Urbanization effects on the food-water-energy nexus within ecosystem services

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Urbanization effects on the food-water-energy nexus within ecosystem services: A case study of the Beijing-Tianjin-Hebei urban agglomeration in China

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Food-Water-Energy (F-W-E) Ecosystem Services (ES) Trade-offs and Synergies Ecosystem service bundle County-based

ABSTRACT

This research centers on the necessity for synchronized management of natural resources in urban agglomerations. This study utilizes the ecosystem services theory to analyze the interplay between land use and the Food-Water-Energy (F-W-E) nexus in the Beijing-Tianjin-Hebei (B-T-H) region from 2000 to 2030. Assessment of ecosystem services is conducted using InVEST models, which include Habitat Quality (HQ), Water Yield (WY), Carbon Sequestration (CS), Soil Retention (SDR), and Food Production (FP). The findings indicate an annual increase in construction land with a concurrent notable decrease in cultivated land. Furthermore, HQ, CS, and per capita FP show an annual decline until 2020, which is expected to continue until 2030. Conversely, WY and SDR have been growing annually, albeit projected to decline by 2030. Spearman coefficient analysis uncovers synergies between HQ and CS, SDR and CS, and SDR and HQ, alongside trade-offs between CS and WY and HQ. Trade-offs are also observed between FP and SDR, CS, and HQ. Applying K-means clustering analysis facilitates county-based spatial planning for the F-W-E system, providing crucial insights and suggestions for sustainable resource management.

1. Introduction

The Food-Water-Energy (F-W-E) nexus is crucial for sustainable urban development (Ghodsvali et al., 2022). Yet, research on its implementation at the urban agglomeration scale remains underdeveloped and warrants further exploration. Studies in this domain cover a broad spectrum of perspectives. Ghodsvali et al. (2019) and Pittock et al. (2015) explored the social and cultural dimensions, primarily focusing on the impact of policies on the F-W-E nexus and community decision-making processes. From an economic standpoint, Wang et al. (2021) analyzed F-W-E consumption across diverse industries. Regarding policy, Wen et al. (2022) employed system dynamics to project urban planning scenarios. Zhang et al. (2019) investigated resource dependence, integration, and coordination at a natural scale. Furthermore, Shen et al. (2023) assessed ecosystem services within urban agglomerations through a supply-demand framework. Collectively, these varied methodologies underscore the complex nature of the F-W-E system’s role in advancing urban sustainability.

Several studies focus on the correlation between land use and ecosystem services (ES). Shi et al. utilized the InVEST model to assess the impact of urbanization on ES in Shenzhen (Shi et al., 2021), finding a negative correlation. Yuan and Lo (2020) applied the ARIES model and GIS to analyze land use changes and their effects on various ES in Taiwan and Shanghai. However, numerous studies have examined the relationship between land use and the F-W-E system. Yuan et al. (2021) used the analytic hierarchy process to compare F-W-E indicators in Taipei, Tainan, Amsterdam, and Eindhoven. Wang et al. combined Remote Sensing and GIS techniques, FRAGSTATS landscape index analysis, and...
multiple regression analysis to investigate the relationship between land use changes and the F-W-E system in Beijing (Wang et al., 2019). Lee adopted the ecological footprint approach to analyze historical changes in Taiwan’s environmental, carbon, and water footprints (Lee, 2015). However, these studies mainly focus on metropolitan areas like Shanghai and Shenzhen, with less emphasis on the broader urban agglomeration scale. The ecological footprint approach can be helpful to characterize past resource consumption but not to forecast future trends. Additionally, there is a lack of research on small-scale resource management concerning policy proposals and development recommendations.

Compared with the above studies, research on ES at the urban agglomeration scale is relatively extensive and can be categorized into perspectives of supply and demand, trade-offs and synergy analysis, and the viewpoint of losses and benefits. Zhang et al. (2022) explored land use changes and ES, including trade-offs and synergies, in the Chengyu urban agglomeration. Chen et al. examined the relationship between land use types and carbon emissions (Chen et al., 2020). Kang et al. investigated the link between ES and ecological health in the B-T-H region, identifying a threshold for urban construction land control (Kang et al., 2018). Zhou et al. (Zhou et al., 2018) revealed an inverse U-shaped relationship between urbanization and ES in the B-T-H region. Xiaomin et al. (2022) investigated the changing relationship between urbanization levels and ES in B-T-H. Gao et al. studied the benefits and damages of ES in the Yangtze River Delta urban agglomeration (Gao et al., 2019). Xin et al. researched the supply–demand dynamics of ES in the Fujian urban agglomeration (Xin et al., 2021). Dai et al. focused on supply and demand changes at different scales in provincial and county-level cities, noting more pronounced contradictions at the provincial level (Dai et al., 2022).

