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Unveiling the impacts of climate change and human activities on land-use evolution in ecologically fragile urbanizing areas: A case study of China's Central Plains urban agglomeration

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ABSTRACT

Environmental changes driven by climate change and human activities have significantly influenced the spatiotemporal evolution of land–use in urbanizing, ecologically fragile areas. However, these dynamics remain inadequately explored in terms of their evolution over space and time. In this study, we used a combination of CA-Markov and Coupling coordinated models to analyze the impacts of climate change and human activities on land–use evolution in China's Central Plains Urban Agglomeration (CPUA) from 2000 to 2060. Our results reveal that environmental changes significantly influence the spatiotemporal evolution of land use, accelerating rural-to-urban conversions in ecologically vulnerable regions, as validated by a CA-Markov model Kappa coefficient of 0.8378. These impacts, however, are predicted to diminish over time, with the strongest effects observed in areas with high ecological fragility. Specifically, increasing variability in climate conditions and intensifying human activities have resulted in cropland reduction at a rate of −260 km^2/year and a simultaneous increase in built-up areas at a rate of 200 km^2/year. This study underscores the critical influence of environmental changes on land–use dynamics and provides insights for policymakers and planners on promoting ecological resilience and sustainable land–use management to tackle the evolving challenges of climate change and human-induced disturbances.

1. Introduction

Environmental changes, caused by climate change and human activities are significant factors influencing ecosystem services and human well-being (Esperon-Rodriguez et al., 2022; Lu et al., 2023; Zhou et al., 2023). For instance, in the past two decades, the frequency of extreme weather events, such as super heatwaves (Chen et al., 2023; Smale et al., 2019; Woolway et al., 2021), widespread flooding (Li et al., 2020; Zhang et al., 2018), and extreme droughts (Yuan et al., 2023; Zhao et al., 2022), has doubled compared to that in previous years. Global environmental changes have triggered disasters that endanger food security, ecosystem services, and the safety of livelihood (Yang et al., 2018). Climate change exacerbates the uncertainty surrounding natural resources, while human activities serve as the significant drivers of this change. Together, they interact across multiple levels and scales, altering environmental conditions and the demand for land resources, thereby driving or influencing land use patterns and their dynamics (Wen et al., 2023). Land resources are the foundation for agricultural production, environmental protection, and social production (Smith, 2018; Zhou et al., 2019). Environmental change and land–use pattern dynamics are intricately interconnected, with Land Use/Cover Change (LUCC) both shaping and being shaped by the complex interplay of climate change and human activities(Liao et al., 2020). The evolution of land–use also reflects the resilience of the ecological environmental system and the intensity of human activities (Luiza Petroni et al., 2022; Newbold et al., 2016). Revealing the influences of environmental changes on the

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spatiotemporal evolution of land–use is crucial for rationally guiding land–use planning and enhancing the capability to respond to climate shocks and anthropogenic impacts.

In rapidly urbanizing areas, such as urban agglomerations, land-use changes can be dramatic due to human activities, significantly impacting the ecological environment and natural resources sustainability (He et al., 2023; Kong et al., 2022). These activities can lead to biodiversity destruction, deforestation, and disorderly expansion of built-up areas (Allan et al., 2022; Carrasco et al., 2017; Zhou et al., 2022). Ecologically fragile urbanizing areas are regions undergoing rapid urban development where the natural environment is particularly sensitive or vulnerable to degradation due to climate change and human activities (Shi et al., 2023). Urban agglomerations, as an advanced stage of urbanization, represent a highly developed form of spatial resource elements that require coordinated organization (Fang and Yu, 2017; Yu et al., 2024). LUCC is a crucial characteristic of urban agglomeration development. It promotes the circulation and complementarity of urban and rural resources by transforming natural land surfaces through human activities (He et al., 2019). Existing studies have analyzed the impacts of climate change and human activities on the Earth's system from local and regional perspectives, with a focus on their relationship with land–use. (Asamoah et al., 2021; Gao and Bukovsky, 2023; Pan et al., 2020). These studies employed relevant theories and methods from the fields of ecology, economics, and geography. They focused on land–use structure (Liang et al., 2021; Lin et al., 2024a), trends in the evolution of land–use spatial patterns (Jiang et al., 2022; Masoudi et al., 2021), and ecological and environmental effects of land–use (Li et al., 2021; Liang et al., 2023). They reported significant differences in the spatial structure of land–use, intensity of land–use changes, and external spillover effects of land–use changes among urban agglomerations of different regions and levels of development. Research has shown that the non-stationarity of land–use spatial structures is a common characteristic of urban agglomeration development (Ouyang et al., 2021; Qiao et al., 2023; Shen et al., 2022). This trend exacerbates the interference of human activities with land–use patterns, indirectly causing climate shocks and social issues such as urban heat islands (Lin et al., 2024b), air pollution (Han et al., 2020; Lee, 2020), urban flooding (Luo and Zhang, 2022), and habitat degradation (Wu et al., 2022). Scientists have recently started to focus more on the interaction between climate change and spatial evolution patterns of land–use.

More recently, in preparation for the World Climate Research Program Coupled Model Intercomparison Project (CMIP), under integrated scenarios of shared socioeconomic pathways (SSPs) and representative concentration pathways (RCPs), a basis was for the Sixth Assessment Report (AR6) of the Intergovernmental Panel on Climate Change (IPCC), as part of CMIP (O'Neill et al., 2016). Within this unified global climate change analysis framework, it is becoming increasingly important to explore optimization management strategies for the spatial patterns of land–use in urban agglomerations. This exploration should be approached from the perspectives of climate change mitigation actions and ecosystem restoration. Some research on the relationship between land use and environmental change in urban agglomerations primarily focuses on indicator measurement. These studies often emphasize the impact of specific land use type change patterns on individual environmental factors (Xiao et al., 2020), such as the relationship between the normalized vegetation index and forests (Yang et al., 2021), or surface temperature and impervious surfaces (Xiao et al., 2022). However, they insufficiently address the overall impact of different environmental change indicators on land use patterns (He et al., 2023; Liao et al., 2020). Furthermore, there is a lack of differentiated research across various hierarchical levels within urban agglomerations, leading to results that fail to meet the comprehensive demands for coordinated, sustainable development of urban agglomerations (Xiao et al., 2024). This underexplored aspect in research makes it challenging to reveal the complex interactions between land–use evolution and alterations in the ecological environment and human activities in ecologically fragile urbanizing areas. Consequently, the findings of previous studies are insufficient for meeting the needs of sustainable development of urban agglomerations in the context of global environmental changes.

Considering the unclear relationships between environmental changes and spatiotemporal evolution of land–use in urban agglomerations in ecologically fragile urbanizing areas, this study aimed to elucidate these complexities by addressing three research questions. First, how do environmental changes influence the spatiotemporal evolution of land–use? Second, are these influences likely to persist? Third, which strategies should be adopted in response to environmental changes to guide future sustainable land–use? To investigate this, we developed systematic methods to analyze the influence of environmental changes on land–use spatiotemporal evolution by quantifying the integrated effects of climate change and human activity as well as by simulating future land–use trends. We then revealed the response modes and influential mechanisms between environmental changes and land–use spatiotemporal evolution.

2. Methodology

2.1. Methodological approach

This study introduced a three-step research methodology aimed at bridging the knowledge gaps mentioned in the Introduction. In the first step, we reviewed the future environmental change patterns described by Shared Socioeconomic Pathways (SSPs) and quantitatively analyzed climate change and human activities from 2000 to 2060 to characterize the intensity of environmental changes. In the second step, using the geospatial method of Cellular Automata-Markov (CA-Markov), we simulated the spatiotemporal evolution of land–use under environmental change scenarios. In the third step, by integrating the coupling coordination degree with the geographically weighted regression model, we analyzed the influences of environmental changes on the spatiotemporal evolution of land–use. Subsequently, we explored the mechanisms by which environmental changes influenced and will influence land–use from 2000 to 2060 by analyzing the response modes of land–use adapted to future environmental changes. The detailed research flow of this systematic methodology is illustrated in Fig. 1.

2.2. Study area

China's urban agglomerations are experiencing urbanization at a speed and scale unparalleled by those of any other country globally (Ouyang et al., 2021). The Central Plains Urban Agglomeration (CPUA) is one of China's primary urban agglomerations, characterized by high ecological fragility and rapid urbanization (Mu et al., 2023), with the core development area encompassing 14 cities: Zhengzhou, Kaifeng, Luoyang, Pingdingshan, Xinxiang, Jiaozuo, Xuchang, Luohe, Jiyuan, Hebi, Shangqiu, Zhoukou, Jincheng, and Bozhou, covering a total area of 101,702.63 km2 (Fig. 2). The permanent population of CPUA stands at 73.55 million, with a Gross Domestic Product (GDP) of 4,642.687 billion yuan in 2021, accounting for 4.06 % of China's total GDP. In recent years, owing to updating the production structure and the booming population, significant transformations in land–use patterns and socioeconomic development have occurred in CPUA. Additionally, under the influence of environmental changes (such as climate change and unreasonable human activity), the ecological and environmental systems of the CPUA exhibit extreme vulnerability and unsustainability. Issues such as energy depletion, ecosystem degradation, and creasing pollution have gradually emerged (Li et al., 2019; Luo et al., 2021). For instance, the extreme rainfall event in July 2021 inflicted substantial damage to the lives and properties of residents within the CPUA. To meet the sustainable development goals for the CPUA, it is essential to scientifically elucidate how environmental changes affect land–use spatiotemporal evolution.

