−3%	−1%	7%	41%
	SSP5	7%	7%	7%	13%	199%	126%	12%	0%	10%	169%
2060–2100	SSP1	−8%	−6%	−3%	−10%	49%	35%	−11%	0%	3%	45%
	SSP2	3%	3%	3%	6%	66%	52%	9%	0%	3%	63%
	SSP3	11%	14%	7%	7%	22%	8%	5%	0%	4%	17%
	SSP5	30%	23%	15%	42%	84%	67%	27%	0%	3%	78%
2020–2100	SSP1	13%	16%	13%	10%	613%	334%	9%	−1%	16%	510%
	SSP2	15%	13%	12%	23%	491%	255%	24%	−1%	14%	408%
	SSP3	−1%	0%	5%	1%	188%	73%	−5%	−2%	15%	144%
	SSP5	36%	29%	23%	53%	1024%	577%	35%	−1%	16%	859%

Note: CS: Carbon sequestration; SB: Soil building; GR: Groundwater recharge; AP: Air purification; WP: Water purification; HG: Hydropower Generation (nature's contribution); MR: Microclimate Regulation; SR: Soil retention; CR: Climate regulation.

by groundwater recharge (14%), NPP (7%), carbon sequestration (6%), soil retention (2%). During 2030–2060, ES under SSP1 have obviously larger improvement than these of other scenarios, with hydropower generation, groundwater recharge, carbon sequestration, NPP, soil building, and soil retention increase by 22%, 21%, 21%, 20%, and 9%, respectively.

Different from 2020 to 2025 and 2020–2030, ES under SSP5 during 2030–2060 are expected to exhibit overall larger increase ratio than under SSP2. Different from 2030 to 2060 time period, ES exhibit overall the highest increase rate under SSP5 during 2060–2100, followed by SSP3 and SSP2, while besides air (49%) and water purification (35%), climate regulation (45%) and soil retention (3%) services will increase, other services including hydropower generation (−11 %), groundwater recharge (−10%), NPP (−8%), carbon sequestration (−6%), soil building (−3%), and microclimate regulation (−0.05%) are expected to decrease under SSP1 during 2060–2100. These results suggest that in the first four decades (2020–2060), SSP1 is more helpful to promote the increase of subtypes of the ecosystem services while in the last four decades (2060–2100), SSP5 will facilitate significant increase in ecosystem services.

4. Discussion

4.1. Contributions and limitations of this study

The limitations of this study mainly stem from the driving factors selection. This study, based on the attribution analysis results of ES changes, mainly select the three key drivers: natural drivers R, human drivers S (land use change), and cognition degree driver τ. Actually, expect for these factors, other variables including pollution, biological invasion, and natural resource use and exploitation, etc. also affect ES to some extent. However, this study does not take these factors into consideration due to data availability. With further advancement of monitoring technology and work from other studies, future studies can consider to include these drivers into the framework of simulating ES dynamics to make results more accurate. Meanwhile, the interactions (e.g., trade-offs and synergies) among ecosystem services are extremely important for sustainable ecosystem management which could be another critical and influential research topic potentially. Future studies need to further investigate the trade-offs and synergies among ecosystem services under the impacts of climate change and land use change to provide strategies for sustainable ecosystem management.

Although the limitations do exist above, the defects cannot obscure the virtues, the scientific contributions of this study include: (1) Previous studies mainly simulated ES changes under single influencing factor (climate change or land use change) while this study quantitatively simulates ES dynamics under the interactions of these two drivers. Thus, these results could be closer to reality to some extent. (2) Previous studies used regional overlapping (like overlapping climate and ES changes maps) or using an econometric model to generate a land-use transfer probability matrix to simulate ES dynamics under climate or land use change, which may not fully consider the influencing mechanism of these two key drivers on ES changes. This study, however, selects the main divers based on the attribution analysis results of ES changes of the authors' previous studies. And the attribution analysis method, based on emergy analysis method and Partial Differential Equations, can track and assess the contribution of climate and land use change to variations in ES through energy transfer and material flow. These results indicate that this study can reveal the influencing mechanism of climate-land use change on ES dynamics through tracking the contribution of energy transfer and material flow of the drivers more clearly.

