Science Bulletin 68 (2023) 740–749

Contents lists available at ScienceDirect

Science Bulletin

journal homepage: www.elsevier.com/locate/scib

Article

Future land-use change and its impact on terrestrial ecosystem carbon pool evolution along the Silk Road under SDG scenarios

Min Cao [a,b,c], Ya Tian [d,a], Kai Wu [a,c], Min Chen [a,c,*], Yu Chen [b,e], Xue Hu [a,f], Zhongchang Sun [b,e], Lijun Zuo [b,e], Jian Lin [g], Lei Luo [b,e], Rui Zhu [h], Zhenci Xu [i], Temenoujka Bandrova [j], Milan Konecny [k], Wenping Yuan [l], Huadong Guo [b,e], Hui Lin [d,m], Guonian Lü [a,c,*]

[a] Key Laboratory of Virtual Geographic Environment, Ministry of Education, Nanjing Normal University, Nanjing 210023, China
[b] International Research Center of Big Data for Sustainable Development Goals, Beijing 100094, China
[c] Jiangsu Center for Collaborative Innovation in Geographical Information Resource Development and Application, Nanjing 210023, China
[d] School of Geography and Environment, Jiangxi Normal University, Nanchang 330022, China
[e] Aerospace Information Research Institute, Chinese Academy of Sciences, Beijing 100094, China
[f] The Key Laboratory of Urban Land Resources Monitoring and Simulation, Ministry of Natural Resources, Shenzhen 518034, China
[g] Sierra Nevada Research Institute, University of California, Merced CA 95348, USA
[h] Institute of High Performance Computing, Agency for Science, Technology and Research, Singapore 138632, Singapore
[i] Department of Geography, the University of Hong Kong, Hong Kong 999077, China
[j] Laboratory on Cartography, University of Architecture, Civil Engineering and Geodesy, Sofia 1164, Bulgaria
[k] Laboratory on Geoinformatics and Cartography, Institute of Geography, Masaryk University, Brno 601 77, Czech Republic
[l] School of Atmospheric Sciences, Southern Marine Science and Engineering Guangdong Laboratory (Zhuhai), Sun Yat-sen University, Zhuhai 519082, China
[m] Key Laboratory of Poyang Lake Wetland and Watershed Research, Ministry of Education, Jiangxi Normal University, Nanchang 330022, China

ARTICLE INFO

Article history:
Received 6 September 2022
Received in revised form 15 January 2023
Accepted 16 January 2023
Available online 8 March 2023

Keywords:
Sustainable development goals (SDGs)
Land-use projection
Carbon pool
Scenarios
System dynamics model
Cellular automata

ABSTRACT

Sustainable development goals (SDGs) in the United Nations 2030 Agenda call for action by all nations to promote economic prosperity while protecting the planet. Projection of future land-use change under SDG scenarios is a new attempt to scientifically achieve the SDGs. Herein, we proposed four scenario assumptions based on the SDGs, including the sustainable economy (ECO), sustainable grain (GRA), sustainable environment (ENV), and reference (REF) scenarios. We forecasted land-use change along the Silk Road (resolution: 300 m) and compared the impacts of urban expansion and forest conversion on terrestrial carbon pools. There were significant differences in future land use change and carbon stocks, under the four SDG scenarios, by 2030. In the ENV scenario, the trend of decreasing forest land was mitigated, and forest carbon stocks in China increased by approximately 0.60% compared to 2020. In the GRA scenario, the decreasing rate of cultivated land area has slowed down. Cultivated land area in South and Southeast Asia only shows an increasing trend in the GRA scenario, while it shows a decreasing trend in other SDG scenarios. The ECO scenario showed highest carbon losses associated with increased urban expansion. The study enhances our understanding of how SDGs can contribute to mitigate future environmental degradation via accurate simulations that can be applied on a global scale.

1. Introduction

Food security, economic growth, sustainable urban development, and environmentally friendly development, are essential elements for achieving the United Nations Sustainable Development Goals (SDGs) [1–4]. Land-use change has complex interactions with the economy, society, and environment and plays an important role in regulating climate, food security, and the carbon cycle [2,5–9]. Terrestrial ecosystems are extensively influenced by human land use and management [10]. Global urbanisation offsets 30% of climate-driven terrestrial net primary productivity growth, and cities account for >70% of anthropogenic greenhouse gas emissions [11,12]. Forest loss and afforestation have important implications for terrestrial carbon sinks and climate change mitigation [7]. Projections of future land-use change and their impact on terrestrial ecosystem carbon pools under multiple SDG scenarios could inform the pathways to sustainable development. Herein, we present spatially explicit projections of global land-use change

* Corresponding authors.
E-mail addresses: chenmin0902@njnu.edu.cn (M. Chen), gnlu@njnu.edu.cn (G. Lü).

https://doi.org/10.1016/j.scib.2023.03.012

from 2020 to 2030, analyse land-use change in countries along the Silk Road, and examine their impacts on terrestrial carbon pools (Supplementary Note 1 and Fig. S1 online).

Projecting land-use patterns requires established scenarios that represent possible future socio-economic and environmental conditions [13]. Simulation is a meaningful way to enable us understanding the future better, and scenario-based simulations support the analysis of potential land-use changes in uncertain futures [14,15]. Several previous studies have formulated guiding frameworks for the future use of land resources. Some scholars have studied future land-use predictions under several representative concentration pathways (RCPs) [16], shared socio-economic pathways (SSPs) [17,18], and SSP–RCP scenarios [19,20]. Some studies have modelled a global urban map for 2030, based on the United Nations population and economic projections [9]. The climate scenarios developed by the Intergovernmental Panel on Climate (IPCC) have also been used to simulate future land cover changes globally [6,21,22]. The United Nations 2030 Agenda for Sustainable Development (herein after referred to as the 2030 Agenda) set up a comprehensive and integrated framework of 17 goals, 169 targets, and 231 unique indicators [4], which are designed to guide the progress of sustainable development until 2030. The 17 SDGs integrate the three dimensions of sustainability: economy, society, and environment [4]. Using a system that considers the interaction between SDGs and analyses the relationship between the speed of their progress and land-use in different regions is a topic of great interest in sustainable development research [23,24]. Some scholars have constructed indicator systems and methods [25–30], proposed a framework for evaluating the interaction between the SDG indicators [31–33], and explored the synergy and trade-off effects between these indicators [34,35]. However, few studies have comprehensively considered multiple scenarios of SDGs, including the economic, environmental, and social aspects, to develop projections of land use. To fill this knowledge gap, this study addresses three main questions based on models that integrate system dynamics (SD) and cellular automata (CA). (1) How are SDG scenarios set? (2) What are the trends of future land-use change in different sub-regions under SDG scenarios? (3) How does the impact of land-use on terrestrial ecosystem carbon pools differ under SDG scenarios?

Based on the interaction between land use and the key targets of SDGs, we considered the following scenarios: the sustainable economy (ECO), sustainable grain (GRA), sustainable environment (ENV), and reference (REF) scenarios (Supplementary Note 2 online). In the REF scenario, we observed the actual development of SDGs; in the ECO scenario, we observed a high-speed economy growth rate; in the GRA scenario, people would obtain adequate food and the cultivated land would completely guarantee grain safety; and in the ENV scenario, less environmental pollution was emitted (Supplementary Note 2 online). Rapid industrialisation and urbanisation along the Silk Road have caused a series of environmental problems, including soaring resource consumption, air and water pollution, land degradation, and biodiversity reduction, which jeopardise sustainable development in and beyond the region [36]. Therefore, we selected countries along the Silk Road to forecast land use changes during 2020–2030, under the four SDG scenarios. Considering the economic, climatic, and location factors, we separated the study area into nine regions (Table S1 online, Methods), and their SDG scenarios were constructed based on the regional development characteristics (Tables S2–S4 online).

Several studies have analysed the SDGs, with a focus on regional or global single-goal progress assessments, while considering the synergistic trade-offs among multiple goals [1]. The uncoordinated ratio of the land consumption rate to population growth rate (LCRPGR) affects the progress of sustainable development of cities [37,38] (Supplementary Note 3 online). The SD model is widely used to simulate land-use changes influenced by socio-economic and climate change factors [39]. Since further comprehensive analysis normally need model coupling [40], many scholars use CA [6], combined with SD, to simulate future land-use changes driven by a variety of factors.