Research on the F-W-E nexus in urban agglomerations utilizes diverse methodologies, highlighting this field’s complexity and various dimensions. Input-output analysis, a common method, is extensively used for assessing F-W-E consumption in different settings. This method is exemplified in studies by Luo et al. (2022), Tian et al. (2019), Liu et al. (2021), and Zheng et al. (2017), with specific implementations for F-W-E consumption analysis in the B-T-H region. At the same time, Liu et al. (2020) focused on Southern China. In addition to input–output analysis, other studies have explored different aspects of the F-W-E nexus using varied approaches. For instance, Ouyang et al. (2021) utilized a system dynamics model to analyze the relationship between F-W-E and economic systems. Zhang and Zhu (2022) concentrated on examining the alterations in ecological and resource-carrying capacities within the B-T-H region, and their work is notable for their innovative models and optimization approaches applied to this area. Cao et al. optimized the F-W-E and land use systems through a land spatial optimization model in B-T-H (Cao et al., 2024). However, despite these diverse approaches, there remains a noticeable gap in studies specifically addressing ecosystem services within the F-W-E framework at the urban agglomeration scale. Notable exceptions include the work of Ding in Shanghai urban agglomeration (Ding et al., 2023), who analyzed the coordination between ES and sustainable development, indicating a potential area for further research and exploration in this field.

Our research identifies a significant gap: the scarcity of studies on ES within the F-W-E systems at the urban agglomeration scale, coupled with a lack of detailed ecological management recommendations for smaller scales. Therefore, this study aims to bridge existing research gaps and obtain valuable insights into the interplay between land use, ES, and the F-W-E system within urban agglomerations. It adopts ecosystem service theory to evaluate the impact of changes in land use types on critical indicators (HQ, WY, CS, SDR, and FP) related to the F-W-E system, considering land use types as intermediate indicators of shifting ES during urbanization, investigation of synergies and trade-offs between various ecological services at the urban agglomeration scale, and formulate management development recommendations at the county scale, encompassing ecosystem service bundle (ESB) management.

2. Material and method

2.1. Study area

The B-T-H region, known for its significant political and cultural role in China, includes Beijing and Tianjin, both directly administered by the Central Government. It encompasses eleven cities in Hebei Province (Fig. 1), with 199 counties by 2023 (Du & Sun, 2022). As of 2022, this region’s population reached 110.1 million, with a GDP of 10.0 trillion RMB, indicating its substantial economic and demographic influence and marking it as a critical center for economic and cultural activities in China (National Bureau of Statistics, 2022). From 2000 to 2020, construction land in the B-T-H region saw a 58.35 % increase, while grassland areas decreased by 3.22 % (National Bureau of Statistics, 2022). Notably, the water area in Beijing has experienced decline and fragmentation, illustrating the pressures on urban green and blue spaces (Wang et al., 2019). This trend reflects the decrease in green spaces, such as urban forests and grasslands, and the fragmentation of blue spaces, represented by water areas, alongside a population increase of 21.86 %. The escalating tension between preserving urban green and blue spaces and urbanization underscores the urgency for intensive and efficient ecosystem service management in urban areas (Liang et al., 2018).

A temperate monsoon climate with pronounced seasonal variations, including spring droughts and summer floods, characterizes the B-T-H region. The average annual rainfall is 527.1 mm in Beijing, 484.5 mm in Hebei Province, and 575 mm in Tianjin, with the majority occurring between June and September (National Bureau of Statistics, 2021; 2022a; 2022b). The region faces acute water scarcity, as per capita water availability in these areas falls below international benchmarks. A
significant measure to mitigate this issue is the region’s reliance on the South-North Water Transfer Project (Zhou et al., 2015).

In the B-T-H region, the share of clean energy is 10.4% in Beijing, 9.87% in Tianjin, and 6.82% in Hebei, suggesting limited clean energy sources. Additionally, Beijing and Tianjin predominantly rely on external food sources to meet the demands of their large populations. China’s per capita coal, oil, and natural gas consumption is significantly lower than the global average. As a result, confronting environmental challenges, particularly in the energy and water sectors, constitutes a primary concern for the B-T-H region (National Bureau of Statistics, 2021; 2022a; 2022b; Zhou et al., 2015).

2.2. Data resource and processing

The necessary data for this study encompass several categories, including land use type, digital elevation, road networks, soil characteristics, precipitation, NDVI, and food production data (Table 1). We primarily relied on information from the Regional Statistical Yearbooks to gather food production data in the B-T-H region. These yearbooks, published by the National Bureau of Statistics (National Bureau of Statistics, 2001a, 2001b, 2011a, 2011b, 2021, 2022b), are renowned for providing extensive and reliable regional statistics. The land use and geographical elevation data have a resolution of 30 m. At the same time, other datasets have a resolution of 1 km. All data will be resampled to a uniform resolution of 1 km in GIS. Additionally, references to other studies (Shi et al., 2022; Zheng et al., 2019) support the robustness of using a 1 km scale for analysis in large urban agglomerations and metropolitan cities. In order to account for the unexpected nature of the NDVI in 2030, we classified and extracted the NDVI coefficient for each land use type in 2000, 2010, and 2020. Our analysis revealed that the NDVI coefficient for each land use category remains rather constant and exhibits minimal variation (Table S3). The NDVI in 2030 is obtained by multiplying each land use type by the coefficient of NDVI, as projected by the land use projections.

