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Spatial identification and determinants of trade-offs among multiple land use functions in Jiangsu Province, China

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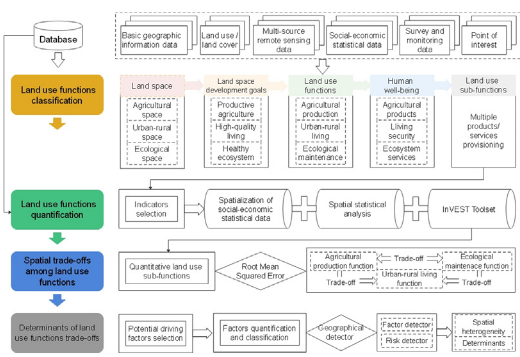
HIGHLIGHTS

- The framework of land use functions (LUFs) classification is established based on the perspective of land spatial planning.
- LUFs are quantified using multi-source data and the spatial trade-offs among multiple LUFs are measured at the grid scale.
- The major drivers and mechanism of LUF trade-offs are investigated using geographical detector model.
- The concepts of LUF trade-offs need to be incorporated into the processes of strategic land spatial planning and management

GRAPHICAL ABSTRACT



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ABSTRACT

Understanding the relationships among multiple land use functions (LUFs) is crucial for land-based spatial planning that can guide targeted land use policy-making in complex socio-ecological systems. However, few studies concerned the interactions among various LUFs integrating the issues of economy, environment, and society at a fine scale. In this study, we quantified 12 LUFs using a geospatial model and statistical analysis at the grid scale in Jiangsu Province. Then, we identified the relationships among three primary LUFs—agricultural production function (APF), urban-rural living function (ULF), and ecological maintenance function (EMF)—and further explored the determinants of LUF trade-offs aimed to provide a reference for policy-makers to make decisions in future land use planning and management. The results revealed that the high trade-off areas for APF and ULF are mainly distributed in central and northern Jiangsu, and the trade-offs for both APF-EMF and ULF-EMF were higher in the area covered with water and forest. The determinants of LUF trade-offs mainly refers to land use/land cover, potential evapotranspiration, and vegetation coverage ratio. Moreover, landscape configuration metrics and distance to the nearest county and nearest road also have remarkable impacts on the trade-offs of APF-EMF and ULF-EMF. Finally, we proposed that the concepts of LUF trade-offs should

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be incorporated into the processes of delineating boundaries for urban growth, farmland, and natural areas. We also propose that land consolidation projects should be implemented in an orderly manner to alleviate LUF trade-offs.

1. Introduction

Human-driven activities on earth's terrestrial surface have a widespread impact on the structure and function of the land use system, with equally far-reaching consequences for human well-being (Steffen et al., 2006; Turner et al., 2007; Mooney et al., 2013; Wu, 2013; Wang et al., 2017). Land use functions (LUFs) refer to the direct or indirect benefits that humans derive from different land use processes (OECD, 2001; MEA, 2005; Wiggering et al., 2006; Pérez-Soba et al., 2008; Verburg et al., 2009). The benefits of LUFs include those that humans obtain from natural ecosystems and those that concern the contribution of LUFs to socio-economic systems and human existence and wellbeing (Pérez-Soba et al., 2008; Verburg et al., 2009; Xue et al., 2019). Population has increased rapidly over the last several decades and will continue to increase over future decades (Gerland et al., 2014). Consequently, land use systems have witnessed rapid and extensive changes over past decades to meet the growing demands for natural resources and human development (Turner et al., 2007; Lambin and Meyfroidt, 2011; Yan et al., 2018; Xue et al., 2019). As a result, issues like climate change, soil erosion, and biodiversity loss are becoming increasingly prominent, and land use systems are being degraded (Wu, 2013; Flörke et al., 2018; Zhang et al., 2019; Achour and Pourghasemi, 2020).

In September 2015, the 70th session of the United Nations General Assembly issued *Transforming our World*: *The 2030 Agenda for Sustainable Development* and approved 17 Sustainable Development Goals (SDGs), which aims to address the issues of economy, society, and environment in an integrated way (UN General Assembly, 2015). As an important linkage between nature and human well-being, LUF describes the ability of a land use system to provide human wellbeing, associated with SDG11 “Sustainable cities and communities”, SDG13 “Climate actions”, and SDG 15 “Life on land” (Pérez-Soba et al., 2008; Verburg et al., 2009). LUFs are diverse and complex, and various LUFs interact with each other (Bennett et al., 2009). Understanding the relationships among multiple LUFs and their determinants will facilitate balanced development of multiple LUFs and is critical for decision making in land spatial planning and management and for achieving the 2030 SDGs (GLP, 2005; Lacher et al., 2019; Zou et al., 2020).

Trade-off analysis is a valuable method to characterize the relationships of multiple LUFs. Trade-offs are generally defined as the situations in which management options result in high benefit in one function at the cost of having low benefit in others (Bradford and D'Amato, 2012). Considerable progress has been made in investigating the relationships among multiple ecosystem services (Bennett et al., 2009; Raudsepp-Hearne et al., 2010; Qiu and Turner, 2013; Feng et al., 2017; Liu et al., 2019) that focus mainly on the benefits provided by natural ecosystems. Artificial ecosystem (e.g., agricultural ecosystem and urban ecosystem) is also an important part of the sustainable world that not only rely on natural capital (e.g., water, soil, atmosphere, and minerals) but also rely on manufactured capital (e.g., machines and buildings) and the human capital of physical bodies (Costanza et al., 1997; Pérez-Soba et al., 2008; Yang et al., 2015). However, there is a gap for the existing literature in analyses on the link of benefits provided by both natural and artificial ecosystems. Therefore, our study focused on the spatial trade-offs among multiple LUFs provide by the land use systems refer to both natural and artificial ecosystems.

The studies on LUFs assessment published over the last two decades usually measured LUF indicators using statistics and weighted analysis at the regional level (Wiggering et al., 2006; Pérez-Soba et al., 2008; Paracchini et al., 2011; Zhou et al., 2017; Fan et al., 2018). These methods have limited application to measuring ecological indicators and identifying spatial interactions among multiple LUFs explicitly. In fact, the spatially-explicit decision-making model InVEST (Tallis et al., 2011; Leh et al., 2013; Lin et al., 2018; Bai et al., 2020), value estimation (De Groot et al., 2012; Zou et al., 2020), and scenario analysis (Hou et al., 2013; Kirchner et al., 2015) have been explored and recognized as powerful tools for ecological services evaluation that vary in scale from global to grid scale. Remote sensing data and point of interest data have also been proven to be available for measuring the agricultural productivity and the land use intensity, respectively (Jin et al., 2017; Wang et al., 2018; Hong et al., 2019; Li et al., 2020). As such, multi-source data and available spatialization methods were applied in this study to quantify the multiple LUFs at the grid scale for better understanding the spatial interactions among multiple LUFs.

The existing methods for identifying trade-off relationships are mainly qualitative description and statistical analyses. A qualitative description is an approach associated with stakeholders' decision-making without explicit quantitative and spatial measures (Sørensen, 2002; Noble and Bronson, 2006). Correlation analysis is the most commonly used statistical analysis method for measuring the degree of the trade-off between two LUFs but cannot quantify the trade-offs among three or more LUFs. Recently, root mean squared error (RMSE) has been proposed to be a simple but effective method to quantify the magnitude of the trade-offs among two or more LUFs following Bradford and D'Amato (2012). Some recent studies have indicated that the RMSE method is an applicable and favorable strategy for understanding the impacts of alternative land use management options at multi-scale levels (Bradford and D'Amato, 2012; Feng et al., 2017; Liu et al., 2019; Feng et al., 2020).

The Yangtze River Delta is one of the most rapid economic development regions in China. As an important part of the Yangtze River Delta, superior geographical conditions and natural endowment in Jiangsu Province have provided unique conditions for rapid urbanization and economic growth. The population density (751 people/km^2) and gross domestic product (GDP) (99.3 billion \$/km^2) of Jiangsu Province per unit area were 5 times and 9 times the national average, respectively (Statistical Bureau of Jiangsu Province, 2019); GDP per capita exceeded \$16,000 in Jiangsu Province which approaches the GDP of high-income regions (Fantom and Umar, 2016; Statistical Bureau of Jiangsu Province, 2019). However, issues such as the loss of farmland and green space, inefficient land use, and ecosystem degradation have posed serious challenges for regional sustainable development. In this study, we conducted the analyses across Jiangsu Province, focused on addressing the following issues: (1) quantify the different types of LUFs at the grid scale and identify the regions of high and low supply of individual LUF, (2) reveal the characteristics of spatial trade-offs among multiple LUFs, (3) explore the determinants of the trade-offs among multiple LUFs in Jiangsu Province. We aim to increase the scope and robustness of LUFs analysis by using interdisciplinary approaches, multi-source data and provide a reference for policy-makers to make decisions in future land use planning and management that better promote regional sustainable development.