Based on the SDG scenarios, we integrated the SD and CA models and considered the socio-economic and climatic factors, to predict future land-use changes [41–43], in the countries located along the Silk Road (Methods) for 2020–2030 (spatial resolution: 300 m), we proposed a kind of new scenario assumption. We built nine SD models to explore the future land-use demand and the interaction between socio-economic and climate change drivers for each scenario (Fig. S2 online) and analysed the changing trends in the land types along the Silk Road. Furthermore, we analysed the distribution pattern of urban expansion and land-type conversion in some representative areas in 2030. We calculated the changes in terrestrial carbon stock caused by urban expansion and forest change in the countries along the Silk Road, using the integrated valuation of ecosystem services and trade-offs (InVEST) and integrated biosphere simulator (IBIS) models for 2020–2030 while considering SDG scenarios [44,45]. Notably, our study provides a new perspective for exploring future land-use change and its impact on terrestrial ecosystem carbon stock under the SDG framework.

2. Materials and methods

2.1. Study region and subregion definition

The Silk Road is the collective name for a number of ancient routes that connected Europe, Africa, and Asia, which has been a bridge between the East and the West for >2000 years. The natural environment along the Silk Road is complex and diverse, spanning tropical, temperate, and boreal zones. The region along the Silk Road has a large geographical span and a variety of land cover types.

We divided the study area along the Silk Road into nine subregions (Supplementary Note 4 and Table S1 online), on the basis of geopolitical and socioeconomic regions from shared socioeconomic pathways (SSPs) database, and agro-ecological zones (AEZs) developed by the Food and Agricultural Organization (FAO) and the International Institute for Applied Systems Analysis (IIASA) [46]. Geopolitical and socioeconomic regions represent economic conditions such as industrial production, energy consumption, trade, and natural resources. AEZs reflect the natural ecosystems and agricultural activities across the global land area [42], and countries located in a specific AEZ have similar or homogenous soil, landforms, and climatic characteristics. The nine subregions are defined as follows: China (CHN), Central and Western Asia (CWS), Eastern Europe (EEU), Europe high-income countries (EU-H), Europe middle-income countries (EU-M), Middle East high-income countries (MEA-H), Middle East middle-income countries (MEA-M), other Asian countries (OAS), and Russia (RUS).

2.2. Setting SDG scenarios

We set SDG scenarios based on trends that may be generated in the future (Supplementary Note 2 online). The SDG trend dashboards indicate whether a country is on track to achieve specific goals by 2030, based on its recent performance on given indicators, providing a visual representation of each country's performance on 17 SDGs. The "traffic light" color scheme (green, yellow, orange, and red) illustrates how far a region is from achieving a particular goal; the colours correspond to on track or maintaining SDG achievement, moderately improving, stagnating, or decreasing, respectively [47]. In this study, we considered four SDG scenarios: REF, ECO, GRA, and ENV (Supplementary Note 2 online). Additionally, we considered four SDG indicators: GDP growth rate (SDG 8.1.1), cereal yield (SDG 2.3.1), prevalence of undernourishment (SDG 2.1.1), and annual average concentration of $PM_{2.5}$ (SDG 11.6.2). For the four SDG indicators, we obtained the thresholds for different development trends based on SDG trend dashboards (Table S2 online). Development trends of the SDG indicators were set separately under different SDG scenarios (Table S3 online), which were developed in nine sub-regions based on regional development characteristics (Table S4 online).

2.3. Application of SD and CA: development of artificial neural networks (CA–ANNs) models

In this study, we built nine SD models to predict the land-use areas by 2030 (Supplementary Note 5 online). The sources of the SD variables included spatial and statistical data (Table S5 online). First, we selected the sustainable development indicators for the four SDG scenarios as the key factors driving the entire system (Fig. S2). We reclassified the European Space Agency Climate Change Initiative (ESA CCI) land cover products (Table S6 online). Different types of land are interconversion by a system feedback loop of coupling population, economy, food, and environment. The formulation and variable abbreviations of the SD models for the nine sub-regions are shown in Tables S7 and S8 (online). Additionally, the trends of land-use change in different scenarios were obtained, by inputting the parameter constraints of different SDG scenarios. The average relative error of the SD model was <5%, which indicated that the simulated results fitted well with the actual land use (Table S9 online).

Based on the land-use demand predicted by the SD model, we employed the CA-ANNs model, to spatialise the land use from 2020 to 2030 for all the SDG scenarios (Supplementary Note 6 and Fig. S1 online), with the World Goode Homolosine Land for spatial reference. The land-use conversion was carried out according to the combined probability estimated by ANNs, neighbourhood effects, conditional constraints, and a random variable during the iteration (Table S10 online), which continued until land-use demands were met. Finally, the annual spatialisation of land use data from 2020 to 2030 was obtained. The CA–ANNs model returned a kappa coefficient of 0.77 (Tables S11 and S12 online). We developed the projection for the four SDG scenarios, in terms of urban, cultivated land, and forest, and calculated the growth of land area from 2020 to 2030 (Fig. 1). Secondly, we selected representative regions of CHN, Thailand, India, Tajikistan, Greece, Romania, Slovakia, and Indonesia for spatialisation of the urban, cultivated land, and forest in 2030 (Figs. 2–4). To improve the presentation, we implemented a focal summation analysis, with radii of 15, 5, and 3 km for the urban (Fig. 2), cultivated land (Fig. 3), and forest (Fig. 4) areas. We calculated the growth rate of land type areas using the following equation:

$$\mathrm{Growth} = (U_j - U_i)/U_i, \tag{1}$$

where Growth indicates growth rates of land-type areas relative to the base year in each interval; U_i and U_j are land-type areas in the beginning and ending years within an interval, respectively.

2.4. Forecasting terrestrial carbon stock

We analysed future ecosystem carbon stock change along the Silk Road, under the SDG scenarios. The carbon density data were obtained using the IBIS model [45]. We calculated the future ecosystem carbon stocks of different land types for 2020–2030 using the InVEST model [44]. The InVEST model divides ecosystem carbon stock into four basic carbon pools:

$$C_{\mathrm{total}} = C_{\mathrm{above}} + C_{\mathrm{below}} + C_{\mathrm{soil}} + C_{\mathrm{dead}}, \tag{2}$$

where C_{total} denotes the total carbon stocks; C_{above} means the aboveground biogenic carbon; C_{below} means the belowground biogenic carbon; C_{soil} denotes the soil organic carbon, and C_{dead} means the dead organic carbon.