2.3. Methods

2.3.1. Research framework

Human activities and urbanization have significantly influenced land use patterns, directly affecting ES evolution. Land use types serve as crucial intermediaries in urbanization processes, with changes in these patterns profoundly impacting the F-W-E nexus within ES. Our study aims to thoroughly understand how urbanization influences the F-W-E system’s functionality, particularly focusing on the critical role of land use types as key indication variables. Fig. 2 presents an overview of our research framework.

Building on ES theory, these services are classified into four primary types: Provisioning, Regulating, Cultural, and Supporting. As detailed in Table 2, the indicators selected reflect their specific relevance to the F-W-E system, emphasizing the interconnectedness within the F-W-E nexus of ES. After extensively comparing various software tools, we chose the InVEST models for simulation due to their ease of use and minimal data requirements (Cong et al., 2020). For simulating land use types for 2030, we utilized the CA-Markov model (Zeng & Li, 2019) and incorporated land use data from 2010 and 2020 (Thongwan et al., 2020).

To effectively coordinate natural resources within the F-W-E systems at the urban agglomeration scale, we assessed the interconnections among these ESs, identifying potential trade-offs and synergistic relationships. A county-based approach was also employed to determine the optimal clustering function, utilizing the ClusGap function in R. The county scale, the smallest administrative unit in China, is congruent with the scale of resource management policy formulation. This alignment with the urban agglomeration scale makes the county level a logical and efficient foundation for natural resource management and policy development. Moreover, we offered valuable development suggestions based on the ES bundles identified within the spatial context of

<table>
<thead>
<tr>
<th>Table 1: Research Data and Source.</th>
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<tbody>
<tr>
<td>Data</td>
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<tr>
<td>Land-use cover</td>
</tr>
<tr>
<td>Digital elevation model (DEM)</td>
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<tr>
<td>The geographical administrative boundary for counties</td>
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<tr>
<td>Soil data</td>
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<tr>
<td>Road map</td>
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<td>Precipitation</td>
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<td>Evaporation data of 2030</td>
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<tr>
<td>Precipitation of 2030</td>
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<tr>
<td>Crop reference evapotranspiration</td>
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<tr>
<td>Unit area production of food</td>
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<tr>
<td>Food Production of 2030</td>
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<tr>
<td>Subbasin boundary</td>
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<tr>
<td>NDVI of 2030</td>
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</table>
2.3.2. The IDRISI CA-Markov model

The IDRISI CA-Markov model is a hybrid approach that integrates the functionalities of Cellular Automata (CA) and Markov models to simulate land use changes within a defined time period. It employs a transition probability matrix (Zeng & Li, 2019) to characterize the likelihood of transitions across distinct land use categories. The main advantage of this approach is its ability to efficiently manage complex and ever-changing land use changes, which are difficult to express using other methods. Owing to the intricacies associated with predicting policy outcomes, a process that entails defining subjective parameters, our future projections do not incorporate measurements of policy factors. Instead, they are derived from the observed land use changes in 2010 and 2020. The following outlines the principal processes for predicting quantitative and spatial changes in land use types (Wang et al., 2022) using IDRISI software’s Markov and CA-Markov modules:

1. Markov Transition Probability Matrix: This involves overlaying 2010 and 2020 land use maps using the Markov model to calculate cell transition probabilities.
2. Suitability Atlas Development: Employing the multi-criteria evaluation (MCE) method with fuzzy membership functions, this step creates a suitability atlas (Luo et al., 2022).
3. Iteration Determination: Starting with the 2010 land use pattern, the model runs eleven iterations from 2020 to 2030 (Luo et al., 2022).
4. CA Filter Construction: This involves using filters in the CA model to define cellular spaces and weight factors. A standard 5x5 IDRISI filter was used as the neighborhood for cellular states.
5. Simulation Accuracy Verification: The simulation’s accuracy is assessed using IDRISI’s Kappa coefficient, with values above 0.7 indicating high accuracy. The method, applied to forecast 2020 land use based on 2000 and 2010 data, yielded a Kappa value of 0.86, demonstrating exceptional predictive accuracy.

2.3.3. The InVEST model

The InVEST software, a component of the Natural Capital Program, is developed to evaluate ecosystem services (ES)’s current state and historical trends (Xi et al., 2023). This program provides comprehensive models supporting ecosystem management and guiding decision-making processes, covering diverse areas, including land, water, and broader ecosystem dynamics. Combining land use data for each year, each ES needs to be run separately for each year.
(1) HQ reflects a specific area’s ability to support organisms’ survival and reproductive success (Sun et al., 2018). A higher HQ indicates enhanced potential for species to thrive and persist in an ecosystem. Focusing on HQ assessment and improvement enables conservationists and land managers to promote ecosystems’ long-term sustainability and resilience, thereby ensuring the well-being and survival of various species (Shi et al., 2022).