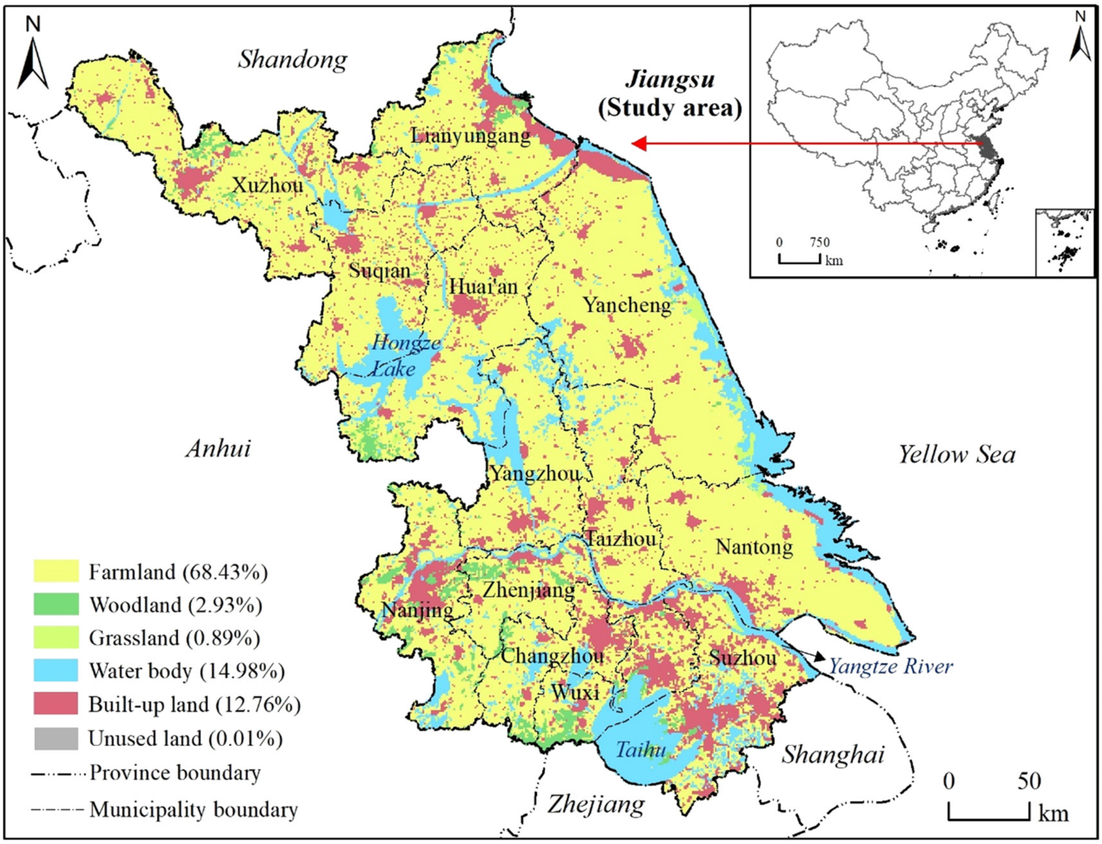

Fig. 1. Location, land use/land cover maps, and geographical division of the study area.

2. Materials and methods

2.1. Study area

Jiangsu province, a core area of the Yangtze River Economic Delta, is located in the coastal region of eastern China (Fig.1). It covers an area of about 107,200 km^2 and includes 13 municipalities and 63 counties. Farmland and bodies of water account for more than 68.43% and 14.98% of the total area in Jiangsu, respectively. There are more than 200 rivers and lakes, the two largest lakes in the area being Taihu Lake (2428 km^2) and Hongze Lake (1597 km^2), which are the third and the fourth largest freshwater lakes in China, respectively (Q. Wang et al., 2016; Qiao et al., 2019). Jiangsu is one of the most developed regions in China with high population density and economic output. The region covers 1.16% of China's total land area, supports 5.76% of the nation's population, and generates 10.05% of the nation's GDP. The region also has a long history of agricultural production and is one of the main grain production areas in China. However, rapid demographic growth and industrial development have accelerated the consumption of natural resources and the degradation of ecosystem function. Farmland area has decreased by 0.66 million ha from 2000 to 2015 in Jiangsu, and the area of woodland and grassland have also decreased during this period. Approximately 38.7% of the key water functional zones in the region are not able to meet the water quality standards set by the government (MWRPRC, 2015). Excessive land reclamation and the decline of vegetation cover have led to considerable soil erosion in parts of the area. The impacts of climate change, such as a rising temperature and frequent extreme weather events, are also a focal issue in Jiangsu. Natural habitats are shrinking and becoming fragmented, and the number of threatened and endangered species of wild animals (e.g., *Lipotes vexillifer, Cololabis sp.*) and plants (e.g., *Ceratopteris sp.*) continues to increase. Thus, there is a pressing need to identify spatial trade-offs and associated mechanism among multiple LUFs for better

Table 1
The description and sources of data used in the study.

Data type	Data source	Spatial resolution
Land use/land cover data	Resource and Environment Science Data Center, Chinese Academy of Sciences	1:10,0000
DEM (ASTER GDEM V2)	Geospatial Data Cloud	30 m × 30 m
Normalized Differential Vegetation Index (MYDND1M)		500 m × 500 m
Net primary productivity (MOD17A3)	National Oceanic and Atmospheric Administration	1 km × 1 km
Evapotranspiration (MOD16A3)		500 m × 500 m
Leaf area index (MOD15A2)		1 km × 1 km
Precipitation	Meteorological data center of China Meteorological Administration	Meteorology station
Soil data	Soil Database of China	1:100,0000
Road data	National Earth System	1:25,0000
Natural reserves of Jiangsu	Scientific Data Sharing Infrastructure	1:25,0000
Landscan population distribution	Oak Ridge National Laboratory, US Department of energy	1 km × 1 km
Socioeconomic data	Statistical Bureau of Jiangsu Province	County level
Root depth	(Fu et al., 2013; Bao et al., 2016)	Land use/land cover
Soil and water conservation factors	Yi et al., 2015; Ganasri and Ramesh, 2016	Land use/land cover
Sensitivity of habitat types	Wu et al., 2015, 2017	Land use/land cover
Habitat stress factors		Land use/land cover

decision making to support future land spatial management in Jiangsu Province (Table 1).

2.2. Data sources

The data used in this study includes: (1) spatial data including land use/land cover; remote sensing data; soil/meteorological data; road, point of interest (e.g., natural reserves, scenic area, and national geological parks), and population distribution data; (2) socio-economic statistical data including crop yield; population; GDP at the county level); and (3) reference data such as parameters (e.g., root depth, soil and water conservation factors, sensitivity of habitat types, habitat stress factors) that refer to the existing literature. Detailed information on the data, including their sources, is shown in Table 1. All spatial data were integrated and merged to quantify the LUF indicators at 1-km^2 grid scale using the Gauss-Kruger projection and the Xi'an 80 geographical coordinate system.

2.3. Methods

2.3.1. Identifying and quantifying land use functions

Land space includes three sub-spaces—agricultural space, urban space, and ecological space—according to the *National Land Planning Outline* (2016–2030), a national strategic guideline document issued by the Chinese State Council. The distinct structure and composition of each type of space determines the differences in the spatial development goals for each space. Therefore, differences also occur in the benefits provided to human beings by the land use system of each space; these benefits can be regarded as multiple LUFs. In this context, we proposed a classification framework of LUFs present in Fig. 2.

For agricultural space, the fundamental development goal is to ensure food security and basic survival (Song and Pijanowski, 2014; Song et al., 2015; Deng et al., 2015). Humans value agricultural space chiefly for the different kinds of agricultural products provided by this space (Power, 2010), which is a type of agricultural production function. Crops (e.g., grain, wheat, corn) are the primary provisions for human wellbeing; consequently, crops are the most important, but not the only, product of agricultural production systems. Supply of aquatic products is an important part of agricultural production in Jiangsu where there is a developed and distinctive fishery industry. The forest industry development in the region also provides important raw materials for secondary production such as processing and manufacturing. Therefore, the agricultural production function is divided into three sub-functions: crop provisioning, timber provisioning, and aquatic product provisioning.