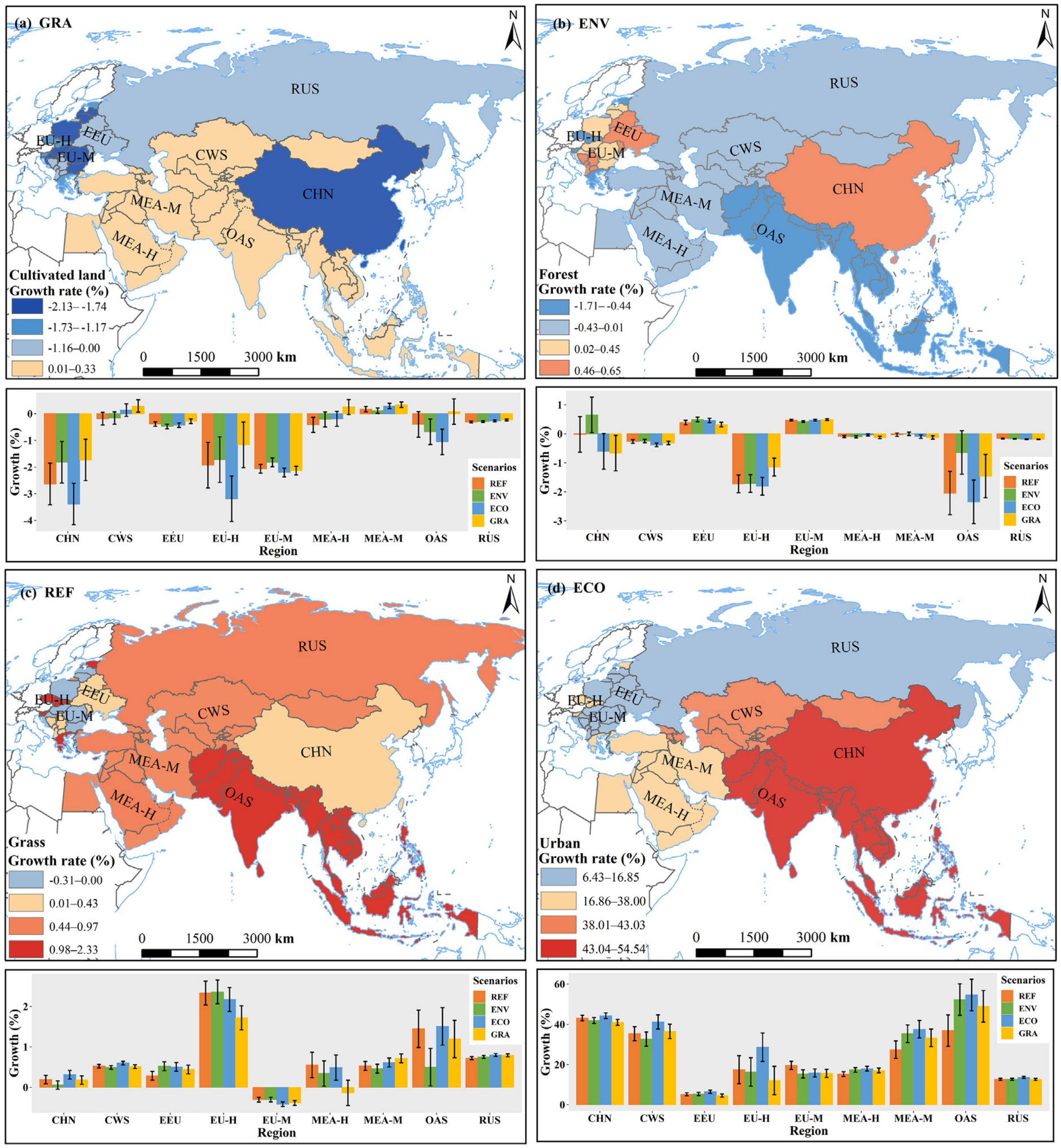
We re-classified the carbon density data from IBIS in 2020 into four types of carbon density [45]. The average carbon density of the four basic carbon pools of different land types was calculated separately according to the classification of land use, and will be assumed to remain unchanged from 2020 to 2030. Then, the future land-use data for the four SDG scenarios were input into the InVEST model to predict land carbon stocks (cultivated land, forest, and grass) from 2020 to 2030. The area of each land-type was multiplied by its carbon density and summed to obtain the total carbon stock. We obtained the predictions for carbon stocks along the Silk Road for SDG scenarios in 2020–2030, and we calculated the changes in forest, cultivated carbon stocks, and carbon losses caused by urban expansion under the SDG scenarios (Table S13 online).

3. Results

3.1. Future land-use change in different SDG scenarios

In our study, land-use conversion in the countries along the Silk Road portrayed significant differences from 2020 to 2030 (Figs. S3–S11 online). Our projection indicated that, in the future, urban and grass areas will increase, whereas the area of cultivated land will decrease. Additionally, from 2020 to 2030, urbanisation will expand rapidly in CHN, OAS, MEA-M, and CWS, while steadily in RUS, EEU, and the EU-M. In the four SDG scenarios, there were significant differences in the future land-use growth of the nine sub-regions (Fig. 1). Predicted changes in land-type areas are shown in Figs. S3–S11 (online). From 2020 to 2030, in all four scenarios, the cultivated land area decreased in most sub-regions along the Silk Road, especially in CHN, EU-M, and EU-H, whereas that in the MEA-M increased (Figs. S3–S11 online). Compared with that in the REF scenario, the cultivated land areas in most sub-regions declined in the ECO scenario. However, in the GRA scenario, the cultivated land area increased in MEA-M, MEA-H, CWS, and OAS. It indicates that cultivated land will be preserved under the GRA scenario which contributes to SDG 2.

There were significant spatial differences in the growth of forest areas in all four scenarios from 2020 to 2030 (Fig. 1). In the ENV scenario, the forest areas in most countries decreased and the loss rates of forest and grassland slowed, whereas, in China, it increased. In the ECO scenario, the declining rate of forest area accelerated, with the most significant decline observed in OAS and EU-H. In the four scenarios, the grassland areas increased, except for the EU-M, and the EU-H region portrayed the highest rate of growth under the ENV scenario. In the GRA scenario, the grassland area increased at a slower rate. In CHN, the forest area increased under the ENV scenario and decreased in the GRA and ECO scenarios. The urban expansion rate of the EEU was the slowest. In the ECO scenario, the urban expansion rate was the fastest, with OAS, MEA-M, and CHN portraying the highest future urban expansion rates among all the nine sub-regions. Notably, CHN portrayed the highest loss rate of cultivated land, whereas the OAS portrayed the highest loss rate of forests; this indicated that the urban expansion in CHN was mainly at the expense of cultivated land and that in OAS could be mainly attributed to encroachments into forestland.



审图号：GS京（2023）0588号

Fig. 1. Future growth rate of different land-type areas predicted by system dynamics (SD) model in the study area, for different sustainable development goal (SDG) scenarios (2020–2030). The map portrays the growth rate of cultivated land in sustainable grain (GRA) (a), forest in sustainable environment (ENV) (b), and grass in reference (REF) (c), and sustainable economy (ECO) (d) scenarios. The bars indicate the comparison of growth rate for land use area in nine regions under the four SDG scenarios. Error bars represent the standard deviation (considered as uncertainty range) among the four SDG scenarios projection.

3.2. Spatial pattern of land use in 2030

In CHN, MEA-M, and OAS, the regions with the fastest urban expansion rates experience intensive erosion of cultivated land. Therefore, we selected representative areas that portrayed significant expansions, including Hubei, Hunan, Jiangxi, and Bangkok, along with their surrounding areas in Thailand and the coastal region of southern China. Notably, we visualised the urban land distribution corresponding to the four SDG scenarios and calculated the main land-type conversion (Fig. 2). The conversion of land types mainly involved the transfer of cultivated land to urban land. Urban expansion was the most significant in the Hubei, Hunan, and Jiangxi provinces in China (Fig. 2a). In the ECO scenario, urban expansion in the three representative districts was the most significant, and their urban distribution areas were estimated to be densely connected by 2030. In the ENV and GRA scenarios, the urban distribution areas of the three regions were small and sparse, with the most common land-type conversion being that from cultivated to urban land. This indicated that rate of urban expansion, with respect to encroachment on cultivated land, could compromise SDG 2.

Cultivated land is crucial for ensuring food security (SDG 2). In this study, we selected regions in the southern part of the Deccan Plateau in India, the lower reaches of the Vakhsh River plain in