(2) WY is estimated using the water balance concept in the WY model (Signorello et al., 2020). This model consolidates WY values throughout the ecosystem, accounting for hydrological processes and meteorological conditions. In the InVEST model, the Z parameter represents the seasonal factor crucial for precise WY estimation, incorporating hydrogeological characteristics and seasonal precipitation patterns. Calibration of the Z parameter has yielded an optimal value of 9, closely matching observed WY, as evidenced by data from various water resources bulletins (B. M. W. Bureau, 2021; H. M. W.; T. M. W. Bureau, 2021).

(3) CS, as modeled, integrates diverse data sources, including land use and land cover maps, timber yield, harvested product degradation rates, and the four carbon pools: above-ground biomass, below-ground biomass, soil, and dead organic matter (Ibeabuchi, 2023; Yang et al., 2021).

(4) SDR of soil retention can be influenced by many factors, such as climate, rainfall intensity, soil properties, topography, vegetation, and human interventions like dam construction and agricultural practices. Li et al. (2017) have extensively studied these influences. A higher SDR indicates a more effective ES of soil retention. The soil erosion parameters in our study were based on Yang et al.’s research (Yang et al., 2021), while considerations of rainfall-related erosion factors were derived from Zhang & Fu’s and Yang et al.’s studies on rainfall erosivity estimation (Zhang & Fu, 2003; Yang et al., 2021).

2.3.4. Statistics of food production and NDVI

The FP statistics are sourced from a range of province and county-level statistical yearbooks that the National Bureau of Statistics compiles. The B-T-H Statistical Yearbook and the County Statistical Yearbook provide data especially pertaining to the B-T-H region. (National Bureau of Statistics, 2021, 2022a, 2022b). Food crops were classified into seven primary types: rice, winter wheat, corn, potato, soybean, cotton, and oil. Historical data for 20 consecutive years from 2000 to 2020 for these crops were compiled. Given the nonlinear growth patterns, parametric equations were employed in MATLAB to forecast the 2030 FP based on the best match fit of these equations, which are guaranteed that R² is greater than 0.98 with high credibility (Fig S1-S9) to historical data trends (Li et al., 2018). Notably, a significant linear relationship exists between FP and NDVI (Labus et al., 2002), with NDVI being a reliable indicator of FP (Huang et al., 2023; Jiang et al., 2023; Y. Zhao et al., 2023). As NDVI data for 2030 are unavailable, Average parameters for each land use type were extrapolated from data across six distinct land use categories in 2000, 2010, and 2020. The NDVI values for each land use type show minimal variation and stability, permitting the use of their mean values in the analysis for 2030 (Table S3 of Supplementary Material of Figure and Table). Combined with the projected land use types for 2030, these parameters enable a more precise estimation of NDVI for that year. Referring to the formula given by Huang et al. (2023) and Jiang et al. (2023), we calculated the FP and NDVI values on each raster (1 km^2): 

\[ FP_i = \frac{\sum_{j=1}^{n} NDVI_j}{\sum_{j=1}^{n} NDVI_i} \]  

\[ FP_j \] represents the FP of raster i within county j, NDVI_j represents the NDVI value for raster i within county j, and \( \sum_{j}^{n} \) NDVI_j represents the total NDVI in county j. I_j is the sum of the kilometers of all grids in county j, FP_j represents the actual total FP from the statistics of statistical yearbooks.

2.3.5. Spearman coefficient analysis in R language

We employed the Spearman correlation analysis to investigate the complex interplay and reciprocal effects between two sets of ESs. Two reasons drove the choice of this method: firstly, the data variables were suitable for ranking, and secondly, they demonstrated a clear monotonic relationship. This analysis was conducted using the R language and was supported by data from the InVEST model. GIS fishnet analysis was employed to extract values of these ESs from grid cells (Chen et al., 2020), drawing on previous research (Feng et al., 2021; Shao et al., 2022; Zhang et al., 2023), 1 km has sufficient credibility to support research on the urban agglomeration scale and has high robustness. The fundamental unit for this fishnet analysis was set at 1 km × 1 km, from which over 20,000 data points were extracted for detailed examination. Importantly, the reliability index R² reached 99.9 %, substantiating the robustness of our findings.