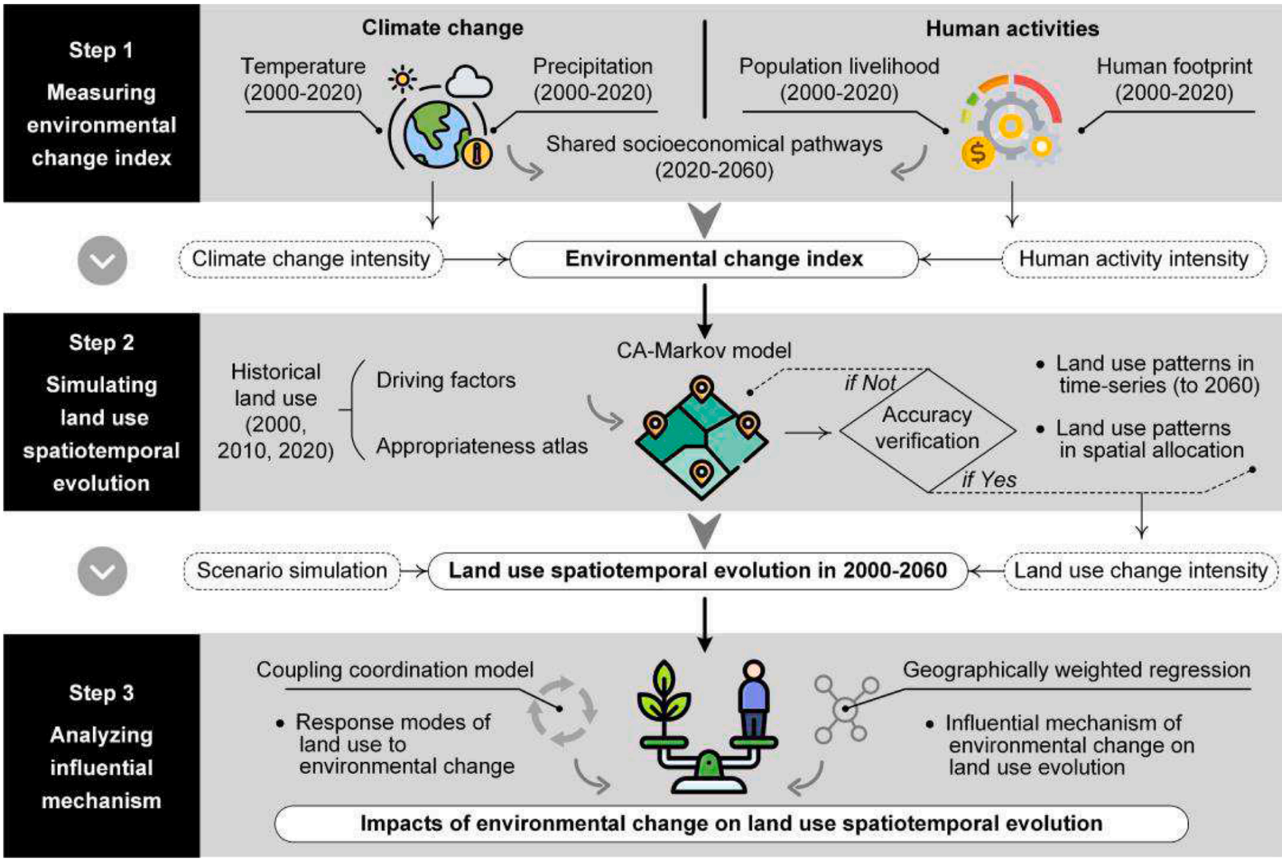

Fig. 1. Methodology flowchart of this study.

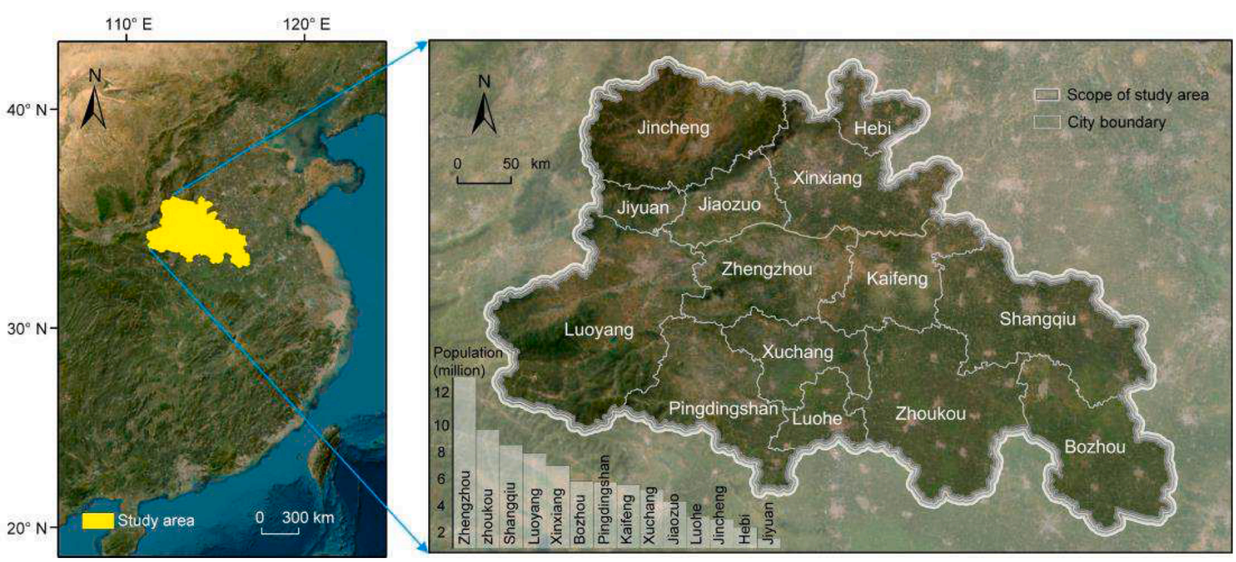

Fig. 2. Location and population scale of the study area.

2.3. Data sources and pre-processing methods

This study utilized various geospatial data, including data on land–use classification, climate, human activities, geospatial features, and socioeconomic statistics. The sources and pre-processing methods for each data type were as follows: (1) Land–use classification data for 2010 and 2020, with a spatial resolution of 30 m, were obtained from GlobeLand30 (https://www.globallandcover.com/). (2) Digital Elevation Model (DEM) data were sourced from the Geospatial Data Cloud (https://www.gscloud.cn/). The initial spatial resolution of the data was 30 m, derived from remote sensing imagery interpretation by the United States Geological Survey. (3) For the period of 2010–2060, climate data on total monthly precipitation, minimum monthly temperature, and maximum monthly temperature were utilized. Historical climate data from 2000 to 2020 were obtained from WorldClim (https://worldclim.org/). The future climate projections for the period of

2020–2060 were sourced from the Sixth Coupled Model Intercomparison Project (CMIP6) (https://www.wcrp-climate.org/wgcm-cmip/wgcm-cmip6) with an initial spatial resolution of 1 km. Population and human footprint data for the period of 2000–2020, with an initial spatial resolution of 100 m, were obtained from publicly available datasets that underwent peer review (Halpern et al., 2022; Popp et al., 2017). (5) Traffic network data, including railways, highways, national roads, provincial roads, and other roads, were obtained from OpenStreetMap (https://www.openstreetmap.org/). (6) Administrative boundaries and statistical data were sourced from Tianditu (https://bzdt.ch.mnr.gov.cn/) and various provincial statistical department websites. The original data were in various formats, including shapefile, GeoTIFF, and text, and had differing spatial resolutions. To enable analysis using a unified standard, these diverse datasets were resampled, georeferenced, and spatially processed. All original data were converted to GeoTIFF format through spatial processing using ArcGIS Pro software. Following this standardization, the data were unified to a spatial resolution of 100 × 100 m and projected onto the WGS 1984 coordinate system.