For urban space, it is critical to emphasize economic and intensive land use to ensure sustainable socio-economic development in China, especially in rapidly urbanizing regions like Jiangsu (Liu et al., 2014; Liu and Li, 2017). Urban space provides support for living in urban areas, which we define as the urban living function. Jiangsu is one of the most rapidly growing regions in the process of China's socio-economic development. Residential space provides a basis for continuously increasing population to maintain the operation of urban living systems in the region. With the rapid development of the economy and society, the basic needs of residents (e.g., education, health care, financial services and entertainment) are increasing in Jiangsu (Hou et al., 2014). Catering, accommodations, and financial services are indispensable to daily life and work. Medical and educational services support physical and psychological health of residents. Tourism and recreation are an essential cultural service for humans to improve their quality of life. As such, we divided urban living function into five sub-functions: residential support, commercial services, educational services, medical services, and recreation services.

Ensuring ecological security by stabilizing natural ecosystems and improving ecosystem resilience has been a key issue of achieving long-term and sustainable coexistence of nature and human societies

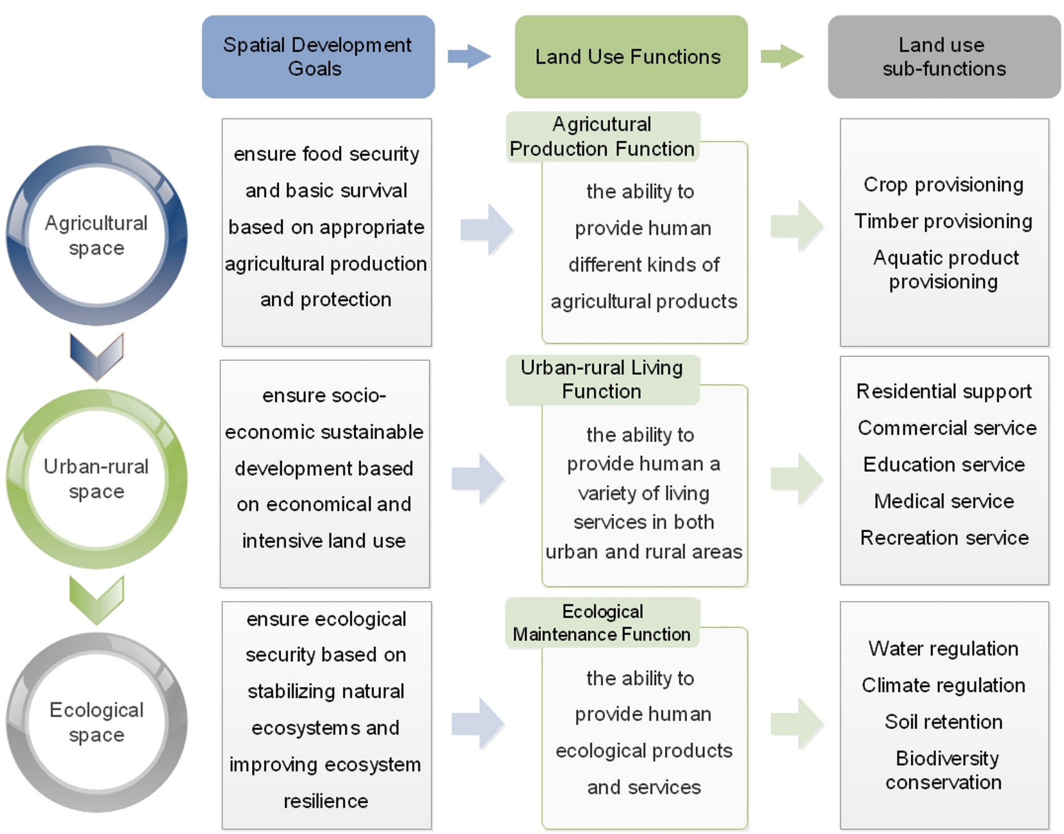

Fig. 2. A classification framework of land use functions.

(Fischer et al., 2006; Sasaki et al., 2015). Natural ecosystems provide ecological products and services to humans, which promote the harmonious development of humans and nature; this is referred to as the ecological maintenance function. Irrigating inappropriately and using water resources extensively may lead to water shortage and pollution in Jiangsu (Huang et al., 2015; Cao et al., 2018). The area of soil erosion in China in 2015 was 295 million ha. The influence of land use activities on climate change has already been an especially relevant environmental issue in China (Huang et al., 2015). Moreover, approximately 44% of wildlife species have decreasing population sizes as a result of poor habitat quality (MEEPRC, 2010). As such, the ecological maintenance function is divided into four sub-functions in this study: water regulation, climate regulation, soil retention, and biodiversity conservation.

In general, LUFs are divided into three primary functions and 12 sub-functions in our study. Each of the 12 sub-functions was measured using unique quantification indicators. The criteria for selecting these indicators are: (1) relevance to the sub-function, (2) use in previous studies, and (3) measurability at the grid scale from available data. Detailed information about indicators and quantification methods of LUFs are shown in Table 2.

2.3.2. Measuring the trade-offs among multiple LUFs

RMSE is a simple and effective statistical parameter that approximates the average deviation from the mean benefit of LUFs for quantifying the degree of the trade-offs between two or more LUFs (Bradford and D'Amato, 2012; Feng et al., 2017; Liu et al., 2019; Feng et al., 2020). It indicates the magnitude of same-direction changes among multiple LUFs regardless of the direction of the correlation. In this study, we used RMSE to quantify the trade-offs between paired primary functions based on sub-function indicator values.

In a two dimensional coordinate plane, the RMSE represents the distance from the 1:1 line of equal benefit for a data point; the relative position of the data point to the line indicates which LUF receives more benefit from the trade-off (Fig. 3). LUF pairs located on the 1:1 line (e.g., points A and E) indicate no trade-offs and point E shows a greater benefit from the trade-off than that of point A. LUF pairs represented by points B, C, and D showed non-zero trade-offs, and the lengths of O_1B, O_1C, and O_2D represent the magnitude of the trade-offs for the LUF pairs at points B, C, and D, respectively. However, B favors LUF1, C and D favor LUF2. The trade-offs for B and C are higher than that for D.

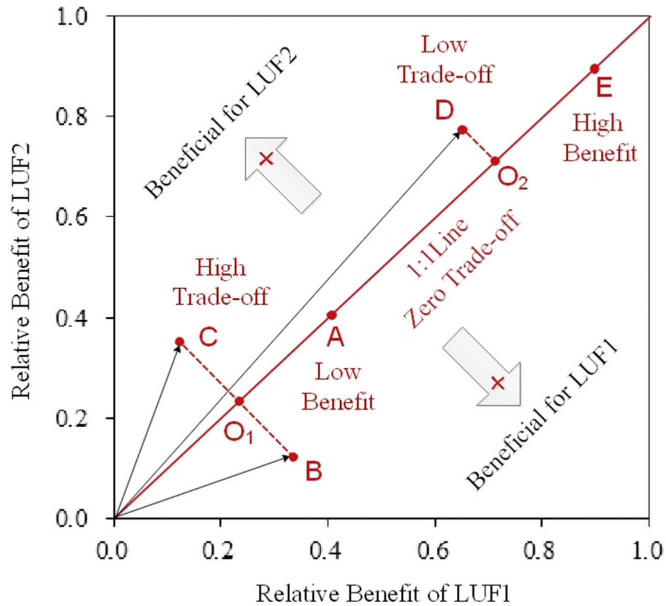

Fig. 3. Illustration of the trade-offs between two LUFs.

We standardized the values of all LUF indicators from 0 to 1 using minimum and maximum values to make all 12 of the LUFs comparable at the grid scale. The LUF indicators were standardized using the following formula:

$$LUF_{std} = (LUF_{obs} - LUF_{\min})/(LUF_{\max} - LUF_{\min}) \quad (1)$$

where LUF_{std} and LUF_{obs} are the standardized and observed value of a LUF indicator, respectively; $LUF_{\min}$ and $LUF_{\max}$ are the minimum and maximum value of a LUF indicator, respectively. Then, the RMSE is calculated as follows:

$$\text{RMSE} = \sqrt{\frac{1}{n-1} \times \sum_{i=1}^{n} \left(LUF_i - \overline{LUF}\right)^2} \quad (2)$$

where LUF_i is the standardized value of LUF_i, and $\overline{LUF}$ is the expected value of the i number of LUFs. *RMSE* represents the average difference

Table 2
Description and quantification methods for different types of land use function indicators in the study. NPP_j, $Tarea_j$, $Aarea_j$ represent NPP, woodland area, water body area of the county j, NPP_{ij}, $Tarea_{ij}$, $Aarea_{ij}$ represent NPP, woodland area, water body area of the grid i in county j, $Cyield_j$, $Tyield_j$, $Ayield_j$ represent crop yield, timber yield, aquatic product yield of the county j.