2.3.6. K-means clustering analysis in R language

Kohonen introduced the self-organizing map (SOM) network (Kohonen, 2006), marking a significant shift from traditional mathematical methods. This innovative approach integrates principal component analysis and K-means clustering, maintaining the topological structure of the input space through a neighborhood relationship function and enriching it with spatial information. The SOM utilizes competitive learning, wherein neurons gradually fine-tune the network for efficient classification (Deng et al., 2021). In our study, the SOM method is applied to discern ecosystem service bundles, with the scale selection anchored in spatial unit size and ecological space characteristics (Zhan, 2015). Reflecting the most recent geographical administrative boundaries as of 2023, the study area has been divided into 199 counties, each delineated by specific geographic and administrative boundaries to ensure enhanced precision. This analysis, grounded in K-means clustering, employs an extensive dataset comprising over 20,000 data points from these counties, enabling a detailed examination of ecosystem service bundles at the level of geographic boundaries.

3. Results

3.1. Results of lands-use changes

The analysis indicates that the region’s cultivated land area decreased by 9.26 % between 2000 and 2020. Projecting this trend forward, a further decrease of 18.98 % is expected by 2030 (Table 3). This decline is predominantly driven by the conversion of cultivated land for urban development (Liang et al., 2021). In contrast, initiatives aimed at reforesting cultivated land have led to the relative stability of forested areas, with only a slight projected decrease of 5.1 % by 2030 compared to 2000 (Zhang et al., 2023), as illustrated in Fig. 3.

Grassland areas experienced a 3.22 % decline from 2010 to 2020 but are projected to recover modestly by 2030. In contrast, water bodies have shown an overall increase, yet with more fragmented distribution patterns. Notably, water areas in Beijing and Tianjin have reduced and fragmented, while in Hebei Province, they have expanded. The construction land area has consistently grown, marking a substantial 58.35

<table>
<thead>
<tr>
<th>Land-use Type</th>
<th>2000</th>
<th>2010</th>
<th>2020</th>
<th>2030</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cultivated land</td>
<td>109,728</td>
<td>108,159</td>
<td>99,572</td>
<td>88,897</td>
</tr>
<tr>
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<td>44,533</td>
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<td>Water area</td>
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</tr>
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<td>27,999</td>
<td>36,147</td>
</tr>
<tr>
<td>Unused land</td>
<td>2168</td>
<td>1988</td>
<td>1846</td>
<td>2046</td>
</tr>
</tbody>
</table>

Table 3

<table>
<thead>
<tr>
<th>Land Use with Different Year (Unit is km²).</th>
<th>2000</th>
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</tbody>
</table>
% increase from 2000 to 2020, with a projected 104.43 % increase by 2030. This growth primarily results from encroaching upon water and cultivated lands, as depicted in Fig. 3. Projections suggest that unused land will remain relatively unchanged. However, the expected conversion of 34.72 % of cultivated land to construction land by 2030 poses a significant challenge to the sustainability of cultivated land.

3.2. Results of the InVEST model

Table 4, Table S1, and Fig. 4 show the InVEST model results. Further elaboration on HQ, WY, SDR, and CS aspects follows.

3.2.1. Habitat Quality

Fig. 4 presents a detailed analysis of changes in HQ, where higher values represent more favorable conditions for organism survival and adaptability. Conversely, lower values signify diminished habitability and adaptability. Among the various land types, forests and grasslands are identified as the most conducive environments for biological survival. On the other hand, construction land and unused land are the most detrimental, with a value of 0 indicating complete unsuitability for organisms. Data from Table 3 shows that the yearly increase in construction land and the decrease in cultivated land have steadily undermined HQ adaptability. Although forested areas have expanded, the impact on HQ adaptability has been relatively minor. In contrast, the HQ adaptability of grasslands has shown gradual improvement, rising from 0.7569 in 2000 to 0.7591 in 2020, and it is anticipated to reach 0.7985 by 2030 (Table 4, Table S1).

The increase in water areas has positively influenced HQ, with values rising from 0.4522 in 2000 to 0.6077 in 2020. However, this growth’s fragmented nature has led to a correspondingly fragmented HQ. From 2000 to 2020, HQ in the B-T-H region decreased from 0.4981 to 0.4871, mainly due to the expansion of construction land and fragmentation of water areas. Projections for 2030 suggest a slight improvement in HQ, reaching 0.4947 (Table 4). Notably, major metropolitan areas like Beijing and Tianjin have experienced a marked decline in HQ, highlighting the profound impact of urban development on HQ.

3.2.2. Water yield

The calculation of the average annual WY is based on per-square-kilometer metrics. In 2020 (Table S1 and Table 4), cultivated land showed an average WY of 13.451 mm, significantly up from 4.609 mm in 2000. During the same timeframe, forests experienced an impressive 443.20 % increase in WY. Grasslands also saw an upturn, with WY rising from 8.508 mm in 2000 to 24.248 mm in 2020. Meanwhile, unused land registered a more modest 57.1 % rise, climbing from 160.64 mm to 252.41 mm, albeit at a slower rate (Table 4). All land use types collectively exhibited a considerable enhancement in average WY in 2020, with a cumulative growth of 258.42 %. This significant rise in WY can be ascribed to several factors between 2000 and 2020: (1) Increased Average Annual Precipitation: The average annual rainfall in 2000 was 430 mm, which increased to 502 mm in 2010 and further to 537 mm in 2020. (2) Expansion of Construction Land: The WY augmentation is
Fig. 4. HQ, WY, CS, SDR, and FP in different years in the B-T-H region.
partly due to higher runoff coefficients from construction land (Han et al., 2022). The average WY of construction land surged by 179% from 2000 to 2020. (3) Growth in Water Area: A notable increase in WY within the water area category (Cao et al., 2021). Nevertheless, a downturn in WY is projected by 2030, owing to variations in rainfall patterns. The 2030 rainfall forecast, based on the 2000–2020 average, is lower than the figures from 2010 and 2020. This shift in rainfall is expected to result in a decrease in WY.

