communications earth & environment

Article

https://doi.org/10.1038/s43247-024-01641-y

Social-ecological heterogeneity drove contrasting tree cover restoration in South China Karst

Tao Hu[1], Jian Peng[1] ✉, Sijing Qiu[1,2], Jianquan Dong[3], Yi'na Hu[4], Yifan Lin[1] & Pei Xia[1]

South China Karst is the world's largest continuous karst zone and is becoming the hotspot of greening earth. However, the greening sustainability remains uncertain due to challenges from carbonate geological constraints and oversights in recognizing synergies within social-ecological systems. Here, the sustainability and drivers of tree cover restoration were quantitatively investigated in South China Karst. The area with tree cover increasing was 652,457 km^2, about 33.67% of the study area. There were differences in ecological elements between karst and non-karst areas, and rural population decrease in undeveloped areas could greatly promote tree cover restoration. Moreover, the correlation degree of social-ecological network in karst area was obviously lower than that in non-karst area, indicating higher heterogeneity of social-ecological system in karst area. This study highlights the social-ecological effects on tree cover restoration in karst area, and a shift in focus from the natural ecosystem to coupled social-ecological systems is crucial for sustainable forest management.

Human demand for natural resources is rising since population growth and economic development, which leads to major issues such as resource scarcity, ecological degradation, and biodiversity loss[1–3]. Since 1990, due to the combined effects of climate change and human activities, the global net loss of forest area has reached 178 million hectares[4]. In recent years, a series of policy initiatives aimed at reducing deforestation and enhancing tree cover restoration have been widely promoted to reverse ecological degradation and increase vegetation's ability to store carbon[5,6]. Tree cover restoration involves intricate processes between society and the ecosystem[7,8], and a thorough analysis can give the scientific foundation for forest management.

Currently, researches on tree cover restoration primarily focused on assessing spatial patterns of forest change[9,10] and analyzing the driving factors[11,12]. The terrestrial ecosystem model demonstrated that in addition to the enhancement effect of environmental factors on vegetation growth, human activities such as urbanization were leading to the earth's greening[13]. Recently, many studies have explored the factors affecting tree cover restoration. The environmental factors were recommended as the primary driving factors of vegetation growth[12–14]. For example, water and soil properties have an impact on vegetation[15,16]. Soil nutrient content was a limiting factor for plant physiology, and has been proven to be related to the photosynthetic rate[17]. Additionally, it has been suggested that socio-economic factors also have varying effects on vegetation greening. Some studies proved that socio-economic growth would have a negative effect on vegetation greening, while recent studies also recommended that socio-economic development would promote vegetation greening due to the construction of green infrastructure and reduction of negative human interference[18–20]. The social-ecological system promotes a comprehensive assessment of social systems and ecosystems at a holistic level[21,22], which is potential for identifying the factors of tree cover restoration[23,24]. To date, there is no knowledge on the drivers of tree cover restoration based on the perspective of coupled social-ecological system, and the socio-economic effect on tree cover restoration remains uncertain.

As the world's largest continuous karst zone, South China Karst covers ~1.9 million km^2 and hosts over 220 million people, plagued by increased exploitation of natural resources and land degradation[25] (Supplementary Fig. 1). Characterized by vegetation degradation and exposed rock, this region is regarded as the main ecologically fragile area in China[2,26]. Affected by the slow speed of soil formation and thin soil layer in karst landforms, the vegetation in this region is sparse. Under these circumstances, the rapid vegetation growth in South China Karst over the past two decades has attracted the attention of the world. The mechanism

[1]Technology Innovation Center for Integrated Ecosystem Restoration and Sustainable Utilization, Ministry of Natural Resources, College of Urban and Environmental Sciences, Peking University, Beijing, 100871, China. [2]The High School Affiliated to Renmin University of China, Beijing, 100000, China. [3]College of Landscape Architecture, Beijing Forestry University, Beijing, 100091, China. [4]School of Environmental and Geographical Sciences, Shanghai Normal University, Shanghai, 200234, China. ✉e-mail: jianpeng@urban.pku.edu.cn

of tree cover restoration in this region was complicated, involving ecological engineering, urbanization as well as environmental factors[13,15,16]. There are karst and non-karst counties in South China Karst, where the lithology and economic development are different, which may lead to diverse impacts on tree cover restoration in karst and non-karst area, yet have not been fully explored. Understanding the social-ecological driving forces in this region, especially in terms of the contrast between karst and non-karst areas, is necessary for tree cover restoration, and provides a way for the coordinated eco-socio-economic development of ecologically fragile areas around the world[27,28].

Based on the satellite-based socio-economic and ecological datasets, we explored the forest land change in South China Karst and analyzed the social-ecological factors' impacts on tree cover restoration in karst and non-karst area. Here, we investigated and reported on (1) tree cover restoration in South China Karst from 2000 to 2020; (2) the difference in social-ecological factors between karst area (KA) and non-karst area (NKA); and (3) the contrast of social-ecological factors' impact on tree cover restoration between KA and NKA. Here we demonstrated that the slope of tree cover proportion change in KA (0.50) was higher than that of NKA (0.36) from 2000 to 2020. Rural population decrease promoted tree cover restoration in undeveloped counties. The correlation degree of the social-ecological network in KA was lower (47/78) than that in NKA (62/78), showing the social-ecological systems in karst areas were more heterogeneous.

Results

Tree cover restoration contrast in karst and non-karst area

There were 880,951 km^2 of forest land with no land use change from 2000 to 2020, accounting for 45.46 % of the study area (Fig. 1a). Among them, the area was 627,887 km^2 in NKA, which was 2.48 times of that in KA (253,064 km^2) (Fig. 1b). Moreover, it was found that the area of increased forest land in South China Karst was 77,635 km^2, with the area of 53,797 km^2 in NKA and 23,838 km^2 in KA. The forest land increasing proportion was high in counties in the northeastern and southwestern regions, while it was relatively low in the northwestern region (Supplementary Fig. 2a). The median of forest land increasing proportion in undeveloped counties (3.96%) was higher than that in developed counties (3.28%) (Supplementary Fig. 2b). A total of 47.86% of forest land increased area was converted from grassland and 40.15% was converted from cropland (Supplementary Fig. 3). The area of cropland and grassland converted to forest land in KA were 9817 km^2 and 11,258 km^2, while that in NKA were 21,352 km^2 and 25,897 km^2, respectively. It was worth noting that tree cover proportion increased in KA and NKA in the past two decades (Fig. 1c). The slope of tree cover proportion change in KA (0.50) was higher than that of NKA (0.36) from 2000 to 2020 (Fig. 1d). Tree cover proportion in NKA and KA was 27.54% and 27.07% in 2000, and 33.94% and 35.74% in 2020, respectively. The area with tree cover increasing was 652,457 km^2, and counties in the southwestern, southeastern, and northern regions showed a trend of tree cover increasing (Supplementary Fig. 2c). The median of tree cover trend in