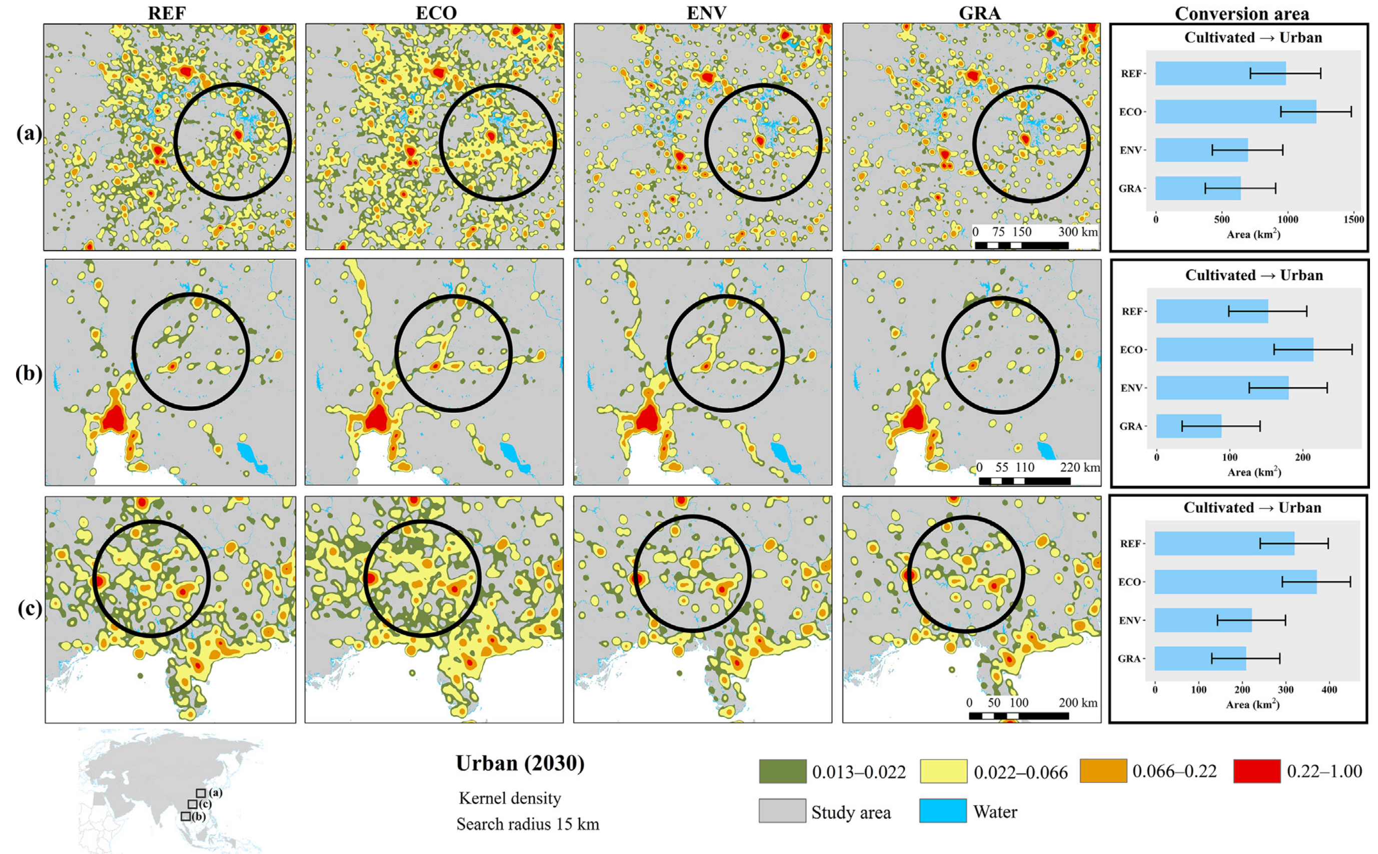


Fig. 2. Spatialisation results of urban land in representative regions for the four scenarios. (a) Hubei, Hunan, and Jiangxi provinces in China; (b) Bangkok and its surroundings in Thailand; (c) coastal area of southern China. The bars indicate the comparison of area of urban land transferred to cultivated land in nine regions, under the four SDG scenarios. Error bars represent the standard deviation (considered as uncertainty range) among the four SDG scenarios projected.

Tajikistan and the Sesalia region in Greece to estimate the area converted to cultivated land under the SDG scenarios (Fig. 3). By 2030, under the GRA scenario, most of the other land types were converted to cultivated land, while the least amount of cultivated land converted to other land types. Fig. 3a, c shows the conversion of mainly forest land and grassland to cultivated land, while Fig. 3b shows the conversion of cultivated land to grassland. The distribution density of cultivated land in the southern part of the Deccan Plateau was highest for all four SDG scenarios (Fig. 3). In the GRA scenario, the three representative areas portrayed a higher distribution density of cultivated land, compared with that in the other scenarios. In the ECO scenario, the distribution density of cultivated land decreased, and the most significant decrease was observed in the lower reaches of the Vakhsh River plain.

As an important carbon sink, forest land is crucial for regulating climate and achieving IPCC temperature goals. In this study, we selected countries in EU-M, EU-H, and OAS that had abundant forest resources to analyse the changes in the forests by 2030 for the four SDG scenarios (Fig. 4). The conversion of areas into and from forests by 2030 is shown in Fig. 4. In the ENV scenario, the forest area is the most transferred in and the least transferred out. Fig. 4a shows the highest conversion of cultivated land and grassland to forested land, Fig. 4b shows the least conversion of forest land to urban and cultivated land, and Fig. 4c shows a minimum conversion of forest land to cultivated land. As per Fig. 4a, cultivated land is the main source of forest land transfer. By 2030, the distribution characteristics of forests in Romania in the four SDG scenarios were similar, with high distribution density (Fig. 4a). In Slovakia and the Java Island, forest distribution was relatively dense in the ENV scenario, and relatively sparse in the ECO and GRA scenarios (Fig. 4b, c). Additionally, Romania showed a decrease in the forest area, resulting from years of deforestation; however, in recent years, the afforestation areas have increased annually, owing to the influence of supporting policies. This proves that considering SDGs in policy development can be effective in conserving forest resources.

3.3. Future impact of land-use change on terrestrial ecosystem carbon pools

We calculated the changes in cultivated carbon, forest carbon stocks, and loss of carbon stocks caused by urban expansion in the nine sub-regions along the Silk Road from 2020 to 2030 for the four SDG scenarios (Fig. 5 and Table S13 online). Future impact of land-use change on terrestrial carbon pools exhibited large spatial variations in different regions. Ecosystem carbon stocks in forest and cultivated land showed a decrease in a majority of regions and a slight increase in a minority of sub-regions. Forest ecosystem carbon stocks of decreased least in the ENV scenario; total ecosystem carbon stocks decreased most in the ECO scenario along the Silk Road.

In the ECO scenario, urban expansion in CHN and OAS returned the largest carbon losses, higher than the REF scenario by approximately 25% and 38%, respectively, from 2020 to 2030. However, under the ENV scenario, the loss of carbon from forest land was much less in OAS, accounting for approximately 29% of the ECO scenario. The carbon stocks of cultivated ecosystems showed a decreasing trend, and the change trend was similar to that of the carbon loss caused by urban expansion under the ECO scenario. The forest carbon stocks in each sub-region portrayed a decreasing