Primary function	Sub-function	Indicators	Unit	Quantification method	References
Agricultural production function (APF)	Crop provisioning	Crop yield	$kg \cdot km^{-2}$	$\frac{NPP_{ij}}{NPP_j} \times Cyield_j$	Crop yield is positively related to NPP (Hong et al., 2019; Li et al., 2020)
	Timber provisioning	Timber yield	$kg \cdot km^{-2}$	$\frac{Tarea_{ij}}{Tarea_j} \times Tyield_j$	Measure the timber yield and aquatic product yield at the grid scale combining statistical data and land use data (Sun et al., 2017)
	Aquatic product provisioning	Aquatic product yield	$kg \cdot km^{-2}$	$\frac{Aarea_{ij}}{Aarea_j} \times Ayield_j$	
Urban living function (ULF)	Residential support	Population density	$Persons \cdot km^{-2}$	LandScan datasets	LandScan population distribution at the grid scale
	Commercial service	Commercial service point density	#	Total number of catering, accommodations, finance service points at 1km^2 grid	The density of the point of interest has strong linear relationships with the land use intensity and can be used to characterize the ability to provide human a variety of living services (Jin et al., 2017; Wang et al., 2018)
	Education service	Education service point density	#	Total number of scientific research and education service points at 1km^2 grid	
	Medical service	Medical service point density	#	Total number of medical service points at 1km^2 grid	
	Recreation service	Recreation service point density	#	Total number of tourism and recreation points at 1km^2 grid	
Ecological maintenance function (EMF)	Water regulation	Water retention	mm	InVEST water yield model	Tallis et al., 2011; Leh et al., 2013; Bao et al., 2016; Lin et al., 2018; Bai et al., 2020
	Climate regulation	Carbon storage	$Mg \cdot ha^{-1}$	InVEST Carbon Storage model	
	Soil retention	Amount of soil erosion	Ton	InVEST sediment delivery ratio model	
	Biodiversity conservation	Habitat quality	#	InVEST habitat quality model	

between the individual LUF and the average LUF at the grid scale and describes the magnitude of trade-offs between paired primary LUFs in this study. In two dimensions, $\overline{LUF}$ is on the 1:1 line. A larger RMSE indicates a higher trade-off and a smaller RMSE value indicates a lower trade-off between the two LUFs.

2.3.3. Identifying drivers of LUF trade-offs

A geographical detector is a set of statistical methods used to detect the spatial stratified heterogeneity of dependent variables and identify their drivers (Wang et al., 2010; J.F. Wang et al., 2016; Song et al., 2020). This approach divides the study area into several sub-regions by variables. Then, the spatial variance within each sub-region and among different sub-regions are compared to identify the determinant power of multiple independent variables (J.F. Wang et al., 2016). The core part of geographical detector is the factor detector that reveals the relative importance of various independent variables X_i for dependent variable Y with a q-statistic. The q value calculation of a potential independent variable X_i is as follows (J.F. Wang et al., 2016; Song et al., 2020):

$$q = 1 - \frac{\sum_{i=1}^{m} N_i \sigma_i^2}{N\sigma^2} \tag{3}$$

where m is the number of strata for explanatory variables in the study area; N and N_i indicate the number of observations in the whole study area and in the i^{th} strata, respectively; σ and σ_i indicate the variance of Y in the whole study area and in the i^{th} strata, respectively. q value ranges from 0 to 1, and a larger q value indicates a relatively higher contribution of the explanatory variable X_i for the dependent variable, Y.

The risk detector, another essential part of the geographical detector, is used to determine if the mean values of the dependent variables among different sub-regions show significant differences. We used a t-test to identify the difference between mean values of the two sub- regions j and k (J.F. Wang et al., 2016; Song et al., 2020):

$$t_{\overline{y}_j - \overline{y}_k} = \frac{\overline{y}_j - \overline{y}_k}{\sqrt{\frac{S_j^2}{N_j} + \frac{S_k^2}{N_k}}} \tag{4}$$

where $\overline{y}_j$ and $\overline{y}_k$ indicate the mean values of observations, N_j and N_k indicate the number of observations, S_j^2 and indicate the sample variance of observations within the j^{th} and k^{th} sub-regions, respectively. The statistic is subject to the distribution of Student's t, for which the calculation of degrees of freedom is given by:

$$df = \left(\frac{S_j^2}{N_j} + \frac{S_k^2}{N_k}\right) \Big/ \left[\frac{1}{N_j - 1}\left(\frac{S_j^2}{N_j}\right)^2 + \frac{1}{N_k - 1}\left(\frac{S_k^2}{N_k}\right)^2\right] \tag{5}$$

The null hypothesis, H_0: $\overline{y}_j =$, can be tested with the Student's t distribution at a given significant level α. If H_0 is rejected at the confidence level α, a significant difference exists between the j^{th} and k^{th} sub-regions. We used the package “GD” (Wang et al., 2010) in R Statistical software (R Core Team, 2020) to compute the factor and risk detectors.

3. Results

3.1. Spatial patterns of land use functions

The spatial distribution of the 12 land use sub-functions showed clear heterogeneity and homogeneity at the 1-km^2 scale across the study area (Fig.4). Higher crop provisioning was clumped in central and northern Jiangsu, which was covered with abundant and continuous farmland. Timber provisioning was low throughout the study area, with most timber provisioning occurring in the north of Jiangsu. The areas with high aquatic products provisioning appeared in the coastal areas due to the dense river network and rapid development of aquaculture.

All five sub-functions of ULF were spatially aggregated in built-up areas because these ULF sub-functions depend less on natural endowment than on socio-economic development. The residential support sub-function had a significant clump in southern Jiangsu—especially in Nanjing, the provincial capital, and in the Suzhou-Wuxi-Changzhou area. The clumped distribution of commercial service, education service, medical service, and recreation service were nearly consistent with that of the population. Generally, the four functions above showed a continuous distribution in southern Jiangsu and scattered distribution in northern Jiangsu.

The distribution of the four sub-functions of EMF exhibited obvious spatial heterogeneity in 2015. Higher water regulation scattered in the southwest hilly area of Jiangsu. High soil retention occurred predominantly in southwest Jiangsu, the high-elevation areas. The areas with high climate regulation values were mainly covered with forest. The distribution of biodiversity conservation was spatial heterogeneous and closely related to vegetation type. The highest values of biodiversity conservation were located in areas where the main land cover was water, such as the coastal area, Taihu, and Hongzehu. Biodiversity conservation in southern Jiangsu was lower than in northern Jiangsu.

3.2. Spatial trade-offs of multiple LUFs

The spatial trade-offs varied greatly among the different primary LUF pairs across the study area at the grid scale. Additionally, the magnitude of the trade-offs among function pairs varied (Fig. 5). For the pair APF and ULF (Fig. 5(a)), the trade-off was low in Jiangsu, with an overall mean RMSE of 0.056. In general, the RMSE value for APF and ULF in southern Jiangsu was approximately half that of both central and northern Jiangsu, indicating higher trade-offs in central and northern Jiangsu (Fig. 5(d)). High trade-offs between APF and ULF also occurred in the built-up area of southern Jiangsu.

As a whole, the RMSE value between APF and EMF was higher than for the other two pairs of LUFs. The magnitude of the trade-off between APF and EMF and between ULF and EMF were higher in areas covered with water and forest. The highest trade-off for APF and EMF occurred in northern Jiangsu. The mean RMSE value between APF and EMF in the area was 0.155. The magnitude of the trade-off between APF and EMF in the southern Jiangsu was slightly lower than that in the northern and central Jiangsu. For the pair ULF and EMF, higher trade-offs occurred in the center of the cities in southern Jiangsu. The RMSE values were similar among different geographical zones for APF-EMF and ULF-EMF.

Moreover, the RMSE values for the three LUF pairs were various across different cities in Jiangsu (Fig.6). For APF and ULF, the RMSE value was the highest (RMSE = 0.083) in Taizhou and lowest (RMSE = 0.024) in Suzhou. Taizhou had the lowest trade-off for ULF and EMF (RMSE = 0.120), and a low trade-off for APF and EMF (RMSE = 0.145), as well. The distribution of RMSE values for APF-EMF and ULF -EMF were similar in each city of Jiangsu. The highest RMSE values between APF and EMF (RMSE = 0.175) and between ULF and EMF (RMSE = 0.153) were located in Yancheng in northern Jiangsu. Also, Nantong is the region that had high trade-offs for both APF-EMF and ULF-EMF. Except for Yancheng and Nantong, the distribution of the RMSE values for APF-EMF and ULF-EMF were similar in the other cities. In southern Jiangsu, the lowest trade-offs for APF-EMF (RMSE = 0.136) and ULF-EMF (RMSE = 0.125) were distributed in Changzhou.