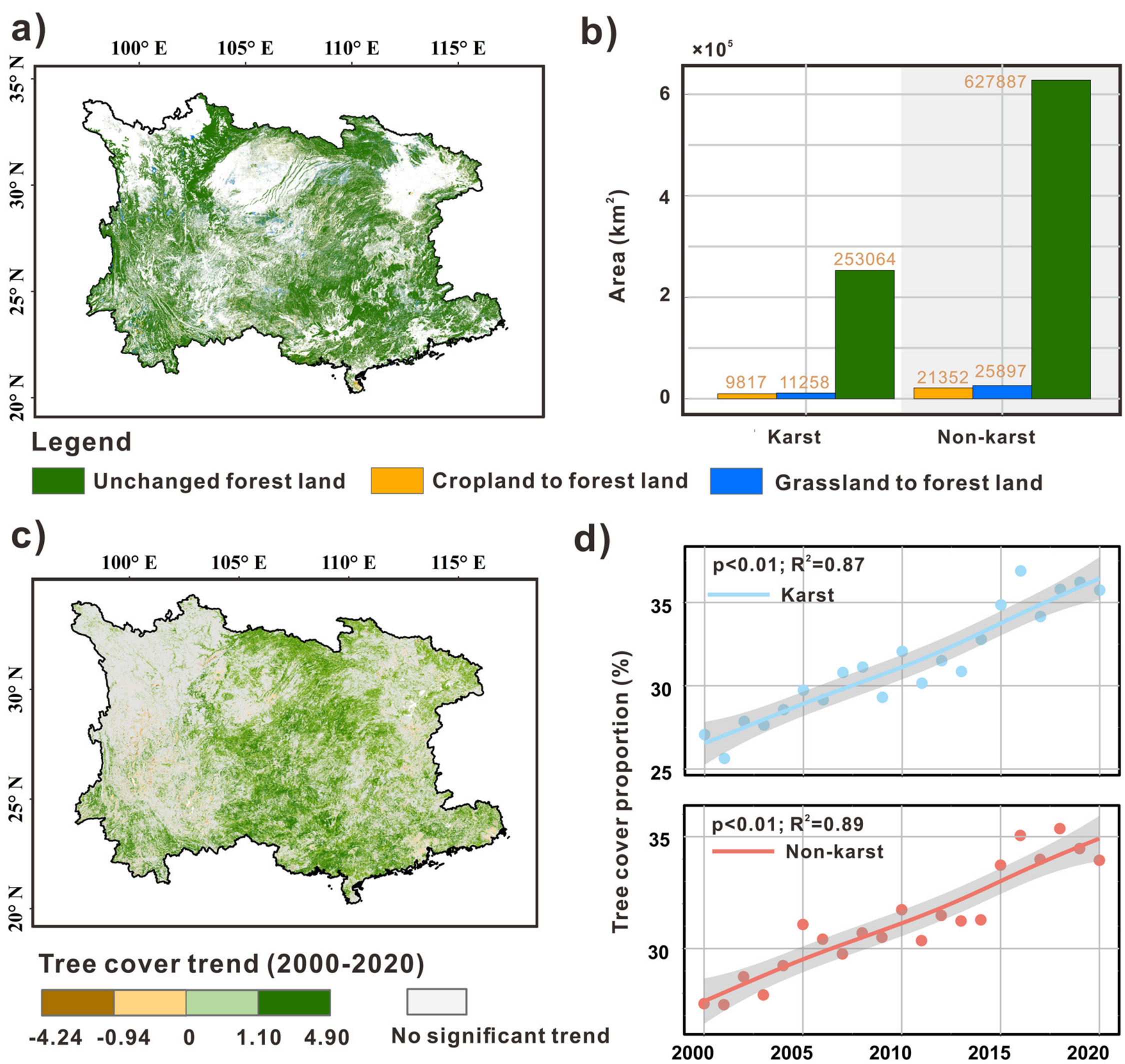

Fig. 1 | Spatial pattern and statistics of forest land change. **a** Forest land changes; **b** area of forest land changes; **c** tree cover trend from 2000 to 2020; and **d** tree cover trend in karst area and non-karst area.

