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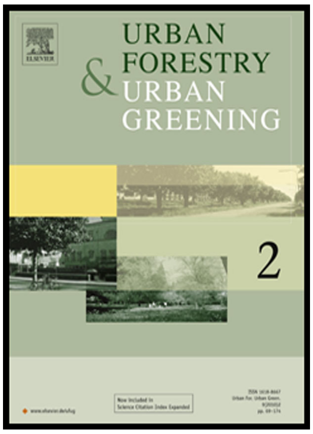

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Forest or grassland? A quantitative analysis of urban residents' green exposure preference by using multi-temporal mobile signal data

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Abstract: Urban forests and grasslands provide diverse services from their unique characteristics. Optimizing green spaces by understanding urban residents' preferences is a critical challenge for sustainable city development amid limited land resources. However, the mechanism influencing exposure across various types of green remains unclear. This study utilized multi-temporal mobile signal data from Shanghai to quantify the exposure intensity (*EI*) and density (*ED*) for forests and grasslands. These metrics addressed the gap by revealing spatiotemporal variations in exposure preference (*EP*) and related socioeconomic influences. Specifically, the study addressed two key questions: (1) Do urban residents exhibit preferences between forests and grasslands in terms of *EI* and *ED*? (2) How do socioeconomic features influence these preferences? Results showed: (1) Forests had almost double the annual *EI* (542.86 p/h) and *ED* (2.69 $p/m^2/h$) of grasslands ($P<0.001$). However, grasslands in central regions exhibited significantly higher *ED* (13.60 vs. 11.83 $p/m^2/h$; $P<0.001$). (2) *Commercial House* (34.4% importance) and *Sports & Recreation* (15.7%) maximized green exposure, while *Road Furniture* reduced it. (3) Evening exposure peaks in central regions extended by 1 hour due to commercial-cultural synergies. Forest *ED*, highly driven by *Commercial House*, clustered in central cores and specific non-central communities, whereas *Road Furniture* most negatively impacted central periphery communities. These findings directly inform differentiated urban planning strategies: forests should prioritize improving accessibility to sustain prolonged exposures, while grasslands need spatial optimization to accommodate peak social demand. By aligning

green space planning with socioeconomic drivers, cities can enhance the effectiveness of their service under land constraints.

Keywords: Urban green space; Green exposure; Exposure preference; Machine learning; Multi-Scale Geographically Weighted Regression.

1. Introduction

In recent years, the development of exposure ecology has led to a growing recognition of the diverse advantages associated with exposure to green spaces (Yu et al., 2024). Urban green spaces (UGS) are open areas with natural vegetation, improving air quality (Nowak et al., 2013), regulating microclimates (Arzberger et al., 2024), and enhancing biodiversity (Paudel & States, 2023). Meanwhile, they also provide various services to residents exposed to them, including health, cultural, educational, and recreational services .et al (Rigolon et al., 2018; Kabisch and Haase, 2014). Equitable exposure to more green spaces has become a key indicator of social well-being (Geng et al., 2024). On the one hand, with the continuous convergence of populations into cities during urbanization, there is increasing pressure for cities to provide more green spaces to fulfill residents' basic demands for green areas (Boulton et al., 2018). At the same time, policymakers have to consider a series of urban issues that are potentially caused by urban expansions (Tian et al., 2021). For example, urban development has shifted from the pursuit of disorderly expansion in scale to high-quality intensive and sustainable development in China with the implementation of *the National New Urbanization Plan* (The State Council, 2024). In this context, the effective utilizing limited and valuable urban space, as well as the targeted deploying of UGS to maintain high-exposure level, represent significant challenges in contemporary urban development. Clarifying the exposure characteristics and preferences of residents to different types of green spaces and the mechanisms through which they are affected by the urban socioeconomic activities features, can provide guidance for the planning, construction and management of high-exposure green spaces, assisting in realizing targets for sustainable cities (Zhang et al., 2024).