3.3. Drivers associated with LUF trade-offs

In this study, we selected 12 potential drivers associated with LUF trade-offs within Jiangsu that satisfy the compromise between relevance to the expected goals and the availability of data at the extent of the study area (Table 3). These potential drivers include variables that were directly used in the quantification methods of the LUFs

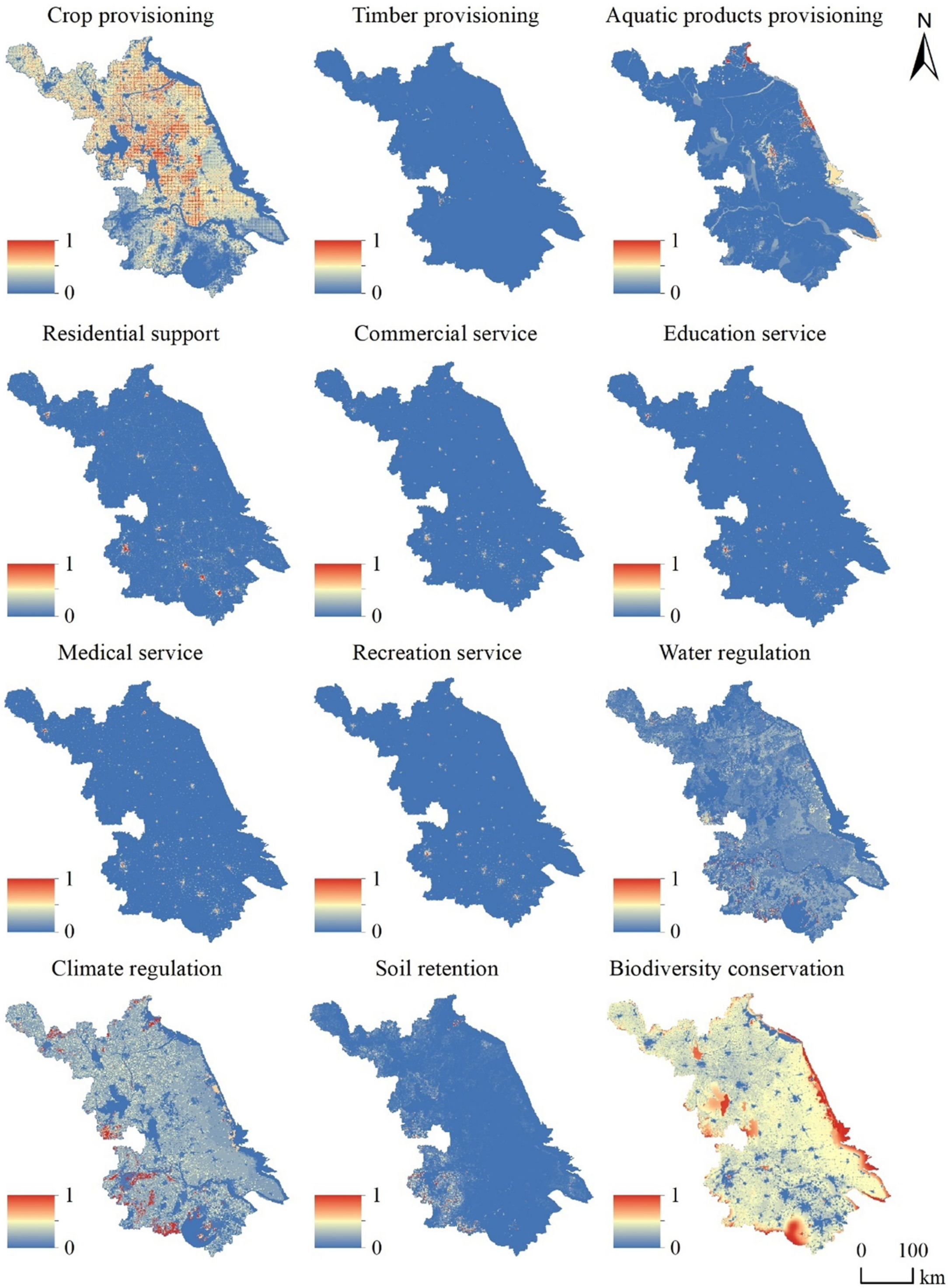

Fig. 4. Spatial distribution of the 12 land use sub-functions across Jiangsu Province.

(e.g., land use/land cover, slope, potential evapotranspiration, precipitation) to account for their effects on LUF trade-offs. Potential drivers also include independent variables that may be associated with the occurrence of LUF supply (e.g., vegetation coverage ratio, distance factors, landscape shape index, aggregation index, Shannon diversity index). All the potential drivers can be obtained from the dataset of this study or be quantified using applicable models or methods (Table 3). Then, we divided each potential driver variable into five groups to facilitate the use of explanatory variables applicable for the geographical detector model, and then mapped these potential drivers (Fig.7).

The q-statistic values—reflecting the proportion of each pair of LUF trade-off explained by the 12 potential explanatory variables—are listed in Table 4. Table 4 also showed all the potential explanatory variables have significant impacts on the LUF trade-offs. The driver with the greatest influence on the three pairs of LUF trade-off was land use/land cover, which had q values of 0.16, 0.50, and 0.48 for the trade-offs of APF-ULF, APF-EMF, and ULF-EMF, respectively. The risk detector analysis also revealed the effects of 12 potential drivers on the three pairs of LUF trade-offs (Fig. 8). The highest trade-off between APF and ULF was distributed in farmland with a RMSE value of 0.66. Woodland