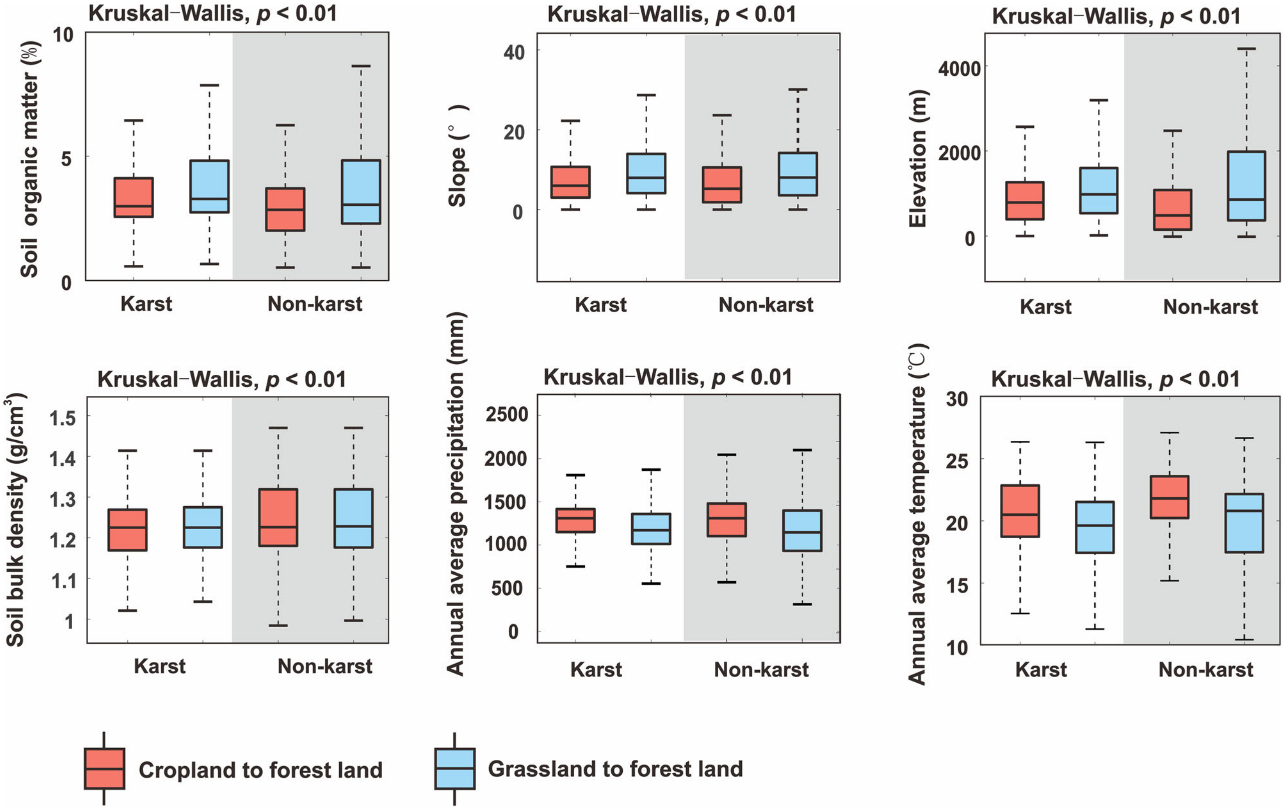

Fig. 2 | Comparisons among ecological factors in the forest land change area between karst area and non-karst area. $p < 0.01$ means there were differences between groups.

undeveloped counties was higher than that in developed counties (Supplementary Fig. 2d).

Difference of ecological factors between karst and non-karst areas

For soil status, spatial pattern of soil organic matter showed a characteristic of being high in the northwestern region and low in other regions, with the average values of 3.92% and 4.04% in karst and non-karst areas, respectively (Supplementary Fig. 4). The soil bulk density showed a feature of being high in the northern and eastern regions, and low in the central and northwestern regions, with the average values of 1.23 g/cm^3 and 1.24 g/cm^3 in karst and non-karst areas, respectively. The average values for slope and elevation were 9.50° and 1247 m in karst area, with 8.74° and 1319 m in non-karst area, respectively. Spatial distributions of annual average precipitation and temperature were similar, showing a spatial pattern of high values in the southwestern and southeastern regions, and low values in the northwestern region, with the average value of 1187 mm and 15.19 °C in karst area, and 1185 mm and 14.76 °C in non-karst area.

The result of the Kruskal-Wallis test showed that there were differences in ecological factors of different forest land change areas between KA and NKA (Fig. 2). For soil factors, we found that the median of soil organic matter in the area of cropland to forest land in KA were 2.99%, which were lower than that of grassland to forest land in KA (3.28%). The value in NKA was 2.84%, which were also lower than that of grassland to forest land in NKA (3.05%). The median of soil bulk density of different forest land change areas was the same between KA and NKA, with 1.22 g/cm^3 in KA and 1.23 g/cm^3 in NKA, respectively. The soil organic matter of the forest land change area in NKA were slightly lower than that of KA. For topographic factors, the median of elevation and slope in the area of cropland to forest land in KA (789 m and 5.98°) and NKA (485 m and 5.22°) were lower than that in the area of grassland to forest land in KA (980 m and 7.95°) and NKA (857 m and 8.02°). The elevation and slope of the forest land change area in KA were higher than those in NKA. Besides, the median of annual average precipitation and temperature in the area of cropland to forest land in KA (1310 mm and 20.49 °C) and NKA (1310 m and 21.80 °C) were higher than that in the area of grassland to forest land in KA (1171 mm and 19.62 °C) and NKA (1146 mm and 20.80 °C).

To further explore the mechanism of the ecological factors' impact on forest land in different karst area, we extracted limestone and dolomite area. In general, the area of limestone area (100,300 km^2) was larger than that of dolomite area (36,900 km^2). The area of forest land increased by 4771 km^2 and 1914 km^2 in limestone and dolomite areas in the past two decades, respectively (Supplementary Fig. 5). There were obvious differences in soil bulk density between the two forest land change ways in limestone and dolomite areas (Supplementary Fig. 6). In addition, we compared the differences in annual temperature and precipitation, and the results showed that compared to limestone areas, the temperature was a little higher, and the precipitation was obviously lower in the dolomite areas[28].

Difference of socio-economic factors between karst and non-karst areas

Taking economic level and rural population into account, the counties were split into four groups: developed and undeveloped counties with rural population decrease and increase (Fig. 3a). 67.13% of counties had a net decrease of the rural population, including 144 karst counties and 342 non-karst counties during the past two decades (Fig. 3b). Among them, 56.25% of karst counties and 48.54% of non-karst counties showed a coexistence of poverty and rural population decrease. The developed counties with rural population decrease were mainly concentrated near urban agglomeration. In contrast, undeveloped counties with rural population decrease were mainly concentrated in KA in Hunan, Hubei, Guangxi, and Sichuan provinces, where the climatic condition was suitable for vegetation growth, with the precipitation of more than 1100 mm. There were 238 counties with