2.4. Measurement of the environmental change index

2.4.1. Evaluation of climate change intensity

We integrated indicators from both the climate change and human activities dimensions to analyze future environmental change trends in the study area. Shared Socioeconomic Pathways (SSPs) are a blueprint for future global socioeconomic development scenarios formulated by the Intergovernmental Panel on Climate Change (IPCC) and designed to quantitatively depict the trends of climate change and socioeconomic development pathways. The SSPs framework includes five socioeconomic development pathways: the sustainable development pathway (SSP1), middle-of-the-road pathway (SSP2), regional rivalry pathway (SSP3), inequality pathway (SSP4), and fossil-fueled development pathway (SSP5). To address the sustainable development goals in the CPUA, we employed the SSP1-2.6 pathway as the baseline scenario for assessing environmental changes. Within this framework, we analyzed projected monthly total precipitation, as well as maximum and minimum monthly temperatures, over the period 2020–2060 (Alexander et al., 2006; Maity and Maity, 2022; Zhang et al., 2011). Given that temperature and precipitation are fundamental indicators of climate change, we utilized the SSP1-2.6 scenario and its associated database to quantify climate change intensity by evaluating variations in monthly average precipitation and temperature throughout the 2020–2060 period. The formulas used for these calculations are as follows:

$$\mathrm{pre_y} = \sum_{i=1}^{12} \mathrm{pre_i} \tag{1}$$

where pre_y represents the total annual precipitation and pre_i represents the average precipitation for month i;

$$t_y = \frac{\sum_{i=1}^{12} \frac{tmin_i + tmax_i}{2}}{12} \tag{2}$$

where t_y represents the annual teamperature and $tmax_i$ represents the maximum temperature for the month I;

$$ICC = \sqrt[2]{pre_y \times t_y} \tag{3}$$

where ICC represents the climate change intensity.

2.4.2. Evaluation of human activity intensity

In the context of human development and increasing demands, human activities have emerged as pivotal factors disturbing the equilibrium of the natural environment(Shrestha et al., 2021; Venter et al., 2016). The human footprint is the most direct indicator of the intensity of human activities(Mu et al., 2022). This study leveraged human footprint data for the period of 2000–2020 and employed trend analysis to forecast the change characteristics of future human footprints. The calculation formula is as follows:

$$S = \frac{n\sum_{i=1}^{n}(i^*HF_i) - \sum_{i=1}^{n} i^* \sum_{i=1}^{n} HF_i}{n\sum_{i=1}^{n} i^2 - \left(\sum_{i=1}^{n} i\right)^2} \tag{4}$$

$$HF_{i+1} = (1+S)^*HF_i \tag{5}$$

where S represents the human footprint trend over time and HF_i represents the human footprint index in year i, with $S > 0$ indicating an increasing trend, $S = 0$ indicating a stabilizing trend, and $S < 0$ indicating a decreasing trend;

$$IHA = \sqrt[2]{POP \times HF} \tag{6}$$

where IHA represents the human activity intensity and POP represents the population density.

2.4.3. Measurement of the environmental change index

In this study, climate change and human activity were regarded as the co-weighting factors of environmental change (Zhou et al., 2021b). Drawing from the indices of climate change and the intensity of human activity, we employed an integrated approach to calculate the environmental change index using the following formula:

$$EC = (ICC + \mathrm{IHA})/2 \tag{7}$$

where EC represents the environmental change index, which represents the degree of environmental elements or quality change. In subsequent calculations, the index will be normalized to the 0–1 interval using the range standardization method (Hillebrand et al., 2020).

2.5. Simulation of land–use spatiotemporal evolution

2.5.1. Construction of the Cellular automaton (CA)-Markov model

In this study, the spatiotemporal evolution of land–use between 2020 and 2060 was predicted using the CA-Markov model, integrating CA with Markov chains (Wu et al., 2019). The key parameters of the CA-Markov model include proportional error and decadal cycles. For proportional error, we set the spatial resolution of all input data of the model to 30 × 30 m and the time scale to 10 years. Additionally, for the decadal cycles, the choice of 2060 as the target year was based on its significance as the year by which the Chinese government pledged to achieve the Carbon Neutrality Goal. Land–use practices are expected to be intentionally planned, leading to this pivotal year. CA are utilized for their pronounced temporal, spatial, and state discreteness, making them ideal for simulating the trends in systems with intricate spatiotemporal dynamics (Wu et al., 2021). The CA framework consists of cells, cell space, an ensemble of cell states, and the extent of neighborhoods, temporal parameters, and transition regulations. The calculation formula is as follows.

$$\mathrm{S_{i,t+1}} = \mathrm{f}\left(\mathrm{S_{i,t}}, \mathrm{S_{N,t}}\right) \tag{8}$$

where $S_{i,t+1}$ and $S_{i,t}$ represent the sets of states of cell i at moments $t+1$ and t, respectively, $S_{N,t}$ represents the set of states of the set of neighborhoods of cell i at moment t, and f represents the transition rule.

The Markov model is a probabilistic method for predicting long-term changes (Zhu et al., 2023). It calculates the probability of transition from one state to another based on the current state of an event. This is determined by modeling the probability of transitions between event states. The calculation formula is as follows:

$$\mathrm{X(t+1) = X(t) \times P} \tag{9}$$

where $X\ (t+1)$ and $X\ (t)$ represent the land–use states at moments $t+1$ and t, respectively, and P represents the transfer-probability matrix.

2.5.2. Parameterization of land–use change simulation

Using the IDRISI software, our model's cellular states reflect the land–use conditions in 2000 and 2010, while land–use data from 2020 serve as a reference to validate simulation accuracy. This validation is conducted by calculating the Kappa value, which quantifies the agreement between simulated outcomes and the actual land–use conditions observed in 2020. Land–use within the study area was divided into seven categories: cropland, forest land, grassland, aquatic resources, built-up land, barren terrain, and other uses (Liang et al., 2021). The cells were configured to dimensions of 100 × 100 m, with neighborhoods employing a 5 × 5 extended Moore scheme. The model was operated on a decadal cycle with a set proportional error of 0.15. In accordance with the SSP 1–26 sustainable development scenario and guided by methodologies documented in pertinent literature, the annual increase rate for built-up areas in future land–use change simulations is anticipated to be between 0.12 % and 0.16 %.

2.5.3. Scenario setup for the simulation of land–use change

To examine the future states of land–use under divergent development pathways, this study used two simulation scenarios of land–use spatiotemporal evolution informed by potential disruptions within the land–use system of the study area: (1) environmental change scenario and (2) "business as usual" scenario. In the "business as usual" scenario, land-use changes reflect existing development trends without additional environmental interventions, providing a baseline for assessing the impacts of current policies if no significant changes are made. On the other hand, in the "environmental change" scenario, land-use changes are modeled under policies aimed at enhancing environmental protection, allowing us to evaluate the potential benefits of proactive policies, such as conservation zoning or sustainable urban planning initiatives, on ecological resilience and resource management. Theoretical and empirical evidence underscores the enduring presence of climate change phenomena alongside human activities, with the latter subjectively remodeling external systems that disrupt the established systematic norms (Bukovsky et al., 2021; Ge et al., 2021). Accordingly, we integrated the dual disturbances caused by climate change and human activities into the land–use system. Considering the objective tendencies of land–use spatiotemporal evolution and drawing on the sustainable development goals championed by the SSP1-2.6 pathway, the environmental change scenario proposes a paradigm shift in land–use modalities from prioritizing rapid economic expansion to fostering a symbiotic relationship between humanity and nature (Bukovsky et al., 2021). The likelihood of transitioning cropland, forest, and grassland into built-up areas was reduced by 65 %, 50 %, and 35 %, respectively. By contrast, the conversion probabilities for water and unused areas were established based on historical patterns. The "business as usual" scenario extends the land–use transformation dynamics observed between 2000 and 2020 in the study area, predicated on the existing rates of land–use conversion and historical urbanization trends, without imposing any new restrictive measures on the transition regulations. This approach underpins a comparative analysis of the spatiotemporal evolution of land–use in environmental change scenarios.