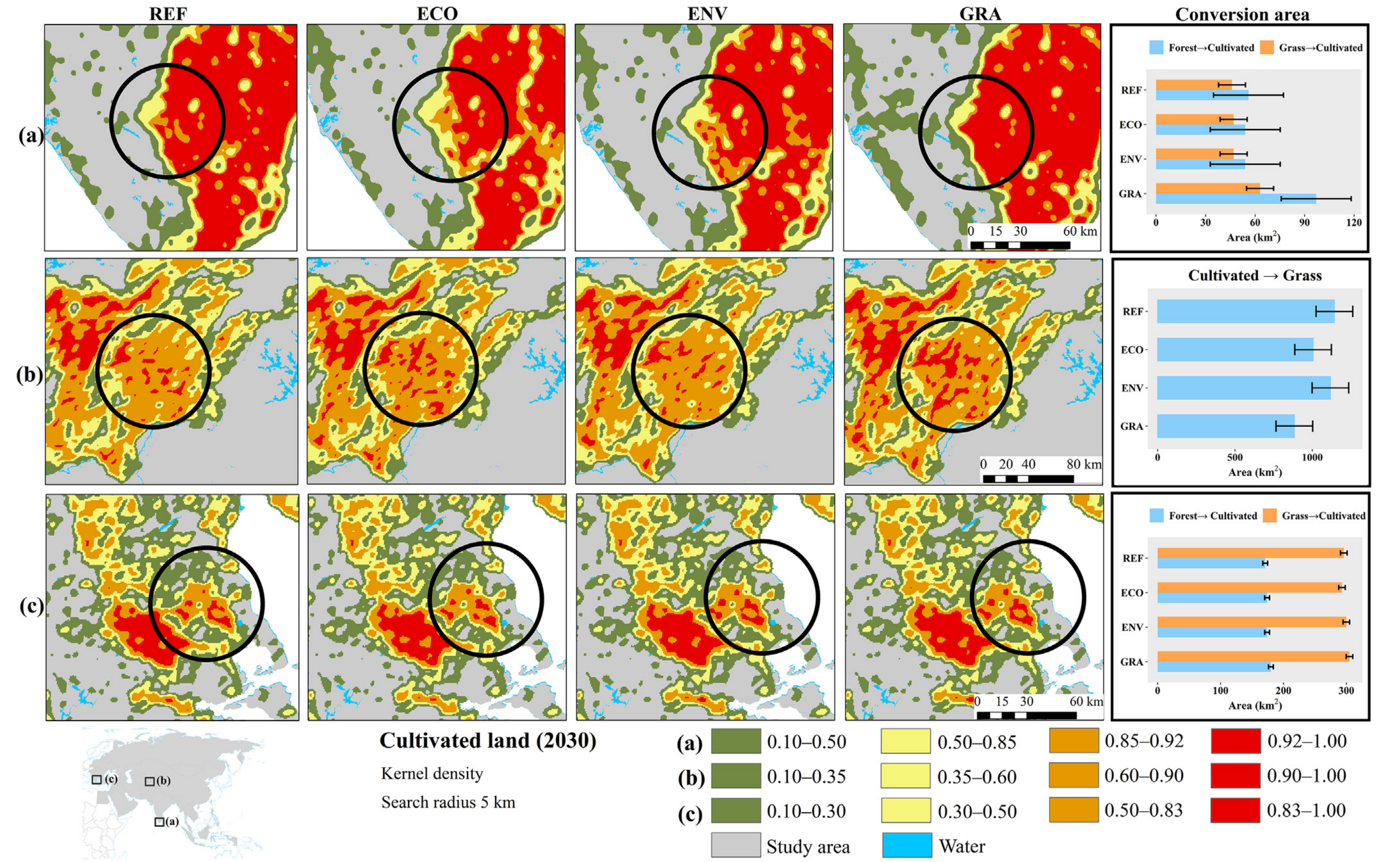


Fig. 3. Spatialisation results of cultivated land in representative regions for the four SDG scenarios. The sub-parts indicate: (a) southern part of the Deccan Plateau in India; (b) lower reaches of the Vakhsh River plain in Tajikistan; (c) Sesalia region of Greece. The bars indicate the comparison of the conversion area of cultivated land in nine regions under the four SDG scenarios. Error bars represent the standard deviation (considered as uncertainty range) among the four SDG scenarios simulated.

trend, except for the EU-M region; that in the EEU region portrayed only a slight increase. The forest carbon loss in the OAS region was higher than that in other sub-regions and larger than the carbon loss caused by urban expansion. Under the ECO scenarios, the loss of forest carbon stocks in OAS is approximately 1.19 times more than in the REF scenario (Fig. 5 and Table S13 online), from 2020 to 2030.

In the GRA scenario, the reduction in forest carbon stock and the carbon loss caused by urban expansion were slightly less than those in the ECO scenario. Under the GRA scenario, the carbon loss in forest was the largest in OAS, accounting for approximately 62% of the REF scenarios; the forest ecosystem carbon stock loss in CHN was slight, accounting for only approximately 9% of the ECO scenario. In the GRA scenario, the cultivated ecosystem carbon stock loss was significantly mitigated compared to other scenarios; the carbon stock change of cultivated land in OAS increased by approximately 1.11 times compared to in the REF scenario. In the GRA scenario, carbon stock loss of cultivated land in CHN accounted for only approximately 65% of the REF scenario.

In the ENV scenario, carbon losses from forestland and urban expansion were mitigated significantly. The forest carbon loss in OAS under the ENV scenario accounted approximately 29% under the ECO scenario. Additionally, carbon loss from forest and cultivated conversion was less than that from urban expansion. In the ENV scenario, the trend of decreasing forest land was mitigated, and forest carbon stocks in CHN increase by 0.60% in 2030 compared to 2020. Notably, in CHN, carbon loss from urban expansion was the least in the ENV scenario. In all the four SDG scenarios, we observed a small increase in forest carbon stocks, along with a small carbon loss from urban expansion, in the EU-M and EEU sub-regions.

4. Discussion

At present, OAS and CHN sub-regions are facing severe population pressure, and thus, food security is an important guarantee for sustainable development in these regions [48–50]. Compared with the reduction in other scenarios, the cultivated land area in OAS increased significantly in the GRA scenario. Reduction in the cultivated land area in CHN was effectively controlled in the GRA scenario. The urban expansion of regions intensified significantly in all the SDG scenarios and sub-regions, with the only exception being the EEU sub-region. In the future, the urban expansion rate in the EEU sub-region would be significantly lower than that in other sub-regions; this was indicated in all four scenarios. This could be due to the lower population rate in the EEU sub-regions, causing an insufficient driving force for urban expansion [51]. The urban expansion in Thailand and China's south-eastern coastal cities has transformed cultivated land and forests into urban areas. The urban expansion causes not only the reduction of forest and cultivated land, but also the loss of terrestrial carbon stocks and an increase in carbon emissions [7,8,10,12,52]. Calculated total terrestrial ecosystem carbon in China for 2020 (112.01 ± 0.06 PgC) is slightly higher than the total carbon stock predicted by studies (99.15 ± 8.71 PgC) in 2018 [53]. In this study, the calculated forest ecosystem carbon (33.56 ± 0.01 PgC) was similar to it (30.83 ± 1.57 PgC) [54]. The carbon loss due to urban expansion

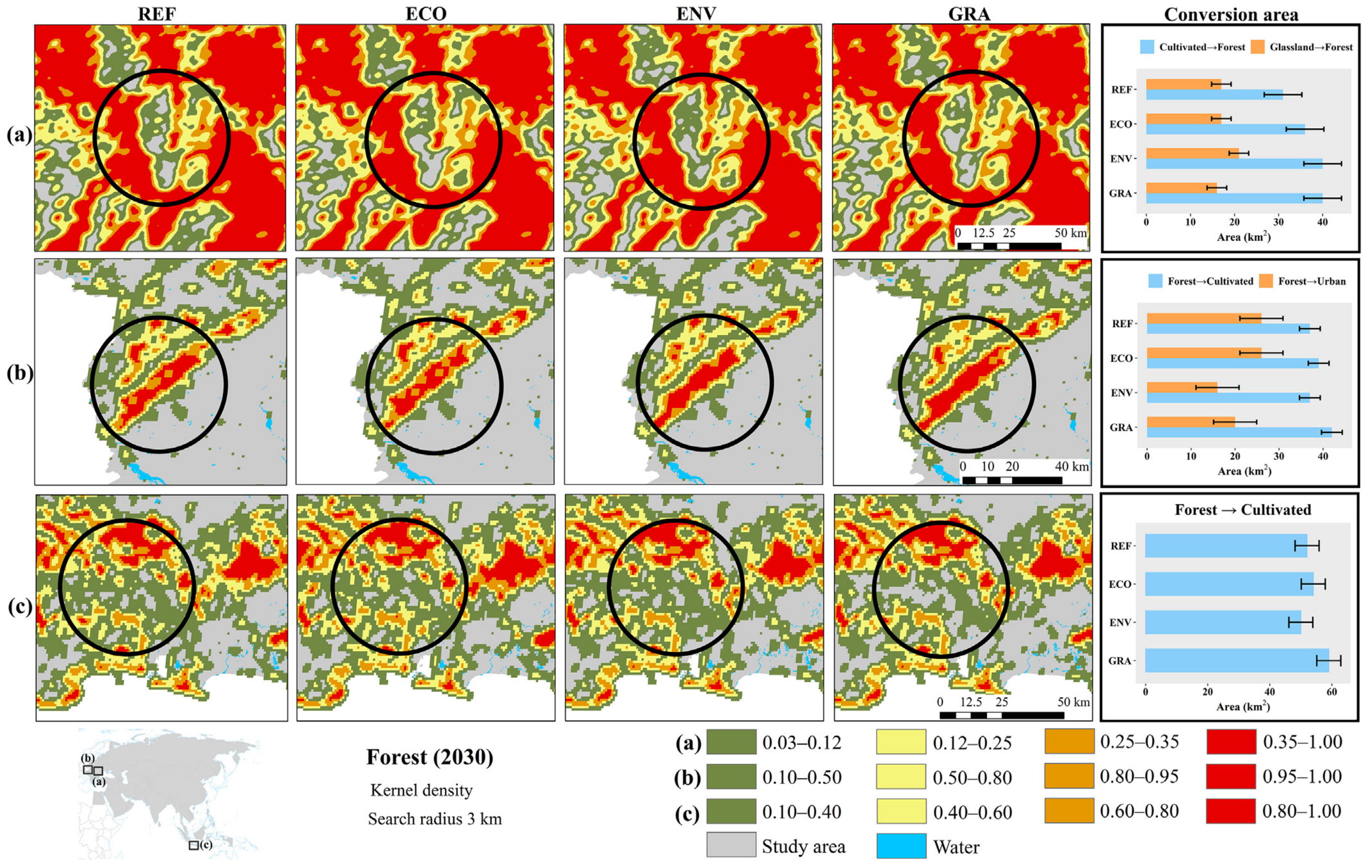


Fig. 4. Spatialisation results of forest area in representative regions for the four scenarios. The sub-parts represent: (a) Romania; (b) Slovakia; and (c) Java Island in Indonesia. The bars indicate the comparison of forest area conversion in nine regions, under four the SDG scenarios. Error bars represent the standard deviation (considered as uncertainty range) among the four SDG scenarios simulated.