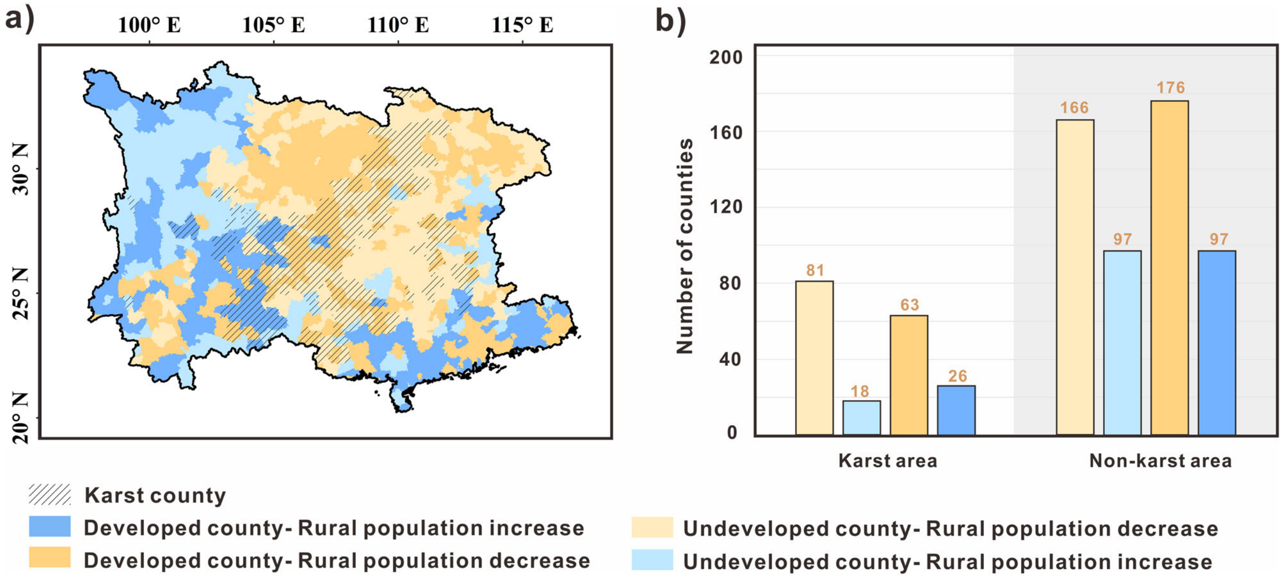

Fig. 3 | Spatial pattern and statistics of socio-economic factors. **a** Spatial pattern of socio-economic factors; **b** statistics of socio-economic factors in karst and non-karst areas. The number of counties was marked in the bar chart.

a net rural population increase, including 44 karst counties and 194 non-karst counties, and 51.68% counties were developed counties.

The impact of the rural population on forest land change was also closely related to the economic development mode, and the correlation between economic development and rural population change was significantly negative ($R = -0.5$, Fig. 4). There tended to be a larger area dedicated to returning cropland to forest land in undeveloped counties with rural population decrease, while in counties with rural population increase, a larger area dedicated to returning grassland to forest land could be observed. The area of increased forest land was large in undeveloped counties with rural population decrease, with tree cover proportion increasing in 43.93% of the area (Supplementary Fig. 7). It indicated that rural population decrease in undeveloped areas could greatly promote forest land increasing[16].

Comparison of social-ecological factors' impact on tree cover between karst and non-karst areas

Tree cover proportion was associated with a variety of social-ecological factors, including human influence, climate factors, land use factors, soil status, and topographic factors (Fig. 5). It was found that tree cover proportion was positively correlated with soil organic matter and slope, and was negatively correlated with cropland proportion, rural population and economic development in both KA and NKA. However, it was worth noting that tree cover proportion was correlated with temperature ($R = -0.33$) in KA, but not correlated in NKA. Besides, soil bulk density ($R = -0.16$), elevation ($R = 0.18$) and village density ($R = -0.32$) were obviously correlated to tree cover proportion in NKA, but not in KA.

According to the relationships among the variables mentioned above, the correlation degree of the social-ecological network in KA (47/78) was lower than that in NKA (62/78) (Fig. 5a, b), showing that the social-ecological systems in karst areas were more heterogeneous. Furthermore, the correlation degree of social-ecological factors in NKA was higher than that in KA (Fig. 5c). Among them, the correlation degree of soil organic matter, slope, village density, and elevation was the highest in the NKA, which were connected to all the other social-ecological factors. In KA, the correlation degree of forest land proportion was 11, which was higher than the other factors, with soil bulk density for the lowest. According to the results of synergy networks, the slope and soil organic matter in NKA had the greatest impact on the synergistic improvement among the social-ecological factors, while the forest land proportion contributed most on the synergy networks in KA (Fig. 5d). In terms of trade-off networks, it was worth noting that the cropland proportion and slope in both KA and NKA had great effect on the social-ecological networks (Fig. 5e).

Discussion

The social-ecological system enhances comprehension of the relationship between humans and nature through an integrated perspective[29,30]. Tree cover restoration involves different stakeholders, and social-ecological factors[31,32]. To give forest land management a scientific foundation, the mechanism of forest land change must be investigated from a social-ecological perspective.

As for ecological factors, soil status, topographic factors, and climate factors of forest land change area were explored in both KA and NKA. It was found that the soil organic matter in NKA were greater than that in KA (Supplementary Fig. 4). Since carbonate rock made up most of the KA, the rate of soil formation was sluggish and the soil cover was thin[33]. The vegetation can only absorb nutrients and water from the barren topsoil layer, which makes it hard to support the vegetation growth[34,35]. Ecological engineering will be carried out in areas where the ecological environment of KA is suitable for the survival of forest[36]. While in NKA, the land unsuitable for growing crops was returned to forest land[10], and thus the soil organic matter of forest land change area in NKA was always low. In terms of topography, the elevation and slope of the forest land change area in KA were greater than that of NKA, indicating the characteristics of strong fluctuation of the bedrock surface[37]. The ways of forest land change were impacted by the slope. In regions with low elevation and gentle slope, the new forest land was primarily converted from cropland, whereas in areas with high altitude and steep slopes, the new forest land was primarily converted from grassland. There were regular droughts despite sufficient precipitation in the KA because of the soil's low capacity to hold water and its quick evaporation[9,38].

The effect of rural population increase and decrease on regional greening was discussed in this study. Area with rural population decrease was primarily centered around urbanized areas (Fig. 3). It was worth noting that the area of cropland and grassland to forest land in developed counties with rural population decrease was smaller (Fig. 4). Although surrounding rural population from these areas have been drawn to the city to work, the cropland and an aspect of the agricultural livelihood have remained[39]. The rural population who lives close to the provincial capital or popular tourist destinations could go to the city for work and come home to work on their farms during the busy farming