2.6. Analysis of the influences of environmental changes on land–use spatiotemporal evolution

2.6.1. Identification of the response modes of land–use spatiotemporal evolution to environmental change

The impact of environmental change on land use is often not one-way, but interacts with land use change. The coupling coordination model can quantify this mutual interactive relationship. This study calculated the degree of coordination between the spatiotemporal evolution of land–use and the environmental change index using the coupling coordination model. In accordance with the definition of this model, the degree of coupling reflects the level of interaction between two or more systems, whereas the degree of coordination reflects the level of coordinated development among the systems (Zhang et al., 2021). The calculation formula is as follows.

$$\mathrm{C} = \frac{2\sqrt{D_{EC} \times D_{LEI}}}{D_{EC} + D_{LEI}} \tag{10}$$

$$T = \alpha D_{EC} + \beta D_{LEI} \tag{11}$$

$$\mathrm{D} = \sqrt{(\mathrm{C} \times \mathrm{T})} \tag{12}$$

where C represents the degree of coupling between the spatiotemporal evolution of land–use and the intensity of environmental change, with a value range of [0,1] (a value closer to 1 indicates a higher degree of coupling), T denotes the comprehensive coordination index between the spatiotemporal evolution of land–use and intensity of environmental change, and D_{EC} and D_{LEI} represent the environmental change intensity and land–use spatiotemporal evolution intensity, respectively. The α and β are the weights of the indices of land–use spatiotemporal evolution and environmental change intensity, and it is assumed that both have equally important impacts, thus $\alpha = \beta = 0.5$. D represents the degree of coupling coordination. A higher D value indicates better coordination between land–use spatiotemporal evolution and environmental change intensity, suggesting a mutually harmonious response pattern. Conversely, a lower D value indicates poorer coordination, implying a trade-off between the two. Based on the recommended classification of the coupling coordination model (Yang et al., 2020), the response patterns of land–use spatiotemporal evolution and environmental change were categorized into four types: highly coordinated ($D \in (0.8–1.0)$), moderately coordinated ($D \in (0.5–0.8)$), verging on discoordination ($D \in (0.3–0.5)$), and serious disordered ($D \in (0–0.3)$) (Dong et al., 2023; X. Zhang et al., 2022b; Zhou et al., 2021c).

Two indicators were used to analyze the spatiotemporal evolution index of land–use: mixing degree and land–use change intensity. These indicators are calculated as follows:

$$LEI = \sqrt[2]{M_{land} \times C_{land}} \tag{13}$$

$$M_{land} = -\sum (P_i)(\ln P_i), C_{land} = \frac{N_c}{N_t} \tag{14}$$

where LEI is the land–use spatiotemporal evolution index, D_{land} is the degree of land–use mixing, C_{land} is the intensity of land–use change. P_i represents the proportion of land–use type i in the total area, N_c represents the area of cells where land–use changes occurred between 2020 and 2060 (on a 100 m grid), and N_t represents the total cell area (on a 1 km grid).

2.6.2. Analysis of the influential mechanism of environmental changes on the land–use spatiotemporal evolution

The Geographically Weighted Regression model was used further to investigate the impacts of environmental changes on land–use spatiotemporal evolution processes. This model enhances conventional linear regression by accounting for the effects of spatial adjacency, allowing the determination of spatially variable influence parameters between independent and dependent variables (Yu et al., 2020). The calculation formula is as follows.

$$y_i = \beta_0(\mu_i, \nu_i) + \sum_{j=1}^{k} \beta_j(\mu_i, \nu_i) x_{ij} + \varepsilon_i \tag{15}$$

where y_i represents land–use spatiotemporal evolution index and the independent variable x_{ij} represents to the environmental change index at location i. The model's regression constant is, β_0 (μ_i,ν_i), alongside the regression coefficient for x_{ij} at region i. β_j (μ_i,ν_i) is critical in delineating the influences of environmental changes on land–use spatiotemporal evolution. A positive β_j value indicates a direct relationship, showing that an increase in the environmental change index is associated with an increase in the land–use spatiotemporal evolution, with the converse being true for a negative β_j. The magnitude of this coefficient indicates the extent of the correlation between environmental change and land–use spatiotemporal evolution. The coordinates (μ_i,v_i) denote the specific geographical location of location i, whereas ε_i represents the stochastic error inherent in the observations at this location.

3. Results

3.1. Trends of climate change and human activity in the CPUA

The CPUA is expected to experience significant nonlinear increases in both climate change and human activity. From 2000 to 2020, the total annual precipitation in the CPUA increased by 1.00 %, from 701.44 mm to 708.41 mm, and the average temperature increased by 0.33 °C, from 14.43 °C to 14.91 °C. These results suggested that the CPUA has experienced increased temperatures and increased precipitation related to global warming. Additionally, the population density of the CPUA increased from 475.35 individuals per km^2 in 2000 to 520.59 individuals per km^2 in 2020, indicating significant population growth in the early 21st century.

Future trends indicated an upward trajectory for both precipitation and the average temperature in the CPUA (Fig. 3). By 2060, total precipitation is projected to reach 791.19 mm, an increase of 89.75 mm from 2000, with total and annual growth rates of 12.80 % and 0.29 %, respectively. The intensity of human activities in the CPUA is expected to undergo significant changes, similar to climate change. Population density is expected to reach its peak around 2040 at 560 individuals per km^2, followed by a decline to approximately 530 individuals per km^2 by 2060. Simultaneously, the human footprint index is projected to increase, with a 10-unit increase by 2060 compared to that in 2020. In addition, the average temperature and precipitation in the CPUA from 2000 to 2060 were found to be significantly higher than the averages in China.

3.2. Land–use change progress of CPUA in the period of 2000–2020

Between 2000 and 2020, the CPUA underwent intensive land–use activities, resulting in significant changes to the spatial pattern of land–use. As shown in Fig. 4, all land–use types experienced varying degrees of change. Forests, wetlands, built-up areas, and unused areas increased from 15,357.17 km^2, 187.54 km^2, 11,450.08 km^2, and 21.16 km^2 in 2000 to 15,687.74 km^2, 333.89 km^2, 17,396.49 km^2, and 23.91 km^2 in 2020, respectively. Conversely, while built-up areas increased by 5,946.41 km^2, croplands, grasslands, and water areas exhibited a declining trend, decreasing from 70,064.32 km^2, 3,715.29 km^2, and 906 km^2 to 64,18.95 km^2, 3,266.21 km^2, and 808.37 km^2, respectively. The most significant changes among the seven land–use types were observed in built-up areas and croplands, which decreased by 5,879.37 km^2 and increased by 5,946.41 km^2, respectively. Wetlands had the highest growth rate of 78.04 %, whereas forests had the lowest growth rate of only 2.15 %.

3.3. Future trends of land–use spatiotemporal evolution in the CPUA in the period of 2020–2060

To ensure the reliability of the simulation results from the CA-Markov model, cross-verification was conducted between the 2020 land–use simulation results and the actual land–use types in the CPUA. Table 2 shows that the CA-Markov model constructed for this study passed all the accuracy parameter tests for simulating land–use in the CPUA in 2020. This indicated that the model is well-suited for simulating future land–use spatiotemporal evolution processes.

The CPUA is expected to experience increased disparities between urban and rural areas, owing to the growing variability in environmental changes. From 2020 to 2060, the CPUA is projected to lose the most significant amount of cropland areas, with an estimated transfer out volume of 4,546.12 km^2. This loss is predicted to mainly be related to the development of built-up areas, indicating a high risk of urbanization encroaching on croplands in the future. Table 1 presents the land–use transition matrix of the CPUA. This analysis indicates that land–use in

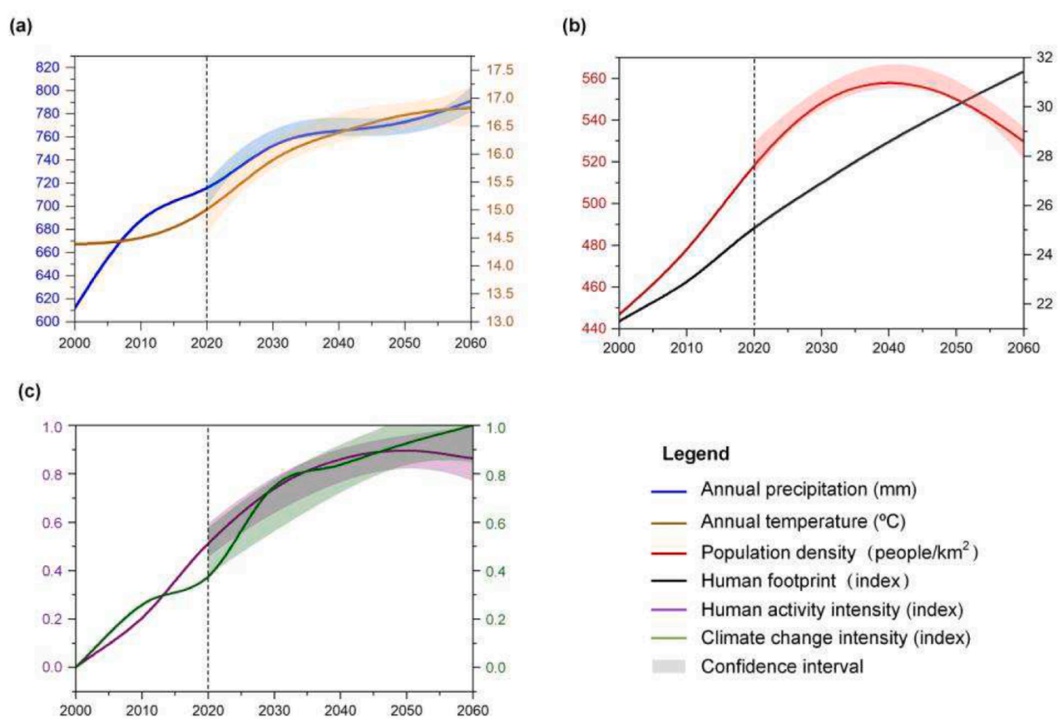

Fig. 3. Environmental changes index of the Central Plains Urban Agglomeration in the period of 2000–2060 under the SSP 1-2.6 scenario. (a) Climate change intensity. (b) Human activity intensity. (c) Combination of climate change intensity and human activity intensity.