Urban forests, defined as the complete collection of woody plants within urban areas, encompass both trees growing individually on streets, in yards, or in parks, and groups of trees forming larger stands (Oke, 1997; Konijnendijk et al., 2006). Numerous studies have demonstrated significant difference between urban forests and grasslands in terms of spatial distribution and services (Boulton et al., 2018; Song et al., 2024). Additionally, environmental emotional perceptions of different vegetation types have also been widely proven in previous studies (Melon et al., 2024; Hoyle et al., 2019). Nevertheless, Previous studies have generally treated urban forests and grasslands as homogenous when assessing green exposure, ignoring their different ecological functions and perceived impacts (Chen et al., 2024). Moreover, from the perspective of exposure ecology, exposure intensity (*EI*) and exposure density (*ED*), are two different dimensional indicators of population exposure, which represent the number of people (visitation magnitude) and population density (spatial efficiency) within the service radius of green spaces over a specific period, respectively (Ding and Wang, 2024). Although previous studies have assessed exposure levels using visitation magnitude

(Tyrväinen et al., 2007), integrated analyses of *EI* and *ED* for characterizing spatiotemporal patterns in population green exposure at scale and over extended durations remain scarce (Huai and Van de Voorde, 2022).

The rapid advancement of internet technologies has realized the availability of mobile signaling data—such as Baidu Huiyan (a location intelligence platform) and cellular network signaling data—which overcome the limitations of traditional data collection like field surveys, thereby making high spatiotemporal-resolution quantification of green exposure feasible (Shi et al., 2024). Moreover, previous research on mechanisms influencing population exposure to green spaces has predominantly focused on the intrinsic attributes of green spaces, such as their size and accessibility (Schipperijn et al., 2010; Pinto et al., 2021); user features, such as socioeconomic status and age (de la Barrera et al., 2016); or broader city-scale characteristics, such as urban GDP, the proportion of highly educated populations, and urban morphology (Wang et al., 2025). However, these studies overlooked the fact that green spaces are not isolated but are surrounded by diverse socioeconomic activities, exhibiting unique "human-environment" interaction patterns and socioeconomic characteristics. Numerous studies have demonstrated that socioeconomic features within the service radius of green spaces can significantly influence exposure levels, overall quality, and perception, making them critical factors that cannot be overlooked (de la Barrera et al., 2016; Pinto et al., 2021). Distinct from the "socioeconomic status" in previous studies, "socioeconomic features" in this study was defined as differentiated socioeconomic activity characteristics surrounding urban green spaces, collectively shaped by diverse human activities such as commerce, cultural and sports facilities, scientific and educational institutions, office functions, etc. These features reflect the interactive outcomes between urban human activities and green spaces (de la Barrera et al., 2016), and can be comprehensively documented by POIs (Points of Interest) as one kind of internet big data. Yan et al. (2024) combined machine learning approaches with geographically weighted regression and achieved an understanding of the travel modeling mechanisms inherent to the built environment. This integration provides potential technical support for further exploring the characteristics and driving mechanisms of green exposure (Lehto et al., 2024). Therefore, rely on internet big data such as POIs, it remains both pending and significant to explore the driving mechanisms of socioeconomic features behind large-scale green exposure using machine learning combined with geospatial analysis techniques (Bertram and Rehdanz, 2015).

Given the limited urban space during urbanization, it is essential to compare the exposure characteristics and preferences between forests and grasslands, to achieve a targeted deployment to maximize the benefits of green exposure. As China's largest economic center, Shanghai's urbanization rate has reached 89.3% by 2020 (Shanghai Statistical Bureau, 2021). In the Outline of Shanghai Master Plan (2015-2040), the city has restricted the continued expansion of its external boundaries, explicitly setting sustainable development as its development goal (Shanghai Municipal People's Government, 2015). This study used Shanghai as a case study, comparing the exposure characteristics of residents between forests and grasslands, and clarifying the impacts of socioeconomic features on exposure is highly relevant. Therefore, this study based on multi-source big data, integrates machine learning and spatial regression methods—a combination that robustly handles non-linear socioeconomic interactions while accounting for spatial heterogeneity in green exposure drivers. It aims to answer the following two scientific questions: (1) is there an exposure preference for forests or grasslands among urban residents? If there is, (2) what are the socioeconomic features that contribute to these differences in exposure preference?

2. Materials and methods

2.1.Study area

Shanghai (120°52′-122°12′E, 30°40′-31°53′N), located on the eastern coast of China, had an administrative area of 6,340.5 km^2 by the end of 2020. The city is divided into 16 administrative districts (7 central urban districts and 9 non-central districts). The 7 central districts are Jing'an, Yangpu, Putuo, Hongkou, Changning, Huangpu, and Xuhui. Additionally, there are 216 subdistricts and townships. As of 2020, Shanghai had a total green space area of 1,646.11 km^2 (Shanghai Statistical Bureau, 2021). Of this, forests account for 83.5% of the total green space area in Shanghai City, with 54.6% of the total number of green patches. In central regions, forests account for 92.9% of the total area, with 82.4% of the total number (Fig. 1).