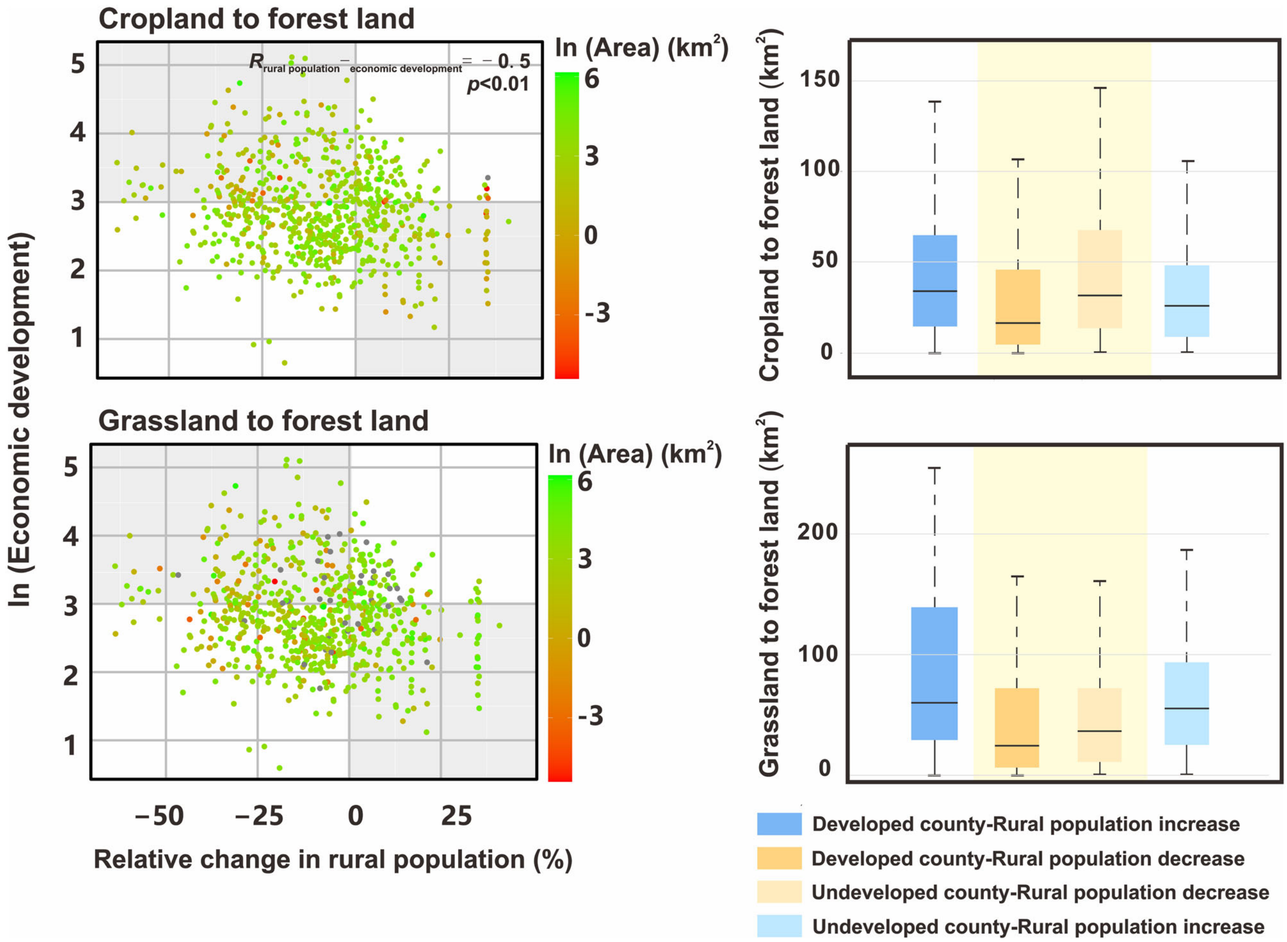

Fig. 4 | Relationships between forest land change and changes in rural population and economic development. The population change is the ratio change of rural population and total population within the county, indicating the change magnitude of rural population; and economic development is divided into two groups with the median value of night light density (DN = 17.6).

season, then affects the forest land change[16] (Supplementary Fig. 7). The area of cropland to forest land in undeveloped county with rural population decrease was relatively large, and the possible reason was that a large number of rural farmers go out to work, leading to relatively more cropland abandonment. Moreover, many of these areas were mountainous, with relatively poor farming conditions[39].

The erosion of limestone leads to the formation of underground fissures and pipes, which creates an environment where vegetation roots can absorb water and grow[40,41]. For dolomite areas, the dissolution mainly occurs in the topsoil layer and the soil thickness is thin, which is hard to support the vegetation growth[34,42]. Therefore, forest land change in limestone areas was often considered to be more effective[43]. In areas with a high proportion of karst landforms, the high cropland proportion and rural population density, would create a hidden risk for ecological degradation and slow economic growth. To restore the tree cover in these areas and enhance the resilience of natural ecosystems, it is vital to focus on forestation in the sloping farmland of NKA and the gentle slope area (compared with the steep slope area) of KA. Besides, we should pay more attentions to local characteristics while designing tree cover restoration projects in KA. We also discovered that both rural population decrease and economic development could affect tree cover restoration, especially in KA. The main approach of tree cover restoration in KA was to reduce farming and encourage rural population to transition to urban areas for jobs[39]. Developing regional economies, directing farmers' livelihood transformation, and promoting a change in the way of life of rural residents, are all essential ways for tree cover restoration[44].

Data and methods

Forest land change analysis

The Grain for Green Program was started in 2002 in South China Karst. It was aimed to return cropland to forest land and planted forest and grass on barren land. This program was designed to prevent land degradation and protect downstream ecosystems[38]. The forest land in 2000 and 2020 was extracted from GlobeLand30 products, with a spatial resolution of 30 m[45]. As an essential vegetation structure parameter[46], tree cover data was derived from the Terra MODIS Vegetation Continuous Fields (VCF) product (MOD44B v061) with a spatial resolution of 250 m. The VCF product provided a continuous and quantitative portrayal of land surface cover with improved spatial details, which was widely used in forest monitoring[47,48].

Social-ecological factors

We used several variables, including human influence, land use factors, topographic factors, soil status, and climate factors to evaluate the impact of socio-economic and ecological factors on forest land change.

For soil status, soil aeration and water transport capacity are affected by the soil bulk density, which in turn affects vegetation growth[49]. In addition, soil organic matter is an important limiting factor for plant physiology and has been experimentally proven to be related to the photosynthetic rate of plants[50]. Thus, we used the product from the National Science Qinghai Tibet Plateau Data Center, including soil bulk density as well as soil organic matter as soil factors.