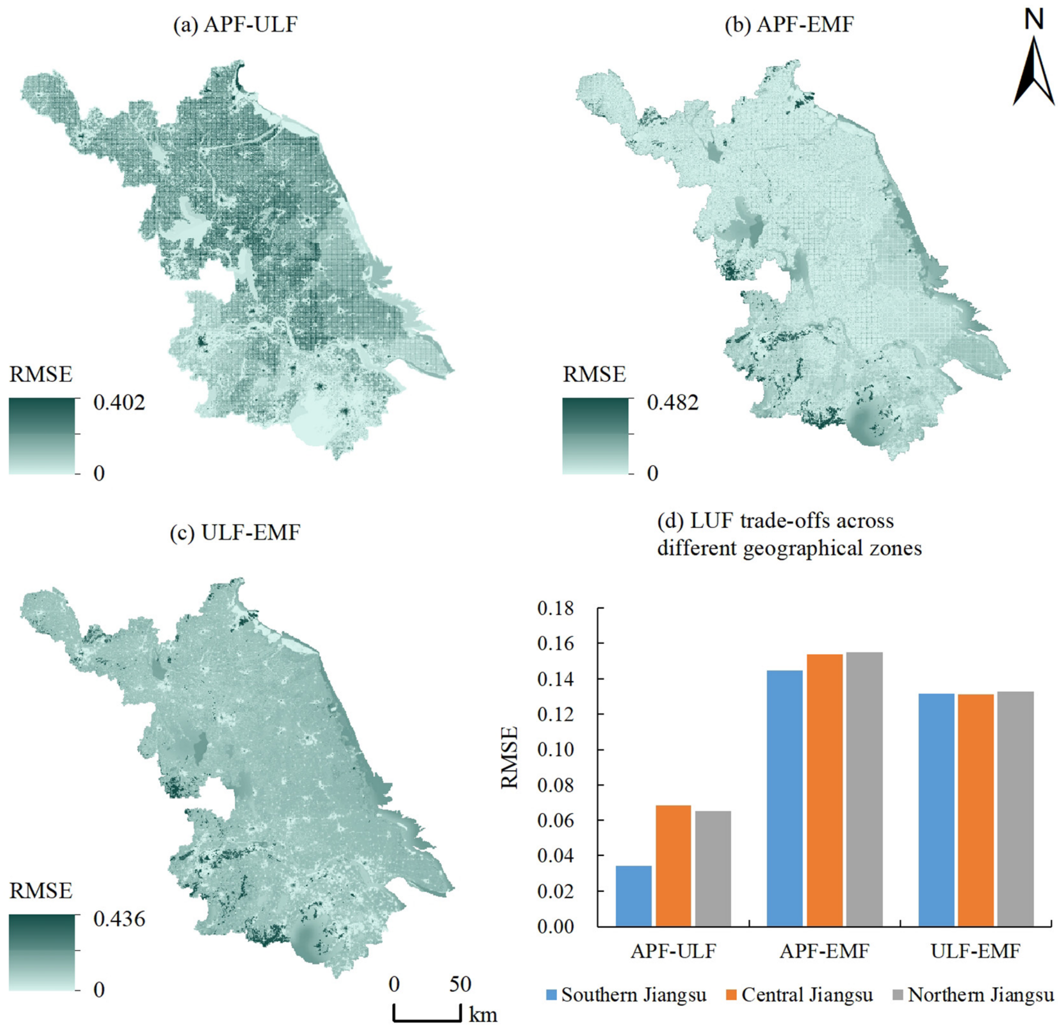

Fig. 5. Spatial patterns of trade-offs across Jiangsu Province (a) and the magnitude of the trade-offs across different geographical zones (b) among the three primary land use functions. Southern Jiangsu includes Nanjing, Suzhou, Wuxi, Changzhou, Zhenjiang; Central Jiangsu includes Yangzhou, Taizhou, Nantong; and Northern Jiangsu includes Xuzhou, Lianyungang, Huai'an, Yancheng, Suqian.

had the highest RMSE values for both APF-EMF (RMSE = 0.296) and ULF-EMF (RMSE = 0.296) whereas the built-up land had the high RMSE values for the two pairs of LUFs.

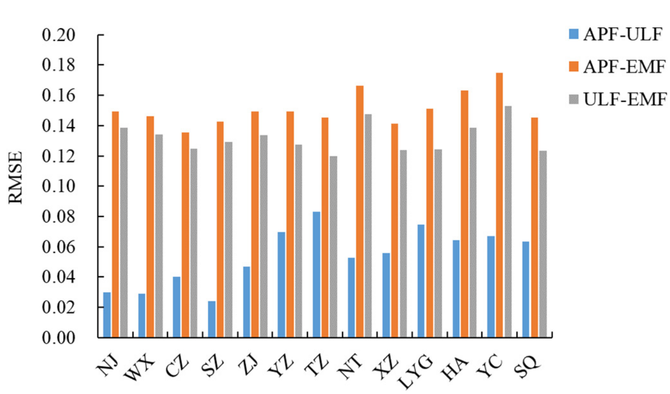

Fig. 6. The magnitude of the trade-offs among the three primary land use functions across cities of Jiangsu Province. NJ, WX, CZ, SZ, ZJ, YZ, TZ, NT, XZ, LYG, HA, YC, SQ are the abbreviations of Nanjing, Wuxi, Changzhou, Suzhou, Zhenjiang, Yangzhou, Taizhou, Nantong, Xuzhou, Lianyungang, Huai'an, Yancheng, Suqian, respectively.

In terms of the contribution (q values) rank of potential drivers of trade-offs for APF-ULF, the major driving factors associated with the trade-off of APF-ULF were potential evapotranspiration ($q = 0.12$), vegetation coverage ratio ($q = 0.09$), precipitation ($q = 0.06$), and Shannon diversity index ($q = 0.06$). The high trade-off of APF-ULF tended to occur in regions with high potential evapotranspiration and vegetation coverage ratio and low precipitation (Fig. 8(a)). Conversely, the trade-off of APF-ULF was weaker in diverse landscapes than in homogeneous landscapes. We also found that three distance factors contribute little to the trade-off between APF and ULF.

The contribution of each potential driver to the trade-off of APF and EMF was similar to the contribution of that to the trade-off of ULF and EMF (Fig. 8(a), (b)). In addition to LULC, the other seven driving factors—slope, potential evapotranspiration, vegetation coverage ratio, distance to the nearest county, distance to the nearest road, Shannon evenness index, and landscape shape index—also had relatively high contributions to the trade-off of APF-EMF and ULF-EMF. For APF-EMF, the rank of q values for the main driving factors was LULC (0.50) > VCR (0.22) > DNR (0.18) > DNC2 (0.15) > PET (0.13) > SLP (0.12) > SHEI (0.11) > LSI (0.11). For the pair of ULF-EMF, the rank of q values for the main driving factors was LULC (0.48) > VCR (0.20) > DNR (0.18) > DNC2 (0.15) > SLP (0.14) > PET (0.13) = SHEI (0.13) > LSI (0.12).

Table 3
The description of potential drivers for the trade-offs among multiple LUFs.

Potential drivers	Abbreviation	Unit	Sources/quantification method	Classification
Land use/land cover	LULC	#	Land use/land cover data	I: Farmland,II: Woodland, III: Grassland, IV: Water body, V: Built-up land
Slope	SLP	°	Slope Tool in ArcGIS	I: [0,2),II: (2, 6], III: (6, 15], IV: (15, 25],V: (25, 60]
Potential evapotranspiration	PET	mm	MOD16A3	I: 0,II: (0,1100], III: (1100,1200], IV: (1200,1300], V: (1300, 1691]
Vegetation coverage ratio	VCR	%	$\frac{NDVI_i - NDVI_{max}}{NDVI_{max} - NDVI_{min}} \times 100\%$	I: [0,20),II: (20, 40], III: (40, 60], IV: (60, 80],V: (80, 100]
Precipitation	PRE	mm	China Meteorological Administration	I: [0,1000),II: (1000,1200], III: (1200, 1400], IV: (1400, 1600],V: (1600, 1764]
Distance to the nearest city	DNC1	m	Near Tool in ArcGIS	I: [0,20,000),II: (20,000, 40,000], III: (40,000, 60,000], IV: (60,000, 80,000],V: (80,000, 108,679]
Distance to the nearest county	DNC2	m		I: [0,10,000),II: (10,000,20,000], III: (20,000,30,000], IV: (30,000, 40,000],V: (40,000, 66,930]
Distance to the nearest road	DNR	m		I: [0, 2500),II: (2500, 5000], III: (5000, 10,000], IV: (10,000, 20,000],V: (20,000, 40,530]
Landscape shape index	LSI	#	Fragstats	Natural Breaks, I: (0, 1.05], II: (1.05, 1.35], III: (1.35, 1.75], IV: (1.75, 2.10],V: (2.10, 2.90]
Aggregation index	AI	#		Natural Breaks, I: (0,23],II: (23, 55], III: (55, 70], IV: (70, 86], V: (86, 100]
Shannon diversity index	SHDI	#		Natural Breaks, I: (0, 0.28],II: (0.28, 0.67], III: (0.67, 0.98], IV: (0.98, 1.30],V: (1.30, 2.13]
Shannon evenness index	SHEI	#		Natural Breaks, I: 0,II: (0, 0.44], III: (0.44, 0.66], IV: (0.66, 0.82], V: (0.82, 1]

The areas with moderate vegetation coverage ratios had the weakest trade-offs of APF-EMF and ULF-EMF. The high trade-offs of APF-EMF and ULF-EMF were mainly located in areas with high slope and low potential evapotranspiration and vegetation coverage ratio. The trade-off of APF-EMF and ULF-EMF became stronger as the distance to county and road increased. Another interesting finding is that the lowest trade-offs of APF-EMF and ULF-EMF were found in the complex, scattering, diverse, and uneven landscapes, indicating that heterogeneous landscapes were better for the balanced supply of APF with EMF and ULF with EMF. In general, precipitation had a small effect on the trade-off of APF-EMF and ULF-EMF.

4. Discussions

4.1. The complexity and mechanism of LUF relationships

The drivers first had an effect on individual LUF and subsequently influenced their interactions for which the mechanisms of LUF relationships were more complex (Bennett et al., 2009; Feng et al., 2017). For LUF trade-offs investigated in this study, LULC was the primary driver of LUFs and their interactions, which is consistent with previous studies (Li et al., 2017; Tao et al., 2018). Crop provisioning, the primary sub-function of APF, was heavily dependent on the benefits of farmland, which provided little support for the sub-functions of ULF. This led to a high trade-off between APF and ULF in farmland area. Forests are beneficial to soil retention and carbon storage (Fu et al., 2011; Feng et al., 2017), but have little contribution to the supply of APF and no correlation with the supply of ULF. This explanation is consistent with our finding that high trade-offs for APF-EMF and ULF-EMF were located in forested areas.