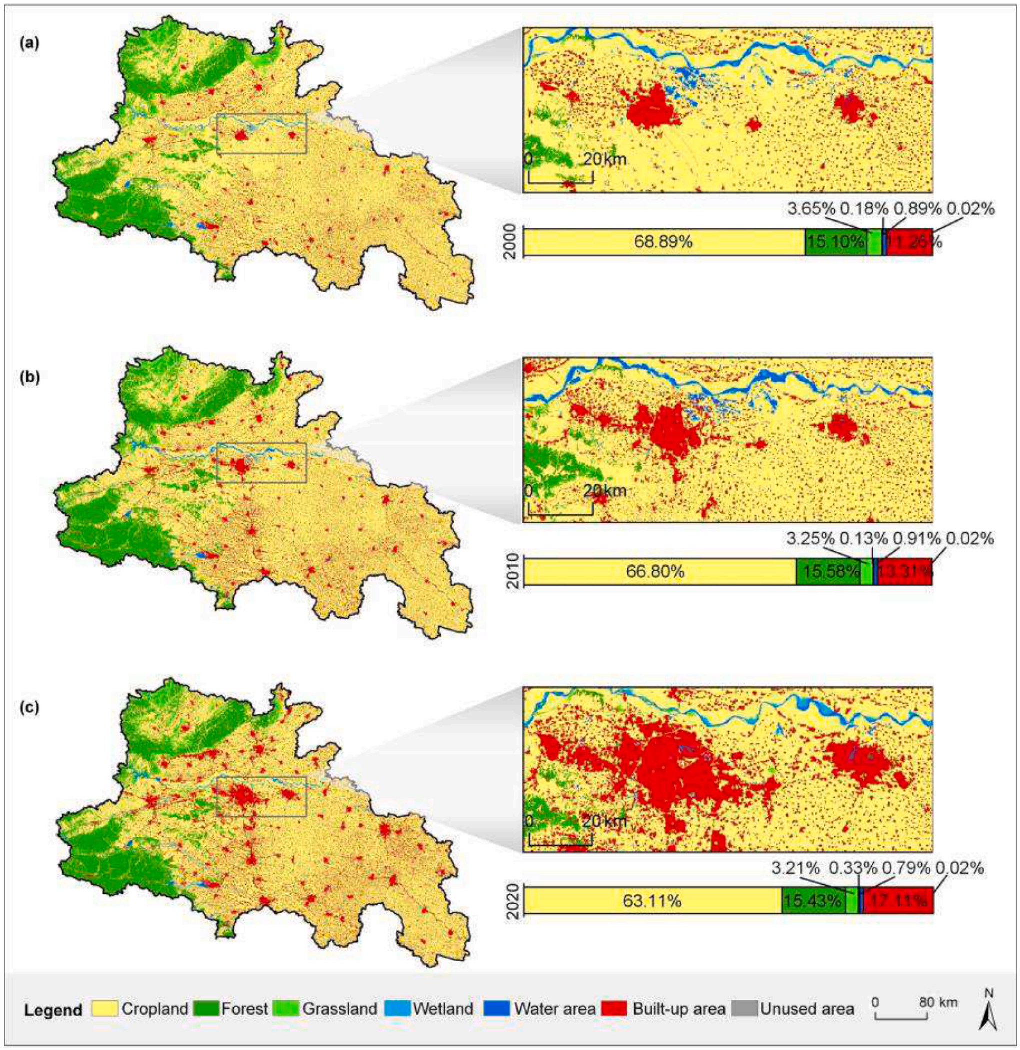

Fig. 4. Historical land-use change in the Central Plains Urban Agglomeration. (a) 2000. (b) 2010. (c) 2020.

Table 1
Land-use transfer matrix of the Central Plains Urban Agglomeration in the period of 2020–2060 (unit: km^2).

2060	2020							
	Cropland	Forest	Grassland	Wetland	Water	Built-up areas	Unused areas	Total transfers in
Cropland	49270.65	1107.09	461.26	245.42	141.34	12956.82	2.37	14914.3
Forest	1636.32	11864.70	1448.39	78.98	71.89	568.47	18.99	3823.04
Grassland	228.66	851.20	2002.06	15.59	26.02	139.99	2.69	1264.15
Wetland	0.00	0.00	0.00	333.78	0.11	0.00	0.00	0.11
Water	0.00	0.00	0.00	21.11	787.26	0.00	0.00	21.11
Built-up areas	2697.80	21.50	15.15	0.00	0.71	14661.02	0.31	2735.47
Unused areas	1.34	12.53	2.50	0.00	0.24	0.34	6.96	16.95
Total transfers out	4564.12	1992.32	1927.30	361.10	240.31	13665.62	24.36	22775.13

Table 2
Results of simulation accuracy validation of the Cellular Automata (CA)-Markov model.

	$K_{standard}$	K_{no}	$K_{location}$	$K_{locationStrata}$
Verification parameter	0.8378	0.8797	0.8739	0.8739

the CPUA will undergo significant spatiotemporal evolution between 2020 and 2060. By 2060, croplands, forests, grasslands, wetlands, water areas, built-up areas, and unused areas in the CPUA are expected to cover 53,834.77 km^2, 13,857.02 km^2, 3,929.36 km^2, 694.88 km^2, 1,027.57 km^2, 28,326.64 km^2, and 31.32 km^2, respectively, under environmental change scenarios. Our results describe area changes in various land–use types, with decreases of 10,350.18 km^2 and 1,830.72 km^2, and increases of 663.15 km^2, 360.99 km^2, 219.2 km^2, 10,930.15 km^2, and 7.41 km^2 from 2020 to 2060. The percentage changes are −16.13 %, −11.67 %, 20.30 %, 108.12 %, 27.12 %, 62.83 %, and 30.99 %, respectively. In addition to substantial growth in built-up areas, wetlands were projected to double in size.

Environmental changes have significantly influenced the spatio-temporal evolution of land–use. Under the environmental change scenario, the built-up areas in the CPUA are expected to increase by approximately 200 km^2 annually between 2020 and 2060. This trend indicated that urbanization demands will conflict with the finite nature of land resources, posing a significant threat to croplands and other natural resources. Anticipating disruptions to land–use caused by environmental change is crucial for mitigating conflicts. Fig. 5 shows the results of the spatiotemporal evolution simulation of land–use. The built-up areas will increase in the future, primarily in the eastern cities of Zhengzhou, Shangqiu, Luoyang, and Zhoukou. In contrast, cropland is expected to exhibit a significantly decreasing trend, with an annual loss rate of approximately 260 km^2. Conversely, changes in forest and grassland areas are expected to be relatively minor.

3.4. Influences of environmental changes on land–use spatiotemporal evolution in the CPUA

3.4.1. Response modes of land–use spatiotemporal evolution to environmental changes

The influence of environmental changes on the spatiotemporal evolution of land–use is predicted to decrease over time. Between 2000 and 2060, the proportion of areas in the CPUA that have serious or moderate incoordination will gradually expand, doubling over a 40-year period (Fig. 6). However, less than 1 % of the total area showed high coordination between land–use evolution and environmental change intensity, and this area is expected to decrease gradually. These results suggested that environmental changes and land–use spatiotemporal evolution will develop in an imbalanced manner in the future.

Using 2060 as an example, the average coupling coordination degree was only 0.43 (Fig. 6g), which was below the threshold of 0.5. This confirmed that the CPUA is experiencing an imbalance between environmental change trends and land–use change processes, suggesting that changes in climate and human activities will make future land–use spatiotemporal evolution more complex. From a local perspective, highly coordinated areas are concentrated only in the suburbs of Zhengzhou City in the central part of CPUA. In contrast, areas with serious incoordination are widespread in the northwestern and southwestern parts, encompassing Jincheng and Luoyang cities (Fig. 6h).