For human influence, we chose the rural population, economic development and village density. These three factors are the main measurement factors reflecting social and economic changes and have been widely used as

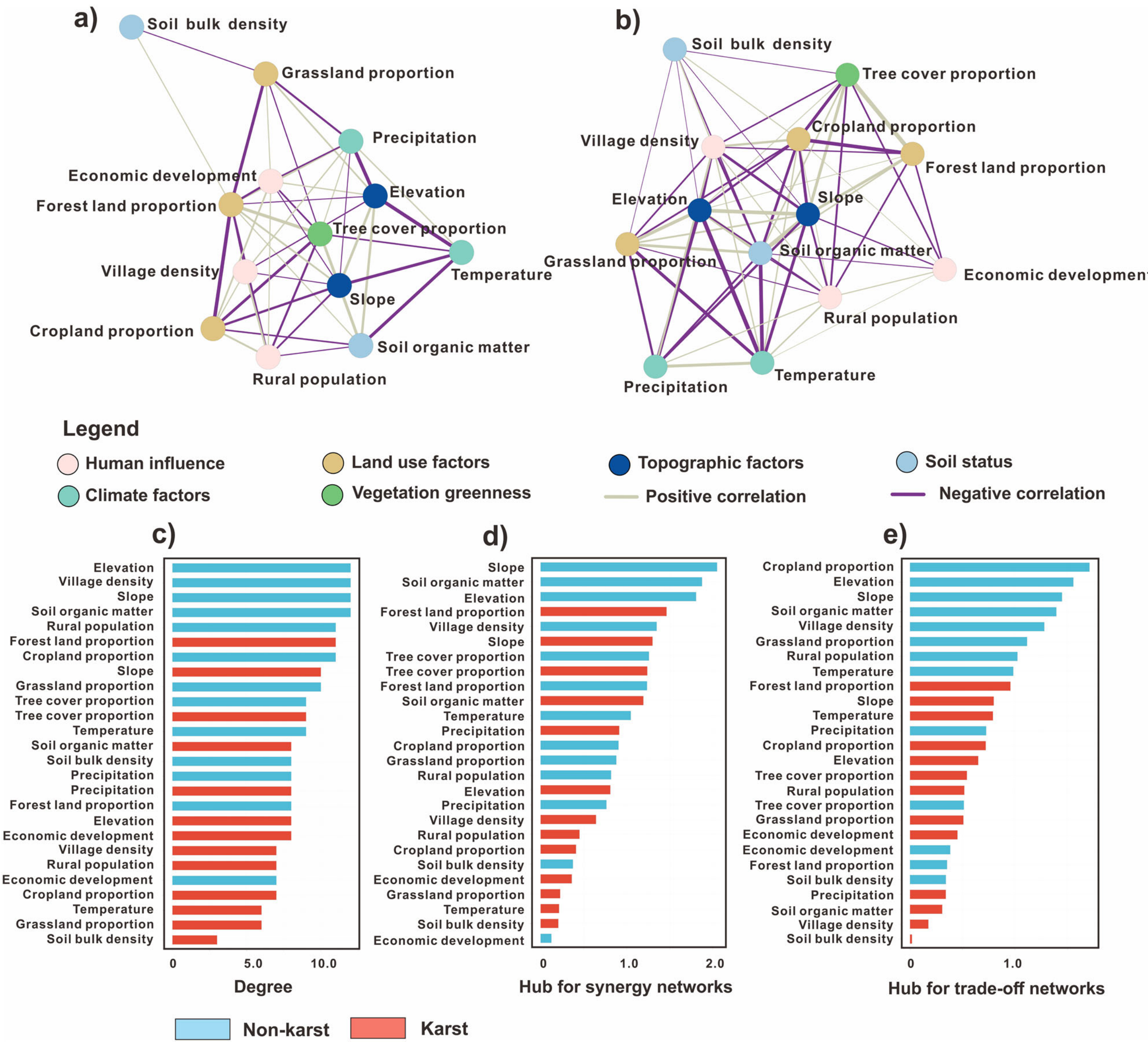

Fig. 5 | Social-ecological networks with the core of tree cover. **a** In karst area; **b** in non-karst area; **c** correlation degree of social-ecological networks; **d** hub in synergy networks; and **e** hub in trade-off networks.

standardized measurements of human impacts on ecosystems[51]. The population data and urban boundary data[52] were used to calculate the rural population per county. The population data of 1 km spatial resolution was derived from World Pop. The urban boundary data was used to eliminate the urban area of the county, and then we used it to calculate the rural population of the county. Besides, the nighttime light data of 500 m spatial resolution was used to characterize the economic development[53]. The maximum value of the mean nighttime light intensity from 2000 to 2020 was calculated in each county to represent the overall economic development. Counties with nighttime light intensity above-average were defined as the developed counties, with the others for undeveloped counties[54,55]. As for village density, we calculated the number of villages per square kilometer.

Topography is an important factor affecting vegetation growth and socio-economic activities and the difference in photosynthetic response caused by barometric pressure depends on altitude. We calculated the altitude and slope of the terrain using the Shuttle Radar Topography Mission.

For land use factors, we selected the proportion of grassland, forest land, and cropland. As the primary vegetation types in the region, they are essential to vegetation greenness. Land use factors were also extracted from GlobeLand30 products[45].

For climate factors, we selected the annual average temperature and precipitation. The climate data of 1 km spatial resolution was derived from Peng et al.[56].

We used the county as the basic analysis unit, and the county with the proportion of karst landforms over 50% was defined as the karst county[9,38].

Tree cover trend analysis

The trend of the tree cover change was obtained using the Mann–Kendall method, a nonparametric estimate technique that is unaffected by data outliers. To evaluate the trend's significance, the Z-test was computed. In this investigation, the significance threshold of $\alpha = 0.05$ was employed. When $Z \geq 1.96$, the sequence had a rising trend; when $Z \leq -1.96$, it displayed a falling trend. The sequence exhibited no significant trend when $-1.96 < Z < 1.96$.

Significance test

The Kruskal–Wallis test is a commonly used nonparametric method to test whether variables have statistically differences between groups, which was usually used to explore vegetation change and its drivers[57,58]. It was used to contrast the various ecological factors' effects on forest land change. The data was preprocessed using normal distribution test.

Social-ecological network analysis

The social-ecological network approach has the potential to analyze the internal factors' correlations of the social-ecological system[59,60]. The construction process is as follows: (1) the definition of social-ecological dependencies of a particular study; (2) the definition of social-ecological nodes; and (3) the definition of the links between social-ecological factors. We used the social-ecological network to explore the social-ecological factors' impact on tree cover in 2020. The 'network' and 'visNetwork' packages in R software were used to explore the network.