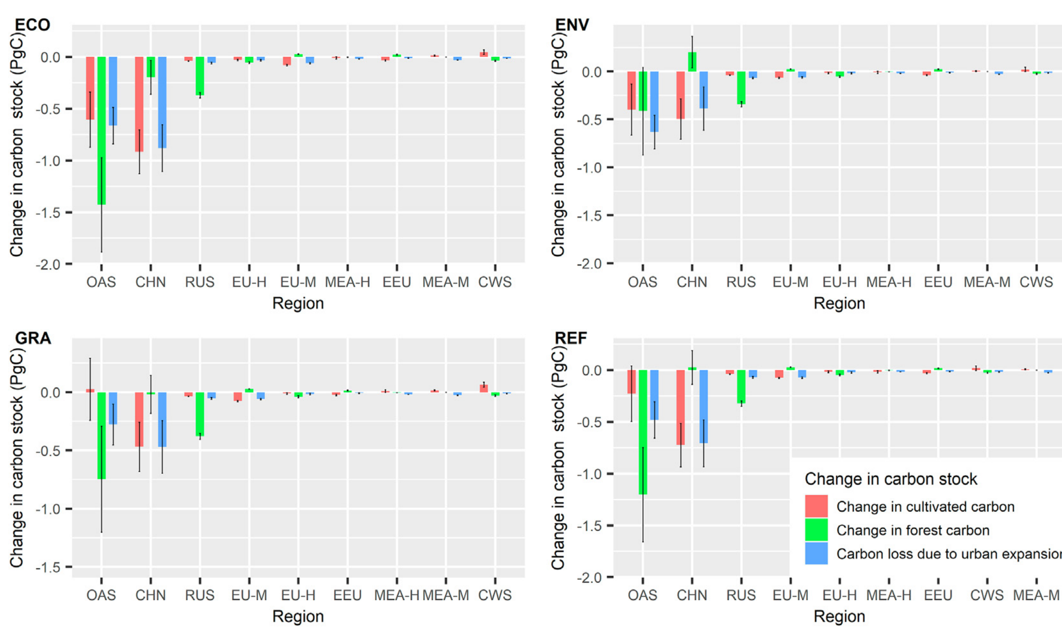


Fig. 5. Future changes in cultivated carbon, forest carbon stock, and carbon losses due to urban expansion in different regions from 2020 to 2030 for the different SDG scenarios. Error bars represent the standard deviation (considered as uncertainty range) among the four SDG scenario projections.

for China projected in this study is 0.61 ± 0.23 PgC, which is similar to the average annual carbon loss rate of 0.05 PgC a^{-1} due to urban expansion from 2000 to 2030, as predicted by previous studies [9]. Therefore, achieving multiple SDGs depends on the harmonisation of socio-economic environment, and land use and conservation.

The coordination of future urban expansion and population growth (SDG 11.3.1) is an important step towards sustainable development [9,55]. In this study, we calculated the LCRPGR in the countries along the Silk Road from 2020 to 2030 for all the SDG scenarios (Fig. 6 and Figs. S12–S15 online), which can quantify the relationship between urban expansion and population growth in different regions [3]. Generally, the closer the value of LCRPGR is to 1, the more coordinated is the population growth and urban land expansion in the region, and more sustainable is the urban development [56]. The most significant factor for regional urban expansion was observed in the ECO scenario (Fig. 6). The LCRPGR values between 0 and 1 were mainly concentrated in the coastal cities and scattered in the inland cities, indicating a relatively harmonious relationship between urban expansion and population growth in these places. The regions with an LCRPGR value <0 were mainly distributed in Europe, which indicated that there may be depopulation and urban surplus. The predicted results portrayed that the regions with LCRPGR value >2 were mainly distributed in Southeast China and Northeast India, suggesting that urban expansion in these regions may be more intensive than that in other regions.

In SDG scenarios, the future LCRPGR in different regions portrayed significant spatial heterogeneity in 2030 (Fig. 6). In the OAS and CHN sub-regions, which indicated significant urban expansion, the coordination between the urban areas and the population (0 < LCRPGR < 1) in the GRA and ENV scenarios was higher than that in the ECO and REF scenarios. This indicates that coordinated development of urban expansion and population growth requires comprehensive consideration of sustainable goals that support food security and environmental protection. Clean air and sufficient food supply are important guarantees for sustainable urban development (SDG 11) [3,9,57]. The area of LCRPGR (>0 but <1) in the GRA and ENV scenarios were larger in the ECO and REF scenarios (Fig. 6). The number of grids with LCRPGR values in the A and B regions (>0 but <1) in the GRA scenario were approximately 2.6 and 3.4 times in the ECO scenario, respectively. Additionally, in CHN, the coordination of eastern coastal cities in the urban expansion (0 < LCRPGR < 1) was higher. Among the OAS sub-regions, we observed significant differences in India, where there was higher urban expansion in the north-eastern regions of the Ganges Plain (LCRPGR > 2). Intensive urban development (0 < LCRPGR < 1) was observed in the coast of Southeast Asia. The EEU and EU-M regions portrayed an opposite trends in terms of urban expansion and population growth (LCRPGR < 0), which is mainly due to a decrease in the population growth rate (PGR) of the region from 2020 to 2030. Therefore, promoting the coordinated development of urban expansion and population growth can help countries achieve sustainable cities and communities sooner (SDG 11).

Our study has some limitations. The scenario setting is determined by the interaction between the economy, environment, and land-use aspects [6,21,22]. Considering the availability of data and the complexity of the model, we covered only a subset of the full SDG space. Despite this limitation, our results are reliable, especially regarding land demand projections, LCRPGR, urban expansion, and the impact of forest land change on terrestrial carbon pools for the four scenarios. Additionally, the detrimental effects of the COVID-19 pandemic [47,58] and wars are not yet cap-