3.4.2. Influence mechanism of environmental changes on land–use spatiotemporal evolution progress

Our results showed a positive correlation between environmental change and the spatiotemporal evolution of land–use. However, the area exhibiting a positive correlation gradually decreased. From 2000 to 2060, the area in which environmental changes had a positive impact on the spatiotemporal evolution of land–use decreased from 93,450 km^2 to 52,104 km^2 (Fig. 7), i.e., approximately 40 % over the 60-year periods. Moreover, the strength of this positive correlation weakened over time, decreasing from 0.66 to 0.25. This revealed that the spatiotemporal evolution of future land–use will be influenced by a more comprehensive array of factors. Concurrently, the proportion of built-up areas within regions positively influenced by environmental changes was

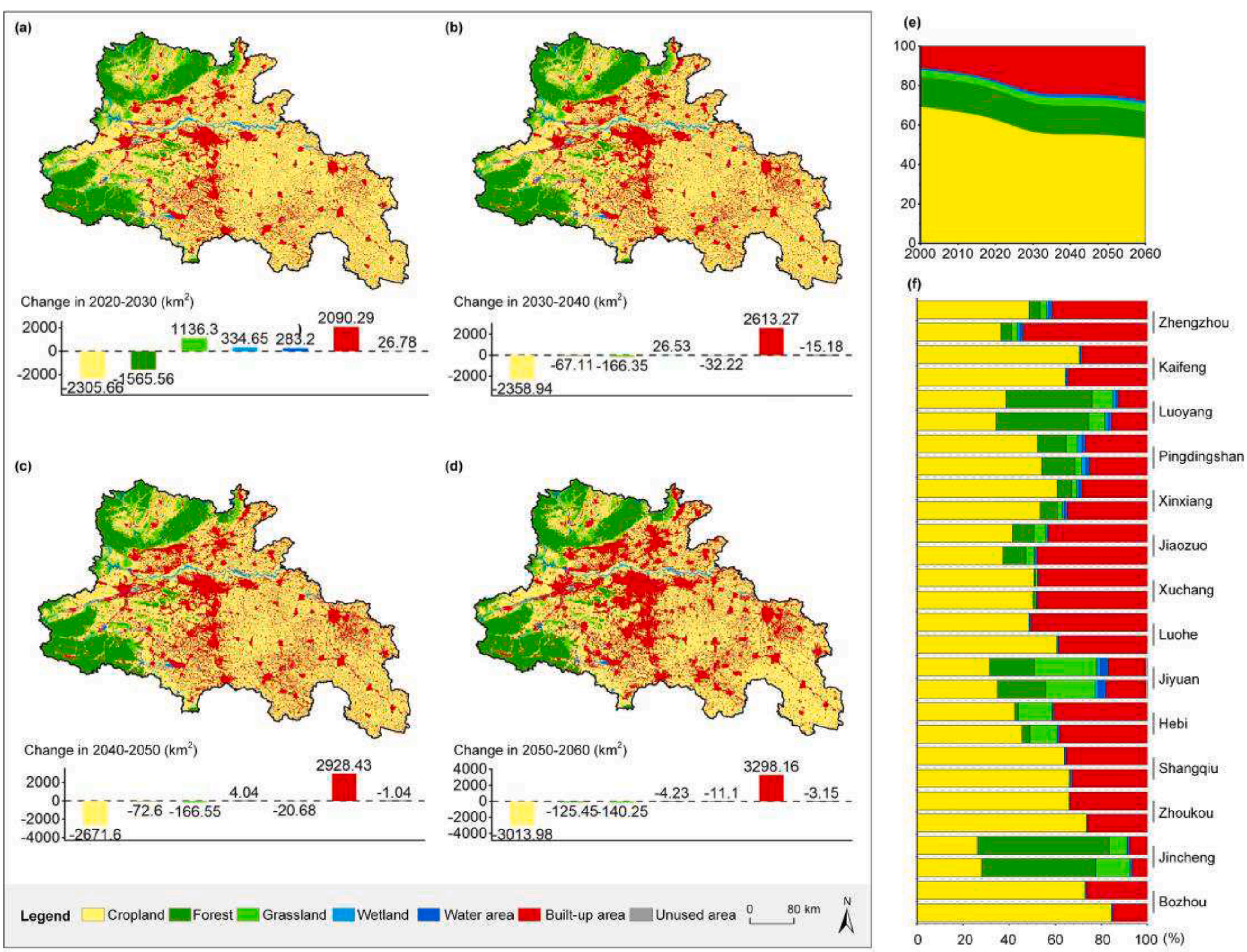

Fig. 5. Trends of land-use spatiotemporal evolution under environmental change scenarios in the Central Plains Urban Agglomeration. (a) Projected land-use in 2030. (b) Projected land-use in 2040. (c) Projected land-use in 2050. (d) Projected land-use in 2060. (e) Area changes of various land-use types from 2020 to 2060. (f) Area proportion of land-use in CPUA's cities under the environmental change scenario (first bar) and "business as usual" scenario (second bar) in 2060.

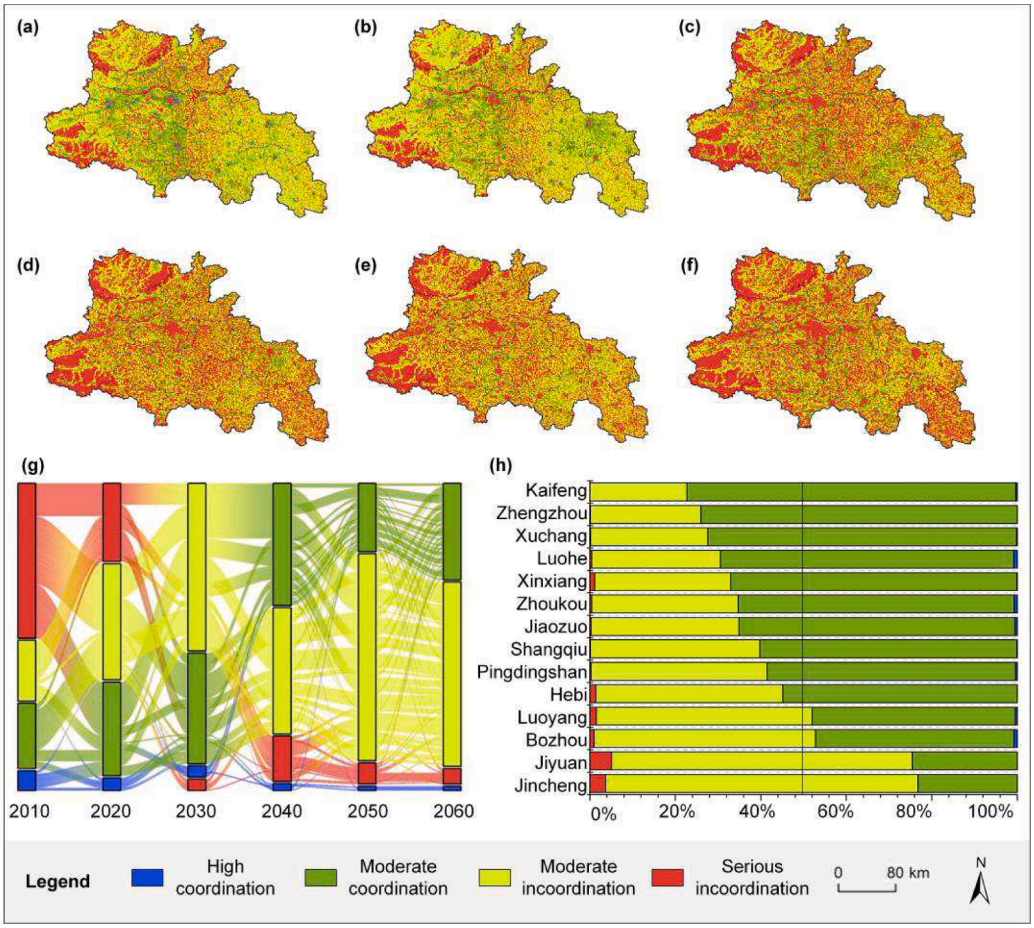

Fig. 6. Response modes of land-use spatiotemporal evolution to environmental changes in the Central Plains Urban Agglomeration. (a–f) Spatial distribution of response modes in 2000–2060. (g) Sankey diagram of response modes in 2010–2060. (h) Percentage of response modes for cities in CPUA in 2060.

significantly lower than that in areas with negative influences. This disparity became more pronounced over time (Fig. 7c).. This finding underscores that environmental change has exerted the greatest impact on built-up areas, with its intensification expected to further accelerate urban expansion. This continued growth in urban construction land will likely heighten conflicts between urbanization, agricultural production, and forest conservation, posing challenges for the sustainable development of land resources.

The influences of environmental change on the spatiotemporal evolution of land–use are more significant in areas with high ecological vulnerability than in highly urbanized areas. From the perspective of spatial distribution, between 2000 and 2060, the areas within the CPUA where environmental change had the strongest and weakest positive effects on land–use changes were Luoyang and Zhengzhou, respectively (Table 3). These two cities also represented areas with the highest topographical relief and highest levels of urbanization within the CPUA, respectively.