Network metrics can be used to provide integrated measures of the relationships between social-ecological factors, and to determine how these relationships change between ecosystems[61]. Since there were positive and negative correlations, separate networks were built for the synergies and trade-offs. We chose degree and hub as the key network metrics. The strength of factors relevant to components of the ecosystem was represented by correlation degree. The node with the largest trade-offs (or synergies) for the components was represented by the hub. Hub was calculated as follows:

$$D_i = L_i * pcc_i/(n-1) \tag{1}$$

where D_i is the hub of node i, L_i is the number of negative (or positive) links of node i, and pcc_i is the sum of the absolute correlation coefficient of node i with other nodes, and n is the number of nodes. The positive correlation coefficient is set to be 0 in trade-off networks, with 0 for negative correlation coefficient for synergy networks.

Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Data availability

The land use data were available at https://map.tianditu.gov.cn/. The forest cover data were available at https://lpdaac.usgs.gov/products/mod44bv061/. The urban boundary data were available at https://data-starcloud.pcl.ac.cn/zh. The nighttime light data were available at https://eogdata.mines.edu/products/vnl/#annual_v2. The precipitation data were available at https://doi.org/10.5281/zenodo.3114194. The temperature data were available at https://doi.org/10.5281/zenodo.3185722. The data processed in this study were available at https://zenodo.org/records/11530050.

Code availability

The code used in this study was available at https://zenodo.org/records/11530182.

Received: 9 January 2024; Accepted: 21 August 2024;
Published online: 04 September 2024

References

1. Bryan, B. A. et al. China's response to a national land-system sustainability emergency. *Nature* **559**, 193–204 (2018).
2. Strassburg, B. B. N. et al. Global priority areas for ecosystem restoration. *Nature* **586**, 724–729 (2020).
3. Wells, G. J. et al. Social as much as environmental: the drivers of tree biomass in smallholder forest landscape restoration programs. *Environ. Res. Lett.* **15**, 104008 (2020).
4. FAO. Global Forest Resources Assessment 2020, Food and Agriculture Organization of the United Nations. https://www.fao.org/forest-resources-assessment/past-assessments/fra-2020/en/ (2020).
5. Dave, R. et al. *Second Bonn Challenge progress report. Application of the Barometer in 2018.* (IUCN, Gland, Switzerland, 2019).
6. Cowie, A. et al. Land in balance: the scientific conceptual framework for Land Degradation Neutrality. *Environ. Sci. Policy* **79**, 25–35 (2018).
7. Ferraro, P. J. & Hanauer, M. M. Quantifying causal mechanisms to determine how protected areas affect poverty through changes in ecosystem services and infrastructure. *Proc. Natl Acad. Sci. USA* **111**, 4332–4337 (2014).
8. Redo, D. J. et al. Asymmetric forest transition driven by the interaction of socioeconomic development and environmental heterogeneity in Central America. *Proc. Natl Acad. Sci. USA* **109**, 8839–8844 (2012).
9. Peng, J. et al. Balancing the effects of forest conservation and restoration on South China Karst greening. *Earth Future* **6**, e2023EF003487 (2023).
10. Yue, Y. et al. Large scale reforestation of farmlands on sloping hills in South China karst. *Landsc. Ecol.* **35**, 1445–1458 (2020).
11. Chen, C. et al. China and India lead in greening of the world through land-use management. *Nat. Sustain.* **2**, 122–129 (2019).
12. Piao, S. L. et al. Characteristics, drivers and feedbacks of global greening. *Nat. Rev. Earth Environ.* **1**, 14–27 (2020).
13. Zhu, Z. C. et al. Greening of the earth and its drivers. *Nat. Clim. Chang.* **6**, 791–796 (2016).
14. Fensholt, R. et al. Greenness in semi-arid areas across the globe 1981-2007—an Earth Observing Satellite based analysis of trends and drivers. *Remote Sens. Environ.* **121**, 144–158 (2012).
15. Tong, X. et al. Increased vegetation growth and carbon stock in China karst via ecological engineering. *Nat. Sustain.* **1**, 44–50 (2018).
16. Zhang, X. X. et al. A large but transient carbon sink from urbanization and rural depopulation in China. *Nat. Sustain.* **5**, 321–328 (2022).
17. Terrer, C. et al. Mycorrhizal association as a primary control of the CO_2 fertilization effect. *Science* **353**, 72–74 (2016).
18. Hu, T. et al. Stage response of vegetation dynamics to urbanization in megacities: a case study of Changsha City, China. *Sci. Total Environ.* **853**, 159659 (2023).
19. Qiu, S. & Peng, J. Distinguishing ecological outcomes of pathways in the Grain for Green Program in the subtropical areas of China. *Environ. Res. Lett.* **17**, 024021 (2022).
20. Zhang, Z. et al. Forest transitions in Chinese villages: explaining community-level variation under the returning forest to farmland program. *Land Use Pol.* **64**, 245–257 (2017).
21. Fischer, J. et al. Advancing sustainability through mainstreaming a social-ecological systems perspective. *Curr. Opin. Environ. Sustain.* **14**, 144–149 (2015).
22. Liu, J. G. et al. Coupled human and natural systems. *Ambio.* **36**, 639–649 (2007).
23. Glaser, M. et al. Human/nature interaction in the anthropocene potential of social-ecological systems analysis. *GAIA* **17**, 77–80 (2008).
24. Leslie, H. M. et al. Operationalizing the social-ecological systems framework to assess sustainability. *Proc. Natl Acad. Sci. USA* **112**, 5979–5984 (2015).
25. Jiang, Z. C. et al. Rocky desertification in Southwest China: impacts, causes, and restoration. *Earth Sci. Rev.* **132**, 1–12 (2014).
26. Cook-Patton, S. C. et al. Mapping carbon accumulation potential from global natural forest regrowth. *Nature* **585**, 545–550 (2020).
27. Gutiérrez, F. et al. A review on natural and human-induced geohazards and impacts in karst. *Earth Sci. Rev.* **138**, 61–88 (2014).
28. Wang, K. L. et al. Karst landscapes of China: patterns, ecosystem processes and services. *Landsc. Ecol.* **34**, 2743–2763 (2019).
29. Lu, N. et al. Navigating trade-offs in the social-ecological systems. *Curr. Opin. Environ. Sustain.* **48**, 77–84 (2021).
30. Ding, Z. W. et al. Integrating top-down and bottom-up approaches improves practicality and efficiency of large-scale ecological restoration planning: insights from a social-ecological system. *Engineering* **31**, 50–58 (2022).