### 3.2.3. Carbon sequestration

As the cultivated land area diminishes, its overall CS capacity gradually declines. Between 2000 and 2020 (Table S1 and Table 4), this capacity in cultivated land dropped by 9.27%, with a forecasted further reduction of 18.99% by 2030. In contrast, forest areas grew by 7.44% in CS capacity during the same period but are projected to face a 5.36% decrease by 2030 relative to 2000 levels. The decrease in grassland area resulted in a 3.22% fall in CS capacity from 2000 to 2020, but an increase of 11.16% is expected by 2030. The CS capacity in water areas has remained comparatively weak and stable. With the expansion of construction land, its CS capacity surged by 58.36% from 2000 to 2020 and is anticipated to grow further by 104.46% in 2030. As unused land area shrinks, its CS capacity decreased by 14.85% in 2020, with a projected further decline of 5.64% by 2030. Overall, from 2000 to 2020, the average CS capacity across all land types diminished by 3.83%, and a contraction of 8.01% is expected by 2030. Table 4 illustrates that forests have the highest CS capacity among all land use types, followed by grasslands and cultivated lands. In contrast, water areas, unused lands, and construction lands exhibit lower CS capacities. Therefore, enhancing urban CS capacity involves increasing the share of forest, Grassland, and cultivated lands while reducing the area dedicated to construction.

### 3.2.4. Sediment Delivery Ratio and soil retention

The Ecosystem Service of SDR has consistently increased over the years, culminating in an average growth of 48.62% from 2000 to 2020 (Table S1 and Table 4). Most notably, construction land development has contributed to the highest enhancement in SDR, rocketing up by an extraordinary 158.12%. Water areas, too, have exhibited a notable improvement in SDR, with a 67.88% increase. During this period, forests, grasslands, and cultivated lands have all experienced positive growth in their SDR contributions. However, it is important to note that despite these upward trends, a forecasted decline in forest areas is expected to decrease total SDR by 2030, significantly affecting overall SDR capabilities.

Furthermore, forested land, grasslands, and cultivated land have demonstrated the greatest SDR capabilities (Table S2). This superior performance in forests and grasslands can be largely ascribed to the role of plant roots in stabilizing soil, thereby augmenting SDR. Conversely, the SDR potential of cultivated land is contingent on the types of crops grown and the agricultural techniques applied.

### 3.3. Food production

Analysis of data from the Statistical Yearbook has yielded detailed information on FP for 2000, 2010, and 2020, with an emphasis on grain, oil, and vegetables (Table 5). Using best-fit mathematical curves developed from two decades of historical data allows for the projection of each food category’s output up to 2030.

The average land yield calculation involves dividing total production by cultivated land area. This method reveals that FP’s average annual land yield has displayed a positive trend. In 2000, the yield was 767.75 kg/km², increasing to 784.23 kg/km² in 2010 and 981.93 kg/km² in 2020. The forecast for 2030 predicts a yield of 1295.61 kg/km², indicating a consistent rise in average FP/km². This increase is likely due to advancements in agricultural technology.

Nevertheless, preserving and protecting cultivated land against occupation or conversion is crucial. Furthermore, our annual per capita grain quantity analysis in each province (Fig. 3) shows a decrease in Beijing and Tianjin from 2000 to 2020, a trend expected to continue through 2030, with Beijing experiencing the most significant drop. Conversely, Hebei’s per capita FP has remained relatively stable, showing slight increases from 2000 to 2020, and it is projected to persist into 2030.

#### 3.4. Trade-offs and synergies of ecosystem services

A detailed analysis was carried out to examine the complex interconnections among various ESs (Ding et al., 2023), identifying any existing trade-offs or synergies. Statistical significance was established at a p-value below 0.01. Given the study’s large sample size, all P-values were under this threshold, denoting robust statistical significance. Positive values indicate synergistic relationships between ecosystem services, whereas negative values represent trade-offs or competitive interactions. Furthermore, the extent of the trade-off is inversely proportional to the magnitude of the negative value: smaller negative values suggest greater trade-offs.