4. Discussion

This study integrated the representative phenomena of environmental changes—climate change and human activities—to analyze their influences on land–use spatiotemporal evolution. By combining Shared Socioeconomic Pathways (SSPs) and simulating land–use change trends under future environmental change scenarios, this study examined the effects of climate change and human activities on the spatiotemporal evolution of land–use in the period from 2000 to 2060. Our results showed that the continually rising trend of environmental change has enhanced the intensity of land–use spatiotemporal evolution to varying degrees, but these influences diminish over time. Therefore, our findings suggest that targeted land–use planning and resource and environmental protection efforts should be carried out in regions with different natural and social conditions to identify the practical pathways for the adaption to and mitigation of the impacts of future climate change and human activities.

4.1. Comparisons between climate change and human activities in the CPUA and worldwide

According to reports from governments and scientific institutions, such as the Intergovernmental Panel on Climate Change, global warming-induced climate change affects precipitation patterns (Molotoks et al., 2021). This included both increases and decreases in precipitation in different regions. For instance, high-latitude regions and some equatorial areas are experiencing rising precipitation trends, whereas arid and semi-arid regions are experiencing decreasing trends. In this study, we found that both precipitation and average temperatures in the CPUA show an upward trend, which is consistent with the recent pattern of increased precipitation in northern China (Yang et al., 2023). By 2060, the average temperature is projected to reach 16.83 °C, a rise of 2.4 °C from the average of 14.43 °C in 2020. This highlights the significant risks to societal production and living conditions posed by global warming. The frequent occurrence of natural disasters, such as extremely heavy rainfall and super high temperatures triggered by climate anomalies such as El Niño and La Niña, also corroborates the potential climate change pressures that the CPUA will need to address in the future. Similarly, the human footprint showed a significant upward trend from 2000 to 2020, accompanied by an increase in human

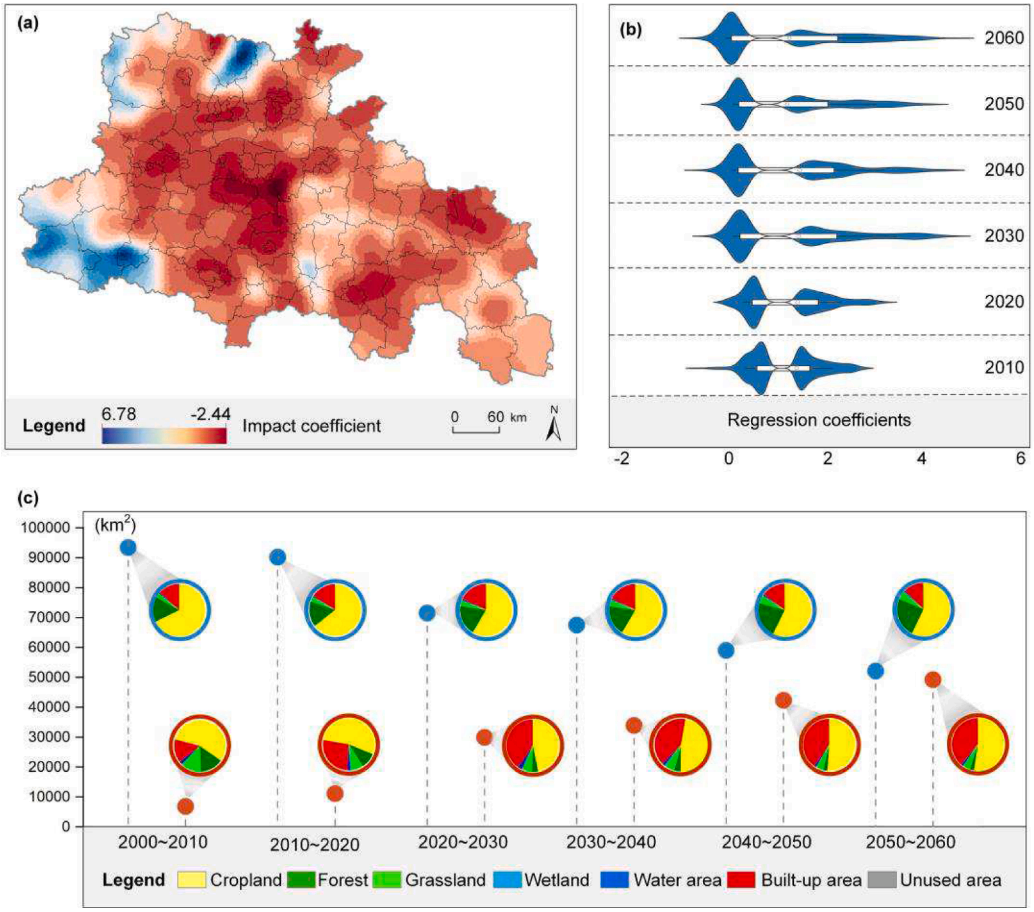

Fig. 7. Influence mechanism of environmental change on land-use spatiotemporal evolution in the Central Plains Urban Agglomeration. (a) Spatial distribution of the impact coefficient of environmental change in land-use in 2060. (b) Violin plot of the impact coefficient of environmental change on land-use in the period of 2020–2060. (c) Area of regions with positive (blue point) and negative (red point) impacts in the period of 2000–2060 and their land-use structures (pie chart). In this study, "positive impacts" refers to the beneficial impact of environmental change on land use patterns, meaning that the more intense the environmental change, the stronger the transformation in land use patterns. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 3
Spatial regression coefficients between environmental changes and land-use changes of Central Plains Urban Agglomeration in the period of 2000–2060.

City	2000–2020		2020–2030		2030–2040		2040–2050		2050–2060		2000–2060	
	Mean	Max	Mean	Max	Mean	Max	Mean	Max	Mean	Max	Mean	Max
Jincheng	0.45	3.32	0.85	7.42	0.90	7.55	1.00	6.75	1.16	6.78	0.87	7.55
Jiyuan	0.41	1.82	0.34	2.19	0.48	3.01	0.45	1.78	0.41	2.81	0.42	3.01
Bozhou	0.57	1.78	0.58	2.25	0.55	2.14	0.29	1.51	0.44	2.08	0.49	2.25
Luoyang	1.17	3.49	1.48	5.36	1.37	4.81	1.26	4.64	1.33	5.22	1.32	5.36
Hebi	0.36	1.37	0.32	1.83	0.22	1.93	0.01	1.45	−0.13	1.20	0.16	1.93
Pingdingshan	0.67	2.52	0.54	4.39	0.41	4.05	0.35	3.41	0.27	3.59	0.45	4.39
Shangqiu	0.65	2.05	0.41	2.26	0.38	2.30	0.07	1.66	0.04	2.20	0.31	2.30
Jiaozuo	0.53	2.71	0.09	4.65	−0.01	4.68	−0.03	3.55	−0.21	4.37	0.07	4.68
Zhoukou	0.64	2.14	0.40	3.17	0.31	2.34	0.23	3.26	0.14	2.56	0.34	3.26
Xinxiang	0.65	2.00	0.48	3.42	0.39	3.68	0.27	4.08	0.14	3.98	0.39	4.08
Luohe	0.76	2.42	0.32	2.42	0.25	1.90	0.13	2.15	0.02	1.93	0.30	2.42
Xuchang	0.72	2.56	0.22	3.61	0.22	2.44	0.12	3.46	−0.03	3.30	0.25	3.61
Zhengzhou	0.45	2.38	−0.04	2.77	−0.17	3.00	−0.23	2.45	−0.45	1.62	−0.09	3.00
Kaifeng	0.71	2.56	0.52	2.54	0.53	2.46	0.41	2.14	0.35	2.70	0.50	2.70
CPUA	0.63	2.32	0.47	3.45	0.42	3.31	0.31	3.02	0.25	3.17	0.42	3.45

development activities linked to population growth, thus increasing the pressure on the land–use system. Further analysis revealed that the urbanization rate in the CPUA increased from 55.05 % in 2000 to 78.40 % in 2020, a 23.35 % increase over 20 years, attracting a large population owing to industrial aggregation and job creation accompanying rapid urbanization. This trend of population density and human footprint indicates that the sustainable development path advocated by the SSP1-2.6 scenario, which shifts the development focus from urbanization to human welfare, also suggests that the future development process of urban agglomeration land–use systems may face the dual threats of reduced human resources and increased human disturbances, potentially leading to significant population outflow and rural depopulation risks.