4.2. Comments on the proposed framework

The proposed framework for ES simulation under climate and land use change interactions has the following advantages, especially related to the challenges of current ES projection methods: (1) it tracks the causation and points out the influential mechanism of climate change and land use change on ES dynamics because the framework selects climate-land use change drivers based on the attribution analysis of changes from recent literatures, making the framework a "natural" improvement of the research; (2) it integrates the interactions between climate change and land use change by designing different development scenarios; (3) it can improve the simulation accuracy of spatial distribution of ecosystem services via the DLUCP model improving the accuracy of spatial simulation of land use change; (4) it addresses the warning of ES declining through simulating ES dynamics at short-, medium-, and long terms as well as at different - national and provincial - scales, as well as at different service types scales. For example, although China's ES are expected to increase on average, decreases exist in some provinces, especially Shandong, as well as for aquatic ecosystem and for service types such as carbon sequestration (2020–2060 under SSP3). The proposed framework therefore can effectively help to predict the decline or abrupt changes of ES, providing an early warning mechanism for ecosystem conditions and for taking response measures in advance.

4.3. Uncertainty analysis

The uncertainty of this study mainly stems from the incomplete selection of drivers. According to the attribution analysis results of ecosystem services dynamics, this study mainly selected natural drivers, human driver (land use change), and cognition degree driver τ (regional total health expenditure per capita) [37]. Actually, other factors also can result in the changes in ecosystem services. Here, we use the error of the attribution analysis to estimate the uncertainties of the simulated results. At provincial scales, we apply the simulated provincial ecosystem services to multiply their corresponding error items of the attribution analysis of ES dynamics [37] as shown by Table S4. The contribution rate of error items plus the contribution of the three key drivers of ES dynamics, i.e. natural, human, cognition degree (τ) drivers are 100% [37]. And the uncertainties of China's ecosystem services before and after multiplying the error items range from 0.26%–0.61%, 0.24%–0.67%, 0.24%–0.58%, and 0.18%–0.56% under SSP1, SSP2, SSP3, and SSP5, respectively (Supplementary table S4). Meanwhile, at China's scale, the contribution of natural, human, cognition degree (τ) drivers and error (δ) item to changes in China's ecosystem services in 2000–2020 were 37%, 55%, 8% and 1%, respectively [37]. These indicate the three key drivers could contribute 99% to changes in China's ecosystem services. It highlights that, although the drivers of ES changes are included incompletely and uncertainty may exist to some extent in this study, the conclusion is considered convincing.

4.4. Is there an ecosystem services growth upper limit?

Although the future trends of ES are simulated to increase under all the scenarios in this study, the increase rates are expected to decrease from around 1% during 2000–2020 [37] to 0.5% or even 0.25% (SSP3) during 2020–2100. At the same time, China's future GDP and population simulated by IIASA exhibit basically a S-shaped increase and decrease, respectively. The smaller and stable ES change rate together with increased GDP addresses the question of whether the growth rate of ecosystem services is limited by the rapid economic development. Several researchers have already acknowledged the certain interactions between ecological and economic thresholds [63,64]. For instance, Peng et al. [65] found that ES would decline quickly when population and economic urbanization exceed some threshold values (calculated as 229 person/km^2 and 107.15 million CNY/km^2 in the cited reference, respectively).

Similarly, the promotion effects of ecological restoration programs on ES improvement also exhibit a threshold. For example, Zhang et al. [66] suggested that overcoming the threshold led to a decrease in the ecological restoration efficiency when vegetation coverage reaches 44%, 32%, 34% and 34% in forest, forest-grass, grass and grass-desert ecosystems, respectively. This can be the reason why although the Grain for Green program is simulated to last during the entire period of 2020–2100, the increase of China's ES tends to slow down. Moreover, Guo et al. [67] also considered the thresholds of multiple drivers of changes in ES under various environments. The results indicated that (1) When ET and precipitation (Pr) reach certain values (1,277 mm $<$ET $<$1317 mm, Pr $>$ 417.55 mm), increasing temperature can greatly foster ES increase; (2) When human impact index (HAI) and land use intensity index (LUI) reach a certain range (0.11 $<$ HAI $<$ 0.29 and 184.32 $<$ LUI $<$ 210.6), they can effectively improve ES, while outside the ranges the opposite effect also happens; (3) Low diversity fragmented landscapes (Shannon's diversity index SHDI $<$ 0.86) can boost ES growth, while fragmented landscapes with high diversity (patch density, PD $>$ 0.14 or SHDI $>$ 0.85) could cause ES decrease. Yet, further studies are still lacking that systematically and comprehensively assess the effect thresholds of natural and human drivers (like climate change, land use change, ecological restoration programs) for ES changes at macro scales, such as national or global scales. Therefore, future studies highly call for this type of approach to identify the effect thresholds of multiple social, economic and ecological factors to ES dynamics, in order to provide an effective support for the management of sustainable ecosystems and ecological restoration programs.