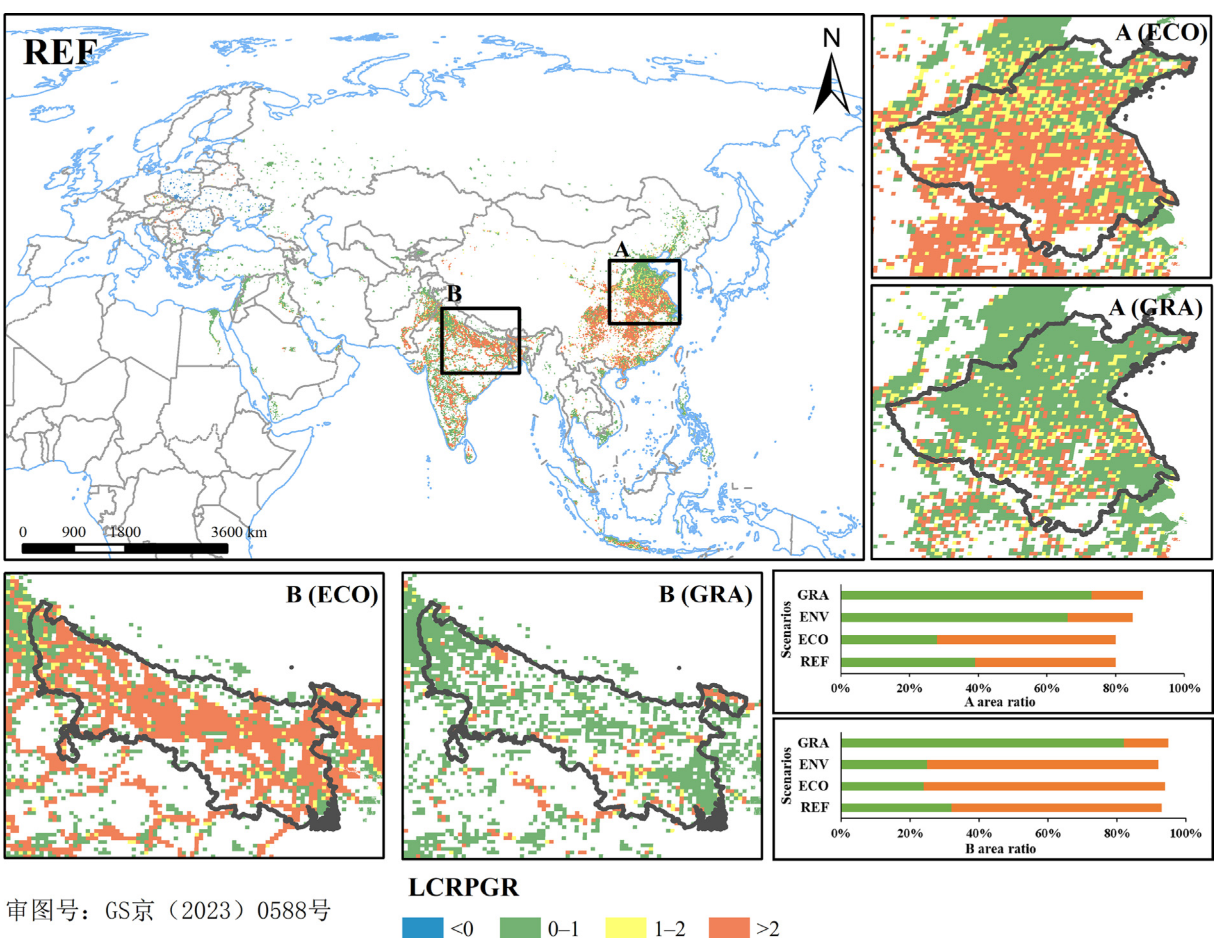


Fig. 6. Ratio of land consumption rate to population growth rate (LCRPGR) in the study area, under the ECO and GRA scenarios from 2020 to 2030. Area ratios of different grades of LCRPGR (0 < LCRPGR < 1, LCRPGR > 2) in regions of A and B, under the four SDGs scenarios: ECO, REF, ENV, and GRA. A: Henan, Anhui, Shandong, and Jiangsu provinces in China, in the ECO and GRA scenarios; B: Bihar, Jharkhand, Uttar Pradesh, and West Bengal in India, in the ECO and GRA scenarios.

tured in our modelling framework; we suppose that considering these factors, certain SDGs will take longer to attain. Hence, future studies could consider the impact of such emergencies in the model prediction process, to accurately reflect future land-use demand and the resulting changes in the terrestrial carbon stocks in SDG scenarios. Nevertheless, this study investigated the implications of projecting future land use change and impacts on terrestrial carbon stocks under different SDG scenarios. It provides new perspectives for exploring scientific pathways to sustainable development and policy development.

5. Conclusion

In this study, we proposed a new strategy to predict future land-use demand in countries along the Silk Road, while ensuring the realisation of the regional SDGs. In general, the CA–ANNs model combined different basic spatial data (topography, climate, economy, and soil), to simulate future land use by 2030. Considering the impact of economic, social, and environmental factors on land use and analysing the carbon stocks loss caused by future urban expansion and the change in carbon stocks in the comparative forest areas, we observed significant differences in the nine sub-regions in the four SDG scenarios. The sub-regions with the most significant changes in urban expansion and forest carbon stocks were RUS, CHN, and OAS. In the ENV scenario, China's forest area experienced a transition from negative growth to net increase. In the OAS sub-region, the rapid decline in the forest area was reduced in the ENV scenario. Significant spatial and temporal differences in future land use demands under the different SDG scenarios were observed. Urban expansion intensified under the economic scenario, which, however, may threaten the achievement of SDG 2, SDG 13, and SDG 15 owing to the encroachment of the cultivated land and forest land. Consequently, focusing on the achievement of one SDG target requires considering the impacts on other SDGs. Combining multiple SDGs scenarios to predict future land-use change and impacts on terrestrial carbon pools will help explore scientific pathways towards sustainable development, which will contribute to the advancement of global sustainable development processes.

Conflict of interest

The authors declare that they have no conflict of interest.

Acknowledgments

This work was supported by the International Research Center of Big Data for Sustainable Development Goals, the National Natural Science Foundation of China (42271422 and 41930648), and the Open Fund of Key Laboratory of Urban Land Resources Monitoring and Simulation, Ministry of Natural Resources (KF-2020-05-025).

Author contributions

Min Cao and Min Chen designed the study. Ya Tian, Kai Wu, and Xue Hu performed experiments and computational analysis. Min Cao, Ya Tian, and Kai Wu drafted the manuscript. Guonian Lü, Huadong Guo, and Hui Lin supervised the project. All authors discussed the results and provided revisions on the manuscript.

Appendix A. Supplementary materials

Supplementary materials to this article can be found online at https://doi.org/10.1016/j.scib.2023.03.012.