All three pairs of LUF trade-offs were significantly influenced by potential evapotranspiration and vegetation coverage, and slope had a significant contribution to APF-EMF and ULF-EMF trade-offs. High trade-offs for APF-EMF and ULF-EMF were found in the regions with slopes steeper than 15° and regions covered mostly with forest, which are beneficial to the supply of EMF, but contribute less to APF and ULF. Vegetation is usually closely and positively related to evapotranspiration due to crop and vegetation growth. Areas covered with natural vegetation or crops have high APF values, but do not contribute much to the supply of ULF. Therefore, the high trade-off between APF and ULF are found in regions with high evapotranspiration and vegetation coverage ratio. In addition, we found the lowest trade-offs of both APF-EMF and ULF-EMF in areas where the potential evapotranspiration is less than 1100 mm and the vegetation coverage ratio is 40–60%, indicating that moderate planting of cover crops could benefit ecosystem conservation and enable a balanced land use system, which is consistent with existing studies (Swinton et al., 2007; Winter et al., 2018). High vegetation coverage usually results in high water consumption and low availability of local runoff water (Farley et al., 2005; Wang and Fu, 2013).

High-yield agricultural products provisioning usually results from intensive agricultural production that increases human impact on ecosystems and leads to ecosystem function degradation, e.g., habitat loss, soil erosion, accelerated water consumption (Grau et al., 2013; Tsiafouli et al., 2015; Gibbs and Salmon, 2015). Contiguous and compact farmland provides more favorable conditions for intensive agricultural production in areas that are far from the county or roads; intensive agriculture improves productivity, but result in the decline of ecosystem function. As such, the trade-off between APF and EMF increases with increasing distance from the county or road. However, the highest trade-offs between ULF and EMF are also located far from the county and road, suggesting the decrease of population density and the reduction of human activities in the urban living space could be useful and info for the maintenance and recovery of natural ecosystem (Cumming et al., 2014; Li et al., 2016; Peng et al., 2017).

All the four landscape configuration metrics (i.e., LSI, AI, SHDI, and SHEI) contribute to the trade-offs between APF and EMF and between ULF and EMF. Our findings that landscape characteristic metrics have important impacts on the indicators of EMF and their influences on the interactions of APF-EMF and ULF-EMF are in line with the findings of previous studies (Qiu and Turner, 2015; Bai et al., 2020). Spatial heterogeneity has been proven to be important in landscapes for sustaining water yield, carbon storage, soil retention, and habitat quality (Turner et al., 2013; Bai et al., 2020). However, as a whole, regular and extremely compact landscapes are more beneficial for agricultural production and urban development (Verburg et al., 2015; Stott et al., 2015). This could be a probable explanation for the highest trade-offs of APF-EMF and ULF-EMF occurring in areas with low LSI, SHDI, SHDI, and AI. It should be noted that LSI, SHDI, and SHDI are positively correlated with the sub-functions of EMF, whereas AI has negative correlation with the sub-functions.

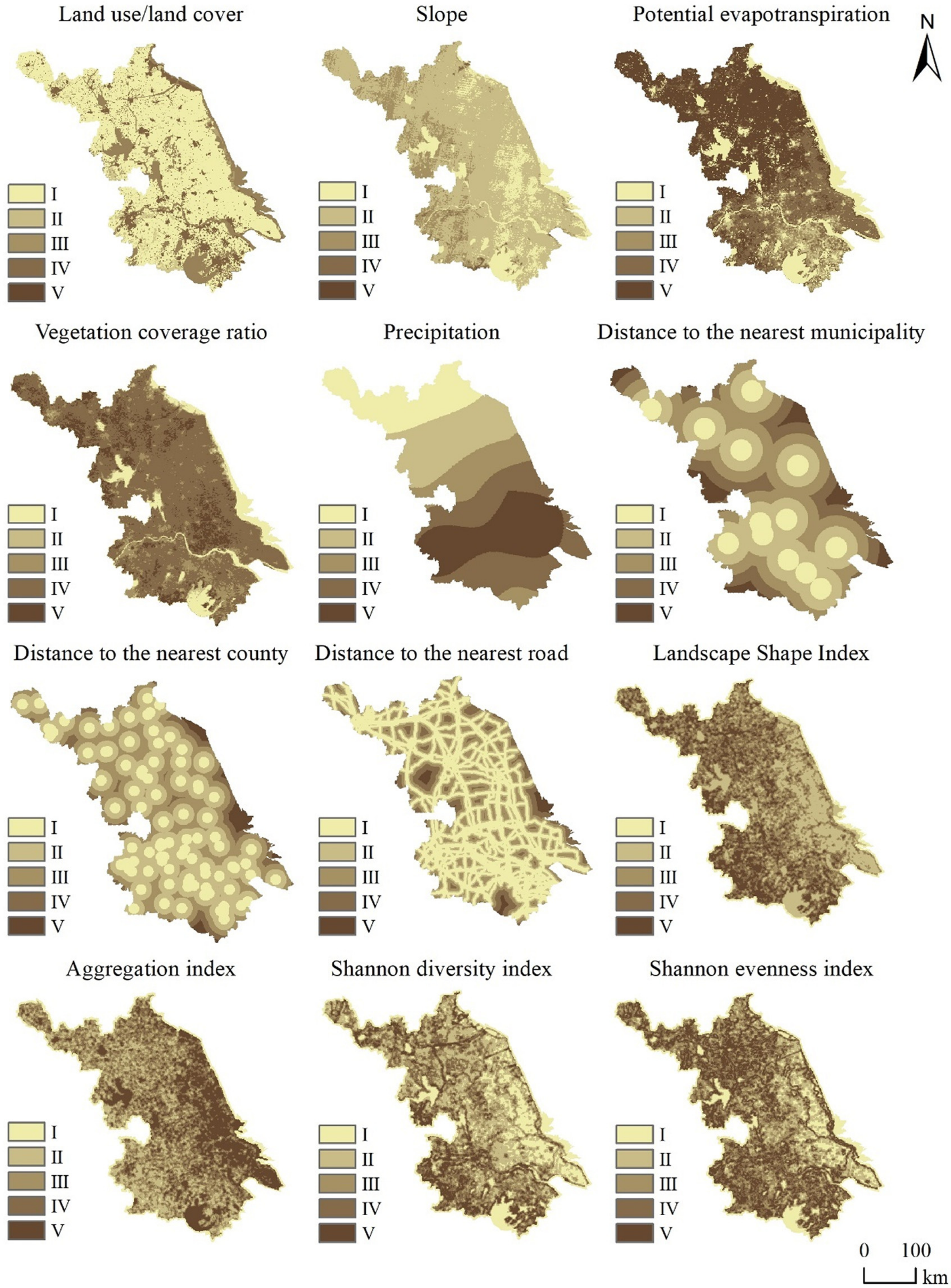

Fig. 7. Spatial patterns of the potential drivers of trade-offs among multiple LUFs.

4.2. Policy implications for sustainable land spatial planning and management

LUFs are significant to global science and policy; however, the application of LUFs analysis to management decision-making remains understudied and unclear (Laurans et al., 2013; Quintas-Soriano et al., 2016). As the most important determinant of the spatial trade-offs among LUFs, land use/land cover can be substantially affected by human activities. Also, vegetation coverage can be readily used by decision makers and local populace to facilitate better LUFs regulation (Feng et al., 2020). By contrast, physical natural conditions like potential evapotranspiration and slope are difficult or almost impossible to change in the short term. In addition, intensive and compact agricultural production provides high-value agricultural products provisioning but has negative impacts on natural ecosystem. Urban sprawl also occupied agricultural and ecological spaces that lead to the decline of APF and the degradation of EMF.

Table 4
The *q* value and significance of different potential drivers for the trade-offs among the three primary LUFs.

Potential driving factor	APF-ULF		APF-EMF		ULF-EMF	
	q value	*sig.*	*q* value	*sig.*	*q* value	*sig.*
LULC	0.16	6.29E-11	0.50	9.46E-10	0.48	8.99E-10
SLP	0.03	6.29E-11	0.12	9.46E-10	0.14	8.99E-10
PET	0.12	2.02E-11	0.13	1.09E-10	0.13	6.91E-10
VCR	0.09	7.22E-11	0.22	4.87E-10	0.20	7.32E-10
PRE	0.06	1.69E-10	0.02	3.83E-10	0.03	1.56E-10
DNC1	0.01	4.31E-11	0.10	3.18E-10	0.09	5.72E-10
DNC2	0.01	3.86E-10	0.15	6.34E-10	0.15	2.37E-10
DNR	0.01	1.19E-10	0.18	5.63E-10	0.18	9.17E-10
LSI	0.03	1.55E-10	0.11	5.83E-10	0.12	3.97E-10
AI	0.02	2.02E-10	0.10	1.95E-10	0.12	3.77E-10
SHDI	0.06	1.20E-11	0.10	6.45E-10	0.11	1.27E-10
SHEI	0.04	8.11E-10	0.11	1.05E-10	0.13	3.98E-10

In the terms of the interactions among multiple LUFs and the most probable challenges in land use, two countermeasures are proposed here as references for land planning and management and for advancing the application of LUF trade-offs in policy decisions to enhance land use sustainability.