4.5. Hidden challenges behind ecosystem services improvement

Our studies revealed the hidden challenges behind China's ES improvement during 2000–2020, especially in the north area over 400 mm precipitation isopleth in China, because parts of local vegetation plantation have already been above local water resource limits based on historical situation [37]. Although China's total ES are simulated to increase under all the scenarios in this study, parts of China's provinces are still shown to undergo ecosystem services declining during 2020–2100, as shown in Fig. 3. From 2020 to 2025, China's ES increase rates are 5%, 6%, −6%, and 2% under SSP1, SSP2, SSP3, and SSP5 scenarios, respectively (the first line chart of Fig. 5), and 9 provinces may have potential ecosystem services decrease pressure under both SSP1 and SSP2 scenarios. This means that to minimize the possible ES declining challenges at both provincial and national scales, SSP1 and SSP2 may be the potential development ways during 2020–2025.

During 2020–2030, as shown by the first line chart of Fig. 3, China's 31 provinces ES improvement ratio under SSP2 scenario is expected to be the largest, with the value of 10%, followed by 5% (SSP1), 3% (SSP5) and −1% (SSP3). Under SSP2 scenario, just two provinces, Fujian and Shandong (Fig. 3), will have a slight ES declining situation. This indicates the SSP2 scenario as a better option to control potential risks of ES declining during 2020–2030. During 2030–2060, as shown the first line chart of Fig. 3, China's ES under SSP1 will have the largest increase rate at 24%, followed by 22% (SSP5), 9% (SSP2), and 3% (SSP3). Similarly, just Shandong province may have potential ES decrease pressure under both SSP1 and SSP5 scenarios, with the declining ratio of −2% and −4%, respectively. This suggests that, from the perspective of ES improvement, China may need to transfer its development ways from SSP2 to SSP1 during 2030–2060 to reduce the potential challenges of ecosystem services declining at both provincial and national scales.

China's ecosystem services will have the largest growth rate (27%) during 2060–2100 under SSP5, followed by 11%, 7%, and 2% under SSP2, SSP3, and SSP1 scenarios, respectively. It is noteworthy that all the 31 provinces are simulated to have their ES increased under SSP5 scenario. This indicates that, on the last four decades of 21th Century, SSP5 scenario might bring both provincial and national ecosystem services improvement (although at a slower increase rate) and economic rapid development. A global rapid economy growth is actually consistent with the description of SSP5 scenario: local environmental issues including air and water pollution are successfully curbed, and it has effective socio-economic and ecological systems management ability, such as using geo-engineering as needed. Nevertheless, Shandong province is simulated as the core region with ES declining challenges, due to (yet different) ES decrease rates during 2020–2030, 2030–2060 and 2060–2100 periods under three scenarios. Therefore, Shandong province needs to propose improved ecosystem management and conservation strategies to overcome potential ES declining challenges.

4.6. Offset effects of terrestrial ecosystem carbon sink to carbon emission

One of the analyzed ES is carbon sequestration, since terrestrial ecosystem carbon sink is critical for carbon emission offset in the process of achieving carbon neutrality. Therefore, we further assess China's future terrestrial ecosystem carbon sink and its offset effects on carbon emission. We obtain carbon sink density (unit: Mg C/ha/yr) of China's terrestrial ecosystem from Yang et al. [68], and then multiply the corresponding ecosystems areas simulated in this study to get China's terres-