The synergistic interaction between CS and HQ has remained robust, as evidenced in Fig. 6, reaching a nearly perfect positive correlation of 0.84 by 2030. Likewise, the synergy between SDR and CS increased from

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**Table 5**

| Land use type with food production (Unit is 10,000 tons). |
|-------------|---------------|---------------|---------------|---------------|
| District    | Beijing       | Tianjin       | Hebei         | Total Statistics |
| Year        | Grain | Oil | Vegetables | Grain | Oil | Vegetables | Grain | Oil | Vegetables |
| 2000        | 144.20 | 3.80 | 466.30 | 124.05 | 1.75 | 530.60 | 2551.10 | 147.00 | 4454.00 | 8424.36 |
| 2010        | 115.79 | 1.60 | 303.00 | 160.56 | 6.04 | 343.94 | 3121.00 | 129.50 | 4306.30 | 8482.2 |
| 2020        | 30.50 | 0.30 | 137.90 | 228.18 | 1.02 | 266.47 | 2795.90 | 119.50 | 5198.20 | 9777.26 |
| 2030        | 75.71 | 1.79 | 246.24 | 315.92 | 0.20 | 196.00 | 4308.96 | 113.83 | 6258.93 | 11,517.57 |

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**Fig. 5. Average Food Production. (Unit: ton/person).**
2000 to 2010 and stabilized at a high positive value of 0.63 in 2020 and 2030. The synergy between SDR and HQ was consistently moderate from 2000 to 2030. Despite a marginal dip in 2020 and 2030, it consistently exhibited synergistic effects, in line with the findings of Zhang and Feng (Feng et al., 2021; Zhang et al., 2022).

A marked trade-off relationship is noted between FP and SDR, as shown in Fig. 6, with the correlation shifting from $-0.47$ in 2000 to $-0.56$ in 2030. Similarly, the trade-off between FP and HQ intensified, from $-0.28$ in 2000 to $-0.53$ in 2030. Moreover, FP exhibited a moderate trade-off with CS, changing from $-0.22$ in 2000 to $-0.39$ in 2030. A slight trade-off between WY and CS altered from $-0.01$ in 2000 to $-0.22$ in 2030. Finally, a minor trade-off relationship between WY and HQ was observed, escalating from $-0.01$ in 2000 to $-0.39$ in 2030, indicating an incremental increase over time.

### 3.5. Bundles of ecosystem services

Analyzing the division of ESB over time shows their evolution every decade (See Fig. 7). Notably, the B1 of 2000–2030 indicates that WY is still predominant in eastern coastal counties but with a decreasing trend by 2030. Counties with high CS capabilities (B2 in 2000: CS-HQ, B6 in 2010–2020: CS-HQ) are mainly located in areas with a higher vegetation coefficient and forests in the northwest. By 2030, many of these areas are expected to transition into B2 of 2030: CS-WY-HQ, where WY will see an increase. Regarding FP, Bundle B3, representing FP-CS in 2010 and WY-FP for 2020 and 2030, is predominantly found in county-level cities near mountainous plains. The area under B3: WY-FP in 2030 is anticipated to expand. Contextually, B6, representing FP-CS in 2000, and B3, representing FP-CS in 2010, were confined to the period from 2000 to 2010, exhibiting a trade-off effect.

Bundles primarily focused on SDR are located in central plain cities with lower altitudes, such as B4: SDR-HQ-CS for 2000, 2010, and 2030 and B5: SDR-HQ-CS in 2020. This distribution reflects the impact of urbanization and ecological engineering, leading to an increase in SDR services. In B5, focusing on HQ with CS and SDR for the years 2000, 2010, and 2030, and B4 in 2020, efficient synergy among these components is evident. A peak in synergy occurred in 2010 with more counties involved, but this is expected to decrease by 2020 and 2030.
to development. In summary, ESBs focusing on CS-HQ, HQ-CS-SDR, and SDR-HQ-CS demonstrate high collaboration, a key management feature. Conversely, CS-WY and WY-FP ESBs exhibit trade-offs, indicating less efficient management.

4. Discussion

4.1. Driving factors and impact of urbanization on the F-W-E nexus

The results indicate significant changes in land use patterns, marked by increased construction land, reduced cultivated land, and fragmented water areas, highlighting the profound impact of urbanization and human activities on the environmental landscape. Without policy intervention, these trends are expected to escalate through 2030. The surge in construction land has led to a notable decline in HQ, and simultaneously, the increase in the water production coefficient has boosted WY. Furthermore, this increase in construction land correlates with decreased CS capacity and reduced cultivated land, aligning with Shi et al.’s findings in metropolitan areas (Shi et al., 2022). Forest cover, grasslands, and the NDVI are key determinants of HQ, echoing Xia et al.’s research (Xia et al., 2023). Climate change, especially increased rainfall, contributes to heightened WY. DEM also plays a critical role in influencing WY. Counties within the WY-ESB are typically situated in Piedmont plains and low-altitude cities. Climate factors lead to considerable vegetation growth variability, significantly impacting CS capacity. The amount of forest, slope, and NDVI directly affects CS’s overall capacity, a finding corroborated by Jiang et al. and Liu et al. (Jiang et al., 2023; Liu et al., 2024). Spatially, cultivated land, NDVI, DEM, and slope primarily influence FP. Implementing the Grain for Green policy has notably enhanced the SDR, the forest cover, and NDVI, directly affecting SDR.