4.2. Factors to consider when analyzing land–use spatiotemporal evolution from the perspective of environmental change

Some studies suggest a complex interrelationship between environmental change and land–use change, with each serving as both cause and effect within the Earth system and influencing the other (Borrelli et al., 2020; Hillebrand et al., 2020; Zhou et al., 2020). Global environmental change is comprehensive and interdisciplinary, exerting widespread impacts on human societies and natural ecosystems (Yushanjiang et al., 2024; Zhou et al., 2021a). In addition to climate change and human activities, phenomena such as biodiversity loss, land degradation, and sea level rise are interconnected with environmental change, although their importance varies depending on the region and time. Thus, this study posits that climate change and human activities are the most significant factors affecting land–use changes in ecologically fragile urbanizing areas. Investigating land–use from these perspectives offers an effective understanding of how these phenomena interact throughout the complex Earth system, thereby affecting land resources and human land–use activities. Recognizing the impact of environmental change on the spatiotemporal evolution of land–use can aid in identifying effective strategies for adapting to future climate change and intensified human activities. For instance, this study found that CPUA wetlands exhibited the highest growth rate (78.04 %), whereas forests had the lowest growth rate (2.15 %). This finding revealed that between 2000 and 2060, the CPUA achieved remarkable success in forest conservation and water source recharge efforts, which correlates with the recent establishment of ecological belts along the Yellow River and groups of wetland parks carried out by the Chinese government (C. Zhang et al., 2022a). In addition, as previously discussed, the CPUA is characterized by abundant agricultural resources, rapid urbanization, and a complex ecological environment. In recent years, against the backdrop of global climate change, the frequency of extreme weather events in the CPUA has increased, particularly in the form of extreme summer heatwaves and heavy rainfall (Chen et al., 2024). These factors have directly or indirectly contributed to the increased vulnerability of agricultural land and exacerbated urban heat island effects in the CPUA. Such changes not only influence land-use transformation but also place greater demands on the region's sustainable development and climate resilience.

4.3. Localized impacts of environmental changes on the land–use spatiotemporal evolution in the CPUA

This study indicates that the impact of environmental change on land–use spatiotemporal evolution is more significant in regions with relatively high ecological environmental vulnerability than in urban built-up areas. This finding is supported by evidence from previous studies. For example, researchers analyzing the stability of ecological environment systems in mountainous and urban areas that in China have found that regions with significant topographical relief and dense populations underwent a gradual increase in human development activities and the demand for land resources (Wang et al., 2022; Wang and Wang, 2021). These land–use systems exhibit pronounced variability and irreversibility when subjected to extreme weather events and sudden anthropogenic disturbances (Cao et al., 2021; Elahi et al., 2022). Further analysis of our results revealed that Luoyang, the city most affected by environmental change in terms of land–use spatiotemporal evolution, is located in the Qinling Fold Belt in the western part of the CPUA. This area's complex terrain of intersecting mountains, rivers, and hills experiences frequent and impactful natural disasters such as landslides, mudslides, droughts, and torrential rains caused by climate change and human activities. The vulnerability of the land resource system is high, making it highly susceptible to changes in usage patterns and intensity due to external risks. On the other hand, Zhengzhou City, which is relatively less affected, serves as an essential transportation and commercial center in China, with a high level of urbanization and a long history of development. Although there has been a surge in demands on land resources in recent years driven by socioeconomic development factors such as population influx, policy drivers, industrial upgrades, comprehensive natural resource management policies, and land–use planning have been well established. Against the backdrop of environmental change, the evolution of land–use in Zhengzhou is expected to be relatively stable.

4.4. Implications for policymakers and planners

From the perspective of spatiotemporal evolution trends in land–use under environmental change scenarios, between 2000 and 2060, changes in cropland areas in the CPUA were primarily concentrated in areas with the fastest urbanization processes, such as Zhengzhou, Shangqiu, and Xuchang, which also experienced the most significant increases in built-up area. This phenomenon indicated that the encroachment of urban and rural development on cropland resources has been frequent over the past two decades, highlighting the stark contradiction between the surging human development demands and the deteriorating capacity of natural resource supply. In contrast, changes in ecological lands, such as forests and grasslands, in the CPUA were mainly concentrated in the western and northern areas, including Luoyang, Jiyuan, Jincheng, and Xinxiang, where rugged terrain and significant topographical relief are prevalent. As the ecological lands underwent changes, ecosystem service functions degraded, leading to ecological risks such as soil erosion, reduced flood regulation capacity, and land desertification. This evidence suggests that the CPUA will face severe food security challenges and will continue to struggle with unbalanced and inadequate urban development in response to future environmental change. Therefore, further improvement in land–use management policies to balance the occupation and compensation of croplands in this region is essential. As one of China's most crucial grain production bases, Zhoukou should pay special attention to balancing urban construction and agricultural production in the face of future environmental changes. Additionally, we found that significant changes in the spatial pattern of land–use in the CPUA will occur regardless of the impact of environmental change. However, compared with that under the "business-as-usual" scenario, the magnitude of land–use change under the environmental change scenario is smaller. For instance, the increase in construction land from 2020 to 2060 is expected to be 1.10 % lower under the environmental change scenario. This indicated that the demand for built-up area expansion would be moderately reduced in the context of environmental change.

The socio-economic drivers of environmental change are multidimensional. Critical factors such as the reliance on fossil fuel energy consumption during industrialization and urbanization, which generates significant greenhouse gas emissions, and the intensification of urban heat island effects alongside rapid population growth—all of which are primary contributors to global warming. In the CPUA, fossil fuel consumption is substantial, emphasizing the need for careful management of natural resource utilization and population expansion patterns, particularly in core socio-economic development areas such as Zhengzhou, Kaifeng, and Luoyang, to foster sustainable land use and natural resources management in the future.

Sustainable land use is one of the core objectives of land-use planning and management. In the CPUA, the intensification of environmental change has markedly variable local impacts on achieving sustainable land use across different regions. For example, major cities like Zhengzhou are more vulnerable to extreme environmental changes, such as intense summer precipitation and heat waves, compared to smaller towns. These areas should focus on increasing green space and water bodies, utilizing green infrastructure to mitigate the heat associated with impervious surfaces, and enhancing urban climate resilience and adaptive capacity. Conversely, in the western Funiu Mountains and the southern Dabie Mountains, environmental changes may pose significant threats to ecosystem stability and land integrity. Land-use policies in these regions should prioritize the protection of ecological functions, reduce development pressures, and prevent land degradation and biodiversity loss.

4.5. Limitations and future research directions

In addition to the impacts of climate change and human activities, the loss of biodiversity, imbalances in water resource supply and demand, and shifts in global trade networks constitute environmental change. In this study, we focused on the characteristics of ecologically fragile urbanizing areas and selected climate change and human activity as the two most prominent manifestations of the ecological environmental system. While this approach offers specificity, it concurrently overlooks the impacts of other environmental change phenomena on the spatiotemporal evolution of land–use, although their effects may be minimal in highly urbanized areas. We believe that future investigations should explore changes in land–use patterns caused directly and indirectly by environmental change from a multidimensional perspective, incorporating more factors related to nature conservation and human development. Simultaneously, the interaction between land–use change and environmental change is bidirectional and intensifies continuously (Wu et al., 2023). Therefore, future studies should investigate the feedback mechanisms and impacts of land–use changes on the global environment and climate system. To provide a comprehensive analysis, these studies should utilize earth observation technologies with high spatial and temporal resolution, integrated with highly dynamic data on daily human activities.

5. Conclusions

The combined effects of climate change and human activities are crucial factors influencing the sustainability of land–use and ecological management. This study employs an integrated research approach, utilizing various ecological and geospatial data and methods, to explore the impacts of environmental changes on the spatiotemporal evolution of land–use, with a particular focus on China's CPUA from the perspectives of climate change and human activities. The main conclusions are as follows: Firstly, environmental changes have had a significant influence on the land–use spatiotemporal evolution. In the CPUA, the intensity of these changes is expected to increase nonlinearly in the future, with the rate of temperature and precipitation increase exceeding the national average in China. The increasing variability in environmental change has worsened the contradictions between urban and rural areas. Second, the influence of environmental changes on the spatiotemporal evolution of land–use will diminish over time. From 2000 to 2060, the area where environmental changes will have a positive impact on land–use spatiotemporal evolution will decrease from 93,450 km2 to 52,104 km^2. In the future, cropland and built-up areas will evolve at rates of -260 km^2/year and 200 km2/year, respectively, making land–use evolution increasingly complex due to changes in climate and the intensity of human activities. Finally, the impact of environmental change on the spatiotemporal evolution of land–use was more pronounced in ecologically vulnerable areas than in highly urbanized areas.

Urban agglomerations are advanced products of urban development. The intensification of climate change and human activities has led to a trend towards complexity in the evolution of urban agglomeration land–use. This study suggests that future urban agglomerations should employ scientific land–use planning and efforts in resource and environmental management to respond to the complex, variable impacts of environmental change. Our research findings revealed the varying degrees of influence of environmental changes on the spatiotemporal evolution of land–use. This provides valuable insights for ecologically fragile urbanizing areas to achieve the United Nations' Sustainable Development Goals and climate objectives outlined in the Paris Agreement.

CRediT authorship contribution statement

Zhimeng Jiang: Writing – review & editing, Writing – original draft, Visualization, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Yan Li:** Writing – review & editing. **Hao Wu:** Writing – review & editing, Project administration, Investigation, Funding acquisition. **Abdul Rashid Bin Mohamed Shariff:** Writing – review & editing. **Han Zhou:** Writing – review & editing. **Kaixuan Fan:** Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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