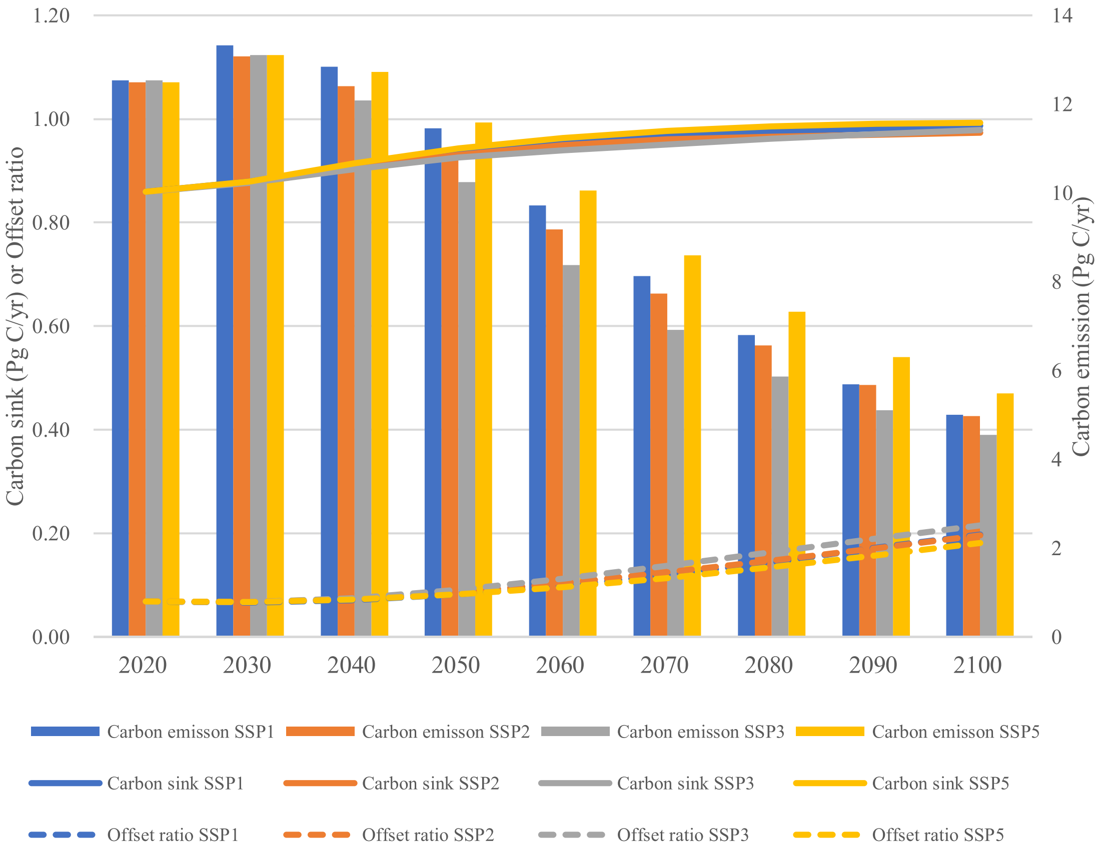

Fig. 5. China's terrestrial ecosystem carbon sink and its offset effects on carbon emission.

trial ecosystem carbon sink. Hereafter, we obtain China's carbon emission projection data under SSP1, SSP2, SSP3, and SSP5 from Zhang et al. [69], then use China's terrestrial ecosystem carbon sink divided by China's carbon emission corresponding to the respective scenarios, finally getting the offset ratio of ecosystem carbon sink to carbon emission, as shown in Fig. 5. Fig. 5 indicates that China's terrestrial ecosystem carbon sink exhibits a slowly growing trend under the four scenarios, ranging from 0.85 to 0.99 Pg C/yr. This value is larger than the ecosystem carbon sink amount at 0.12–0.35 Pg C/yr, estimated by previous studies by using inventory method, ecosystem process models and corrected atmospheric inversion model [70]. This is probably because one value of forest ecosystem carbon sink intensity is used for all subtypes of forest due to the lack of specific data of carbon sink density of each subtype, which may lead to the overestimation of forest carbon sink capacity. Even though, this result still provides an estimation of future China's terrestrial ecosystem carbon sink. Carbon emission exhibits a first increase (from 12.49 Pg C/yr in 2020) followed by a decrease trend (from 13.32 Pg C in 2030 to 4.55 Pg C in 2100), reaching the peak of emission in 2030. Also, the offset rate of carbon sink of China's terrestrial ecosystem to carbon emission exhibits increasing trends ranging from 7% to 22%. This means that carbon sink of China's terrestrial ecosystem could partially offset its carbon emission and the offset effects depend on the decrease in carbon emission significantly. As the forest carbon sink capacity decreases with the tree getting older, the offset effects may get worse. Therefore, the comprehensive use of emission reduction strategies is the essential way for China to achieve carbon neutrality [70].

5. Conclusion

Ecosystem services have experienced degradation worldwide in the last fifty years of 20th century especially under the accelerating climate change and land use change. Yet, the current research on the projection of ES changes still cannot clarify the influence mechanism of these two drivers as well as their interaction mechanisms, which may mislead ecosystem management and weaken ecosystem resistance to these rapid changes. To overcome these challenges, this study proposes a framework for ES simulation under climate and land use change interactions, and takes China as a case study to simulate its ecosystem services. This study can be potentially extended to any area of interest with data available and can provide guidance for ecosystem conservation and management in face of rapidly changing environments.

Author contributions

Z.F.Y. and G.Y. L. were responsible for overall project supervision, conceptualization, data curation, and project management; Q.Y., Z.F.Y., and G.Y.L. contributed to methodology development, conducted validation, and contributed to the writing of early drafts and final draft review and editing; G.F. contributed to manuscript modification.

Data availability

Climatic factors including precipitation, solar radiation and wind data provided by the CMIP6 database at https://esgf-node.llnl.gov/search/cmip6/. Land use change data is simulated by this study. GDP and population provided by IIASA at https://tntcat.iiasa.ac.at/SspDb/dsd?Action=htmlpage&page=citation.

Declaration of competing interest

The authors declare that they have no conflicts of interest in this work.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.fmre.2024.02.017.

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