References

[1] Wu X, Fu B, Wang S, et al. Decoupling of SDGs followed by re-coupling as sustainable development progresses. Nat Sustain 2022;5:452–9.
[2] Fujimori S, Hasegawa T, Krey V, et al. A multi-model assessment of food security implications of climate change mitigation. Nat Sustain 2019;2:386–96.
[3] United Nations. Global indicator framework for the sustainable development goals and targets of the 2030 agenda for sustainable development. New York: United Nations; 2017.
[4] United Nations. Transforming our world: the 2030 agenda for sustainable development. New York: United Nations; 2015.
[5] Liu X, Huang Y, Xu X, et al. High-spatiotemporal-resolution mapping of global urban change from 1985 to 2015. Nat Sustain 2020;3:564–70.
[6] Li X, Chen G, Liu X, et al. A new global land-use and land-cover change product at a 1-km resolution for 2010 to 2100 based on human–environment interactions. Ann Am Assoc Geogr 2017;107:1040–59.
[7] Harper AB, Powell T, Cox PM, et al. Land-use emissions play a critical role in land-based mitigation for Paris climate targets. Nat Commun 2018;9:2938.
[8] Foley JA, DeFries R, Asner GP, et al. Global consequences of land use. Science 2005;309:570–4.
[9] Seto KC, Güneralp B, Hutyra LR. Global forecasts of urban expansion to 2030 and direct impacts on biodiversity and carbon pools. Proc Natl Acad Sci USA 2012;109:16083–8.
[10] Yue C, Ciais P, Houghton RA, et al. Contribution of land use to the interannual variability of the land carbon cycle. Nat Commun 2020;11:3170.
[11] Hopkins FM, Ehleringer JR, Bush SE, et al. Mitigation of methane emissions in cities: how new measurements and partnerships can contribute to emissions reduction strategies. Earth Future 2016;4:408–25.
[12] Liu X, Pei F, Wen Y, et al. Global urban expansion offsets climate-driven increases in terrestrial net primary productivity. Nat Commun 2019;10:5558.
[13] Chen G, Li X, Liu X, et al. Global projections of future urban land expansion under shared socioeconomic pathways. Nat Commun 2020;11:537.
[14] Chen M, Lü G, Zhou C, et al. Geographic modeling and simulation systems for geographic research in the new era: some thoughts on their development and construction. Sci China Earth Sci 2021;64:1207–23.
[15] Sohl TL, Sleeter BM, Sayler KL, et al. Spatially explicit land-use and land-cover scenarios for the Great Plains of the United States. Agric Ecosyst Environ 2012;153:1–15.
[16] Marcotullio PJ, Keßler C, Fekete BM. The future urban heat-wave challenge in Africa: exploratory analysis. Glob Environ Chang 2021;66:102190.
[17] Riahi K, van Vuuren DP, Kriegler E, et al. The shared socioeconomic pathways and their energy, land use, and greenhouse gas emissions implications: an overview. Glob Environ Chang 2017;42:153–68.
[18] Popp A, Calvin K, Fujimori S, et al. Land-use futures in the shared socio-economic pathways. Glob Environ Chang 2017;42:331–45.
[19] Liao W, Liu X, Xu X, et al. Projections of land use changes under the plant functional type classification in different SSP-RCP scenarios in China. Sci Bull 2020;65:1935–47.
[20] Dong N, You L, Cai W, et al. Land use projections in China under global socioeconomic and emission scenarios: utilizing a scenario-based land-use change assessment framework. Glob Environ Chang 2018;50:164–77.
[21] Sohl TL, Wimberly MC, Radeloff VC, et al. Divergent projections of future land use in the United States arising from different models and scenarios. Ecol Modell 2016;337:281–97.
[22] Li X, Yu L, Sohl T, et al. A cellular automata downscaling based 1 km global land use datasets (2010–2100). Sci Bull 2016;61:1651–61.
[23] Ge Y, Li X, Cheng G, et al. What dominates sustainability in endorheic regions? Sci Bull 2022;67:1636–40.
[24] Swain RB, Ranganathan S. Modeling interlinkages between sustainable development goals using network analysis. World Dev 2021;138:105136.
[25] Zhu J, Sun X, He Z. Research on China's sustainable development evaluation indicators in the framework of SDGs. China Popul Resour Environ 2018;28:9–18 (in Chinese).
[26] Xu Z, Chau SN, Chen X, et al. Assessing progress towards sustainable development over space and time. Nature 2020;577:74–8.
[27] Wei Y, Li X, Gao F, et al. The United Nations sustainable development goals (SDG) and the Response Strategies of China. J Earth Sci 2018;33:1084–93.
[28] Costanza R, Daly L, Fioramonti L, et al. Modelling and measuring sustainable wellbeing in connection with the UN sustainable development goals. Ecol Econ 2016;130:350–5.
[29] Chen J, Peng S, Zhao XS, et al. Measuring regional progress towards SDGs by combining geospatial and statistical information. Acta Geod Cartogr Sin 2019;48:473.
[30] Allen C, Metternicht G, Wiedmann T. National pathways to the sustainable development goals (SDGs): a comparative review of scenario modelling tools. Environ Sci Policy 2016;66:199–207.
[31] Weitz N, Carlsen H, Nilsson M, et al. Towards systemic and contextual priority setting for implementing the 2030 agenda. Sustain Sci 2018;13:531–48.
[32] Nilsson M, Chisholm E, Griggs D, et al. Mapping interactions between the sustainable development goals: lessons learned and ways forward. Sustain Sci 2018;13:1489–503.
[33] Nilsson M, Griggs D, Visbeck M. Policy: map the interactions between Sustainable Development Goals. Nature 2016;534:320–2.

[34] Warchold A, Pradhan P, Kropp JP. Variations in sustainable development goal interactions: population, regional, and income disaggregation. Sustain Dev 2021;29:285–99.
[35] Pradhan P, Costa L, Rybski D, et al. A systematic study of sustainable development goal (SDG) interactions. Earth Future 2017;5:1169–79.
[36] Guo B, Fan Y, Yang F, et al. Quantitative assessment model of ecological vulnerability of the Silk Road Economic Belt, China, utilizing remote sensing based on the partition–integration concept. Geomat Nat Hazards Risk 2019;10:1346–66.
[37] Guo H, Liang D, Sun Z, et al. Measuring and evaluating SDG indicators with Big Earth Data. Sci Bull 2022;67:1792–801.
[38] Nicolau R, David J, Caetano M, et al. Ratio of land consumption rate to population growth rate-analysis of different formulations applied to mainland Portugal. ISPRS Int J Geo-Inf 2019;8:10.
[39] Tian H, Liang X, Li X, et al. Simulating multiple land use scenarios in China during 2010–2050 based on system dynamic model. Trop Geogr 2017;37:547–61.
[40] Chen M, Voinov A, Ames DP, et al. Position paper: open web-distributed integrated geographic modelling and simulation to enable broader participation and applications. Earth-Sci Rev 2020;207:103223.
[41] Lauf S, Haase D, Hostert P, et al. Uncovering land-use dynamics driven by human decision-making—a combined model approach using cellular automata and system dynamics. Environ Model Softw 2012;27-28:71–82.
[42] Gu C, Guan W, Liu H. Chinese urbanization 2050: SD modeling and process simulation. Sci China Earth Sci 2017;60:1067–82.
[43] Cao M, Zhu Y, Quan J, et al. Spatial sequential modeling and predication of global land use and land cover changes by integrating a global change assessment model and cellular automata. Earth Future 2019;7:1102–16.
[44] Babbar D, Areendran G, Sahana M, et al. Assessment and prediction of carbon sequestration using Markov chain and InVEST model in Sariska Tiger Reserve. India J Clean Prod 2021;278:123333.
[45] Friedlingstein P, Jones MW, O'Sullivan M, et al. Global carbon budget 2021. Earth Syst Sci Data 2022;14:1917–2005.
[46] Di Gregorio A, Fao R. Land cover classification system: advanced database gateway. Software Version 3. 2016.
[47] Sachs J, Schmidt-Traub G, Kroll C, et al. The sustainable development goals and COVID-19. Sustainable Development Report 2020. Cambridge: Cambridge University Press; 2020.
[48] Otsuka K. Food insecurity, income inequality, and the changing comparative advantage in world agriculture. Agric Econ 2013;44:7–18.
[49] Ghose B. Food security and food self-sufficiency in China: from past to 2050. Food Energy Secur 2014;3:86–95.
[50] Potapov P, Turubanova S, Hansen MC, et al. Global maps of cropland extent and change show accelerated cropland expansion in the twenty-first century. Nat Food 2022;3:19–28.
[51] Ourng C, Vaguet Y, Derkacheva A. Spatio-temporal urban growth pattern in the arctic: a case study in Surgut, Russia. In: Joint Urban Remote Sensing Event (JURSE). New York: IEEE; 2019. p. 1–4.
[52] Huang K, Li X, Liu X, et al. Projecting global urban land expansion and heat island intensification through 2050. Environ Res Lett 2019;14:114037.
[53] Xu L, Yu G, He N, et al. Carbon storage in China's terrestrial ecosystems: a synthesis. Sci Rep 2018;8:2806.
[54] Tang X, Zhao X, Bai Y, et al. Carbon pools in China's terrestrial ecosystems: new estimates based on an intensive field survey. Proc Natl Acad Sci USA 2018;115:4021–6.
[55] Seto KC, Sánchez-Rodríguez R, Fragkias M. The new geography of contemporary urbanization and the environment. Annu Rev Environ Resour 2010;35:167–94.
[56] Guo H, Liang D, Chen F, et al. Innovative approaches to the sustainable development goals using Big Earth Data. Big Earth Data 2021;5:263–76.
[57] Grimm NB, Faeth SH, Golubiewski NE, et al. Global change and the ecology of cities. Science 2008;319:756–60.
[58] Naidoo R, Fisher B. Sustainable Development Goals: pandemic reset. Nature 2020;583:198–201.

Min Cao is a professor at the School of Geography, Nanjing Normal University. Her research interest focuses on sustainable development goals multi-indicator interactions and their spatial-temporal differences, geographic intelligence modeling, etc. She has written the sustainable development cases that have twice been selected in the "Big Earth Data in Support of the Sustainable Development Goals (2021, 2022)".

Min Chen is a professor at the School of Geography, Nanjing Normal University. His research interest includes geographic modeling and simulation and virtual geographic environments. He leads the team at Nanjing Normal University to develop the open geographic modeling and simulation platform (OpenGMS), which allows geographic models to be widely shared as services and further integrated for comprehensive geosystem problem exploration.

Guonian Lü is a professor at the School of Geography, Nanjing Normal University. He is the director of Key Laboratory of Virtual Geographic Environment, Ministry of Education, Nanjing Normal University. His research interest includes geographic information science and virtual geographic environments.