First, the concept of LUF trade-offs must be incorporated into the process of delineating the boundaries for urban growth, farmland, and natural areas. Identification of LUF trade-offs and their drivers at the grid scale provide an applied approach for targeting the conflict areas of agricultural production, urban development, and ecological protection (Yang et al., 2015; Xu et al., 2018). The area with high trade-offs of APF-EMF and ULF-EMF should reinforce ecological restoration for establishing complex, self-sustaining, and resilient interactions between biological assemblages and processes to improve the ecosystem maintenance function (Lu et al., 2014; Suding et al., 2015). Farmland should be defined as permanent basic farmland for better protecting farmland and improving the agricultural productivity in the area with high trade-off of APF-ULF (Song and Pijanowski, 2014; Song et al., 2015). The areas with high values of ULF should be set aside for urban development, where built-up land should be arranged in cluster to avoid occupying farmland with urban expansion.

Secondly, land consolidation projects should be implemented in an orderly manner based on the analysis of LUF trade-offs. It is essential to improve agricultural productivity by implementing high-standard, basic farmland construction (Song and Pijanowski, 2014; Song et al., 2015) to alleviate the trade-off between APF and ULF. Various cropping systems (e.g., crop rotation, intercropping) and integrated crop-livestock/crop-aquaculture can be applied and spread to increase nutrient- and water-use efficiency and to restore soil fertility for sustainable agricultural production (Nhan et al., 2007; Cong et al., 2015). Eco-agriculture should also be encouraged to provide an approach for agriculture that maximizes synergies between socio-economic and ecological benefits (Li et al., 2012). Rural residential land consolidation and

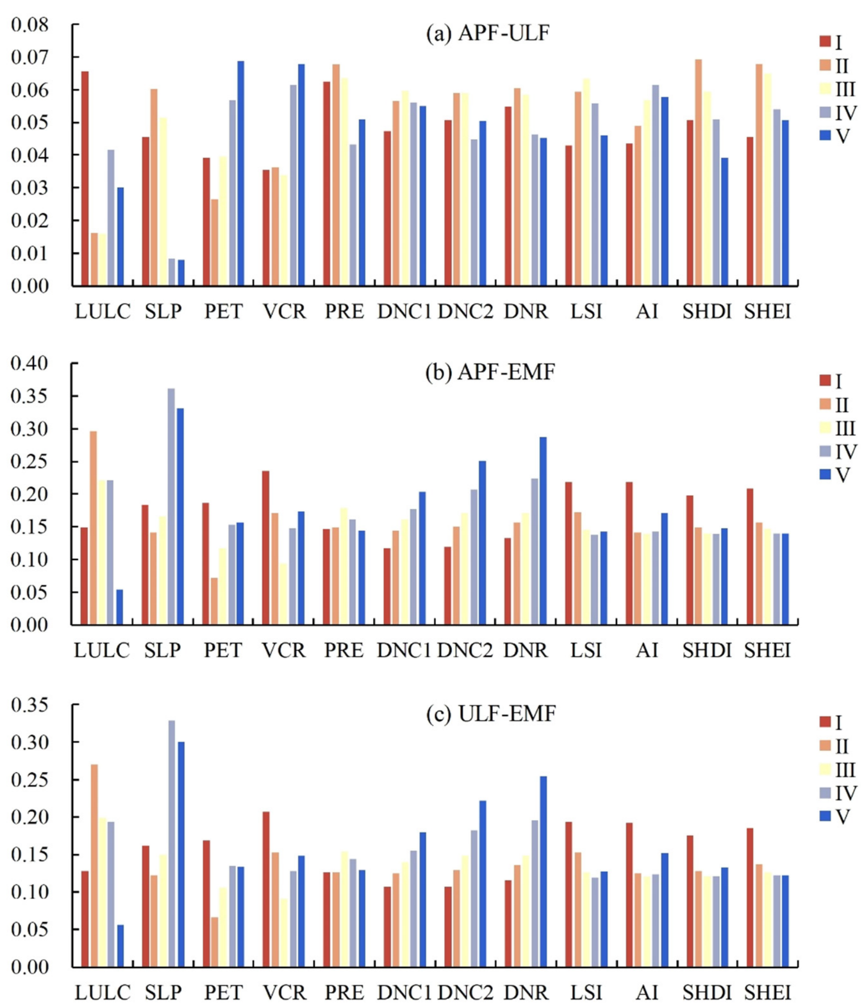

Fig. 8. The RMSE values among the three primary LUFs across the different types of each potential driver.

inefficient urban land redevelopment could be better ways to increase built-up land to reduce the occupation of cultivated land by urban construction (Li et al., 2014; Gao et al., 2018). Green infrastructure construction is also essential to be arranged in agricultural space and urban-rural living space to conserve existing habitats and connect isolated fragments that further enhance landscape heterogeneity and ecological functions (Lovell and Johnston, 2009; Lovell and Taylor, 2013).

4.3. Limitation and further directions

Some common limitations which have been mentioned in previous studies are still the challenges here. The availability of data and the challenge of modeling methods for LUFs quantification and analysis are two primary limitations for practitioners (Guerry et al., 2015; Zhang et al., 2017; Lin et al., 2018). This study focused on spatial trade-offs among multiple LUFs and their drivers, but the changes of these LUF trade-offs over time have not be considered, which limits this type of analysis due to the lack of available data, such as continuous annual land use/land cover data and point of interest. As such, it is necessary to establish a more systematic database or quantify other alternative proxies that better identify the spatiotemporal dynamics of LUF trade-offs.

Furthermore, this study quantitatively measured the magnitude of LUF trade-offs; however, change types of the trade-offs (e.g., convex trade-offs/synergies, concave trade-offs/synergies) were not identified. The thresholds of LUF trade-offs can be determined based on the distinct change types of LUF interactions, and determining these changes in LUF interactions allows policy-makers to better foster synergies and lessen unnecessary trade-offs among functions (Green et al., 2005; Stott et al., 2015; Marr et al., 2016). A necessary next step in this field is to analyze the specific change types of LUF trade-offs to reduce the uncertainties in LUF interactions.

5. Conclusions

This study proposed a LUFs classification framework from the perspective of land spatial planning, including three primary LUFs and 12 sub-functions, and quantified the 12 types of LUFs at the grid scale in Jiangsu Province. We also investigated the spatial trade-offs among the three primary LUFs and the effects of physical natural condition and human activities on LUFs and their relationships. The results revealed that APF exhibited higher values in central and northern Jiangsu, ULF was spatially aggregated in built-up areas and present clear spatial homogeneity, and higher EMF was mainly distributed in the area covered with forest and water. The trade-offs for APF-EMF and ULF-EMF were higher than the trade-off between APF and ULF. The high trade-off areas for APF and ULF were mainly distributed in central and northern Jiangsu, and the trade-offs for both APF-EMF and ULF-EMF were higher in the area covered with water and forest. In addition, our study found that land use/land cover is the primary driver for LUF trade-offs; although, potential evapotranspiration and vegetation coverage ratio were important drivers of LUF trade-offs, as well. Moreover, there was a remarkable impact of landscape configuration metrics and distance to the nearest county and road on the trade-offs of APF-EMF and ULF-EMF. The magnitude of LUF trade-offs varied significantly among distinct sub-regions of individual driving factors. These findings provide an effective reference for decision-makers to target sustainable land spatial system management. We also suggest that explore more spatially-explicit methods for quantifying LUF and their trade-offs be developed.

CRediT authorship contribution statement

Yeting Fan: Conceptualization, Funding acquisition, Data curation, Formal analysis, Investigation, Validation, Visualization, Writing - Original Draft. **Le Gan:** Software, Methodology, Visualization, Funding acquisition. **Changqiao Hong:** Methodology, Investigation, Validation, Data curation. **Laura H Jessup:** Conceptualization, Methodology, Writing - review& editing. **Xiaobin Jin:** Resources, Supervision. **Bryan C Pijanowski:** Conceptualization, Writing - Review & Editing. **Yan Sun:** Investigation, Visualization. **Ligang Lv:** Writing - Review & Editing, Investigation.

Declaration of competing interest

The authors declared that they have no conflicts of interest to this work.

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