31. Benayas, J. M. R. et al. Enhancement of biodiversity and ecosystem services by ecological restoration: a meta-analysis. *Science* **325**, 1121–1124 (2009).
32. Zhang, W. M. et al. Socio-economic and climatic changes lead to contrasting global urban vegetation trends. *Glob. Environ. Change* **71**, 102385 (2021).
33. Zeng, C. et al. Soil erosion evolution and spatial correlation analysis in a typical karst geomorphology using RUSLE with GIS. *Solid Earth* **8**, 721–736 (2017).
34. Qiao, Y. N. et al. Contribution of karst ecological restoration engineering to vegetation greening in southwest China during recent decade. *Ecol. Indic.* **121**, 107081 (2021).
35. Wang, S. J. et al. Karst rocky desertification in southwestern China: geomorphology, landuse, impact and rehabilitation. *Land Degrad. Dev.* **15**, 115–121 (2021).
36. del Campo, A. D. et al. Assessing reforestation failure at the project scale: the margin for technical improvement under harsh conditions. A case study in a Mediterranean Dryland. *Sci. Total Environ.* **796**, 148952 (2021).
37. Zhang, C. et al. The application of geospatial techniques in monitoring karst vegetation recovery in southwest China: a review. *Prog. Phys. Geogr.* **41**, 450–477 (2017).
38. Qiu, S. et al. Understanding the relationships between ecosystem services and associated social-ecological drivers in a karst region: a case study of Guizhou Province, China. *Prog. Phys. Geogr.* **45**, 98–114 (2021).
39. Chang, J. et al. Rural outmigration generates a carbon sink in South China karst. *Prog. Phys. Geogr.* **47**, 030913332311541 (2023).
40. Liu, H. Y. et al. Rock crevices determine woody and herbaceous plant cover in the karst critical zone. *Sci. China Earth Sci.* **62**, 1756–1763 (2019).
41. Jiang, Z. et al. Bedrock geochemistry influences vegetation growth by regulating the regolith water holding capacity. *Nat. Commun.* **11**, 2392 (2020).
42. Wang, S. J. et al. Karst rocky desertification in southwestern China: geomorphology, landuse, impact and rehabilitation. *Land Degrad. Dev.* **15**, 115–121 (2004).
43. Liu, H. Y. et al. Bedrock-associated belowground and aboveground interactions and their implications for vegetation restoration in the karst critical zone of subtropical Southwest China. *Prog. Phys. Geogr.* **45**, 7–19 (2020).
44. Yue, Y. M. et al. A social-ecological framework to enhance sustainable reforestation under geological constraints. *Earth Future* **12**, e2023EF004335 (2024).
45. Chen, J. et al. Global land cover mapping at 30m resolution: a POK-based operational approach. *ISPRS J. Photogramm. Remote Sens.* **103**, 7–27 (2015).
46. Zhu, Z. C. et al. Global data sets of vegetation leaf area index (LAI) 3g and fraction of photosynthetically active radiation (FPAR) 3g derived from global inventory modeling and mapping studies (GIMMS) normalized difference vegetation index (NDVI3g) for the period 1981 to 2011. *Remote Sens.* **52**, 927–948 (2013).
47. DeVries, B. et al. Robust monitoring of small-scale forest disturbances in a tropical montane forest using Landsat time series. *Remote Sens. Environ.* **161**, 107–121 (2015).
48. van Lierop, P. et al. Global forest area disturbance from fire, insect pests, diseases and severe weather events. *For. Ecol. Manag.* **352**, 78–88 (2015).
49. Jiao, F. et al. Changes in soil properties across a chronosequence of vegetation restoration on the Loess Plateau of China. *Catena* **86**, 110–116 (2011).
50. Peng, J. et al. Ten key issues for ecological restoration of territorial space. *Natl Sci. Rev.* **11**, nwae176 (2024).
51. Li, F. et al. The effects of population density changes on ecosystem services value: a case study in Western Jilin, China. *Ecol. Indic.* **61**, 328–337 (2016).
52. Li, X. et al. Mapping global urban boundaries from the global artificial impervious area (GAIA) data. *Environ. Res. Lett.* **15**, 094044 (2020).
53. Chen, Z. et al. An extended time-series (2000-2018) of global NPP-VIIRS-like nighttime light data. *Earth Syst. Sci. Data* **13**, 889–906 (2021).
54. Li, G. et al. Monitoring the spatiotemporal dynamics of poor counties in China: implications for global sustainable development goals. *J. Clean Prod.* **227**, 392–404 (2019).
55. Liu, H. et al. Identification of relative poverty based on 2012-2020 NPP/VIIRS night light data: in the area surrounding Beijing and Tianjin in China. *Sustainability.* **14**, 5559 (2022).
56. Peng, S. Z. et al. 1km monthly temperature and precipitation dataset for China from 1901 to 2017. *Earth Syst. Sci. Data* **11**, 1931–1946 (2019).
57. Bicudo da Silva, R. F. et al. Three decades of land-use and land-cover change in mountain regions of the Brazilian Atlantic Forest. *Landsc. Urban Plan.* **204**, 103948 (2020).
58. Kohlrausch, F. B. et al. Geography influences microsatellite polymorphism diversity in Amerindians. *Am. J. Phys. Anthropol.* **126**, 463–470 (2005).
59. Bodin, O. et al. Improving network approaches to the study of complex social-ecological interdependencies. *Nat. Sustain.* **2**, 551–559 (2019).
60. Wu, X. T. et al. Decoupling of SDGs followed by re-coupling as sustainable development progresses. *Nat. Sustain.* **5**, 452–459 (2022).
61. Felipe-Lucia, M. R. et al. Land-use intensity alters networks between biodiversity, ecosystem functions, and services. *Proc. Natl Acad. Sci. USA* **117**, 28140–28149 (2020).

Acknowledgements

This research is supported by the Interdisciplinary Team of Chinese Academy of Sciences (JCTD-2021-16).

Author contributions

T.H., J.P., and S.Q. designed the study. T.H. and S.Q. conducted the analyses, supported by J.P., J.D., Y.L., Y.H., and P.X. designed the figures. The manuscript was prepared by T.H., J.P., and S.Q., supported by J.D., Y.L., Y.H., and P.X.

Competing interests

The authors declare no competing interests.

Additional information

Supplementary information The online version contains supplementary material available at https://doi.org/10.1038/s43247-024-01641-y.

Correspondence and requests for materials should be addressed to Jian Peng.

Peer review information *Communications Earth & Environment* thanks Yadong Yu and the other, anonymous, reviewer(s) for their contribution to the peer review of this work. Primary Handling Editors: Jinfeng Chang, Aliénor Lavergne, and Martina Grecequet. A peer review file is available.