HQ is vital in supporting biodiversity, providing food sources, enhancing soil fertility, and facilitating water purification. The decline in HQ and CS capacity in the B-T-H region raises significant concerns regarding urban sustainability and environmental management (Liang et al., 2018). Land use types like forests and grasslands exhibit higher CS capacity and are instrumental in countering the urban heat island effect and sequestering CO₂ via photosynthesis. By 2030, a predicted decrease in the overall CS capacity in the B-T-H region indicates a diminished capability to combat the effects of climate change. While the aggregate FP in the B-T-H region has remained stable, Beijing and Tianjin have seen a marked decrease in per capita food self-sufficiency. In contrast, Hebei has witnessed an increase in this regard (Guo et al., 2021), highlighting the challenges to urban resilience in natural disaster response. Additionally, land use changes have led to an initial increase in WY, which is, however, expected to decrease by 2030. The augmented WY offers challenges and opportunities for urban areas, including potential utilization for electricity generation, a topic to be explored in the following section.

4.2. County-based ecosystem service bundle proposal

Based on the ESB analysis in 2020, distinct development strategies have been devised for each of the six identified bundles, as illustrated in Fig. 8. Prioritizing the development of bundles with advantageous ES, as identified by their ranking in ESB, is beneficial for the efficient management of ecological resources (Xia et al., 2023). Bundles of B4, B5, and B6 are identified as highly synergistic, holding significant ecological importance. Effective management of a single resource or ecosystem service in these bundles can lead to considerable improvements in others. B1 is centered on WY, highlighting the need for comprehensive management of water-related ecosystem services. In contrast, B2 is characterized by trade-offs, while the WY-FP relationship in B3 is not clearly defined or deterministic. Ecological management proposals are prioritized based on the balance within each ecosystem services bundle. Given that the dominant elements of the ESB in B4 and B5 are similar, identical ecological development management recommendations have been formulated for both.
4.3. Limitations and future work

Our research currently lacks a detailed examination of the impact of various drivers on ecosystem services across different scales, particularly regarding supply-demand (Ding et al., 2023) (Li et al., 2023) balance and flows at the county scale. In the future, driving factors detection and supply-demand balance can be carried out based on this. Recognizing the limitations of the CA-Markov model (Wang et al., 2022) is crucial in the context of future land use scenarios. More specific policies and comprehensive datasets that capture the intricate relationships and dynamics of land use changes are necessary to improve accuracy. Moreover, scenario simulations can be leveraged to project development outcomes under various potential future scenarios.

In the InVEST model, the prediction of WY is contingent upon future climate conditions, which poses a challenge regarding precise forecasting. This study used average rainfall data from 2000 to 2010 and 2010–2020 for future rainfall projections. Enhancing forecast accuracy demands access to more refined and reliable future climate data. Additionally, continued research and development are vital for advancing the functionalities of the InVEST model.

5. Conclusion

This paper examines land use changes in the B-T-H region over the last two decades and makes predictions for the future 2030, focusing on the impacts of these changes on land use types. Utilizing ecosystem services theory, it explores the interplay of these changes within the F-W-E Nexus. The study assesses five key ecosystem services: HQ, WY, CS, SDR, and FP.

The findings reveal an alarming trend of annual reductions in both HQ and CS in the B-T-H region, largely due to urbanization. These decreases are projected to continue through 2030, highlighting potential future challenges in energy sustainability. The construction land expansion has markedly increased the runoff coefficient, significantly increased WY, and raised concerns about potential urban waterlogging problems. Furthermore, the study shows a marked decline in food self-sufficiency, pointing to emerging food security issues. On a positive note, ecosystem benefits from SDR have shown consistent growth from 2000 to 2020, supporting food and water resources. However, future projections suggest a decrease in these services by 2030.

Expanding on the ecosystem services assessment, this study investigates the dynamics among these services. It reveals a high synergy between HQ and CS, moderate synergy between CS and SDR, and similar synergy between HQ and SDR. A moderate trade-off is noted between FP, SDR, and HQ, and a low-level trade-off is found between FP and CS. These insights inform tailored land management strategies for specific county-based spatial contexts. Ultimately, this research contributes valuable perspectives on resource management within the F-W-E Nexus at an urban agglomeration scale, providing a crucial foundation for future resource management frameworks.

CRediT authorship contribution statement

Ke Yang: Writing – review & editing, Writing – original draft,
Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation. Qi Han: Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Conceptualization, Data curation, Project administration, Validation. Bauke de Vries: Writing – review & editing, Supervision, Methodology, Conceptualization.

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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.

Data availability
Data will be made available on request.

Appendix A. Supplementary data
Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2024.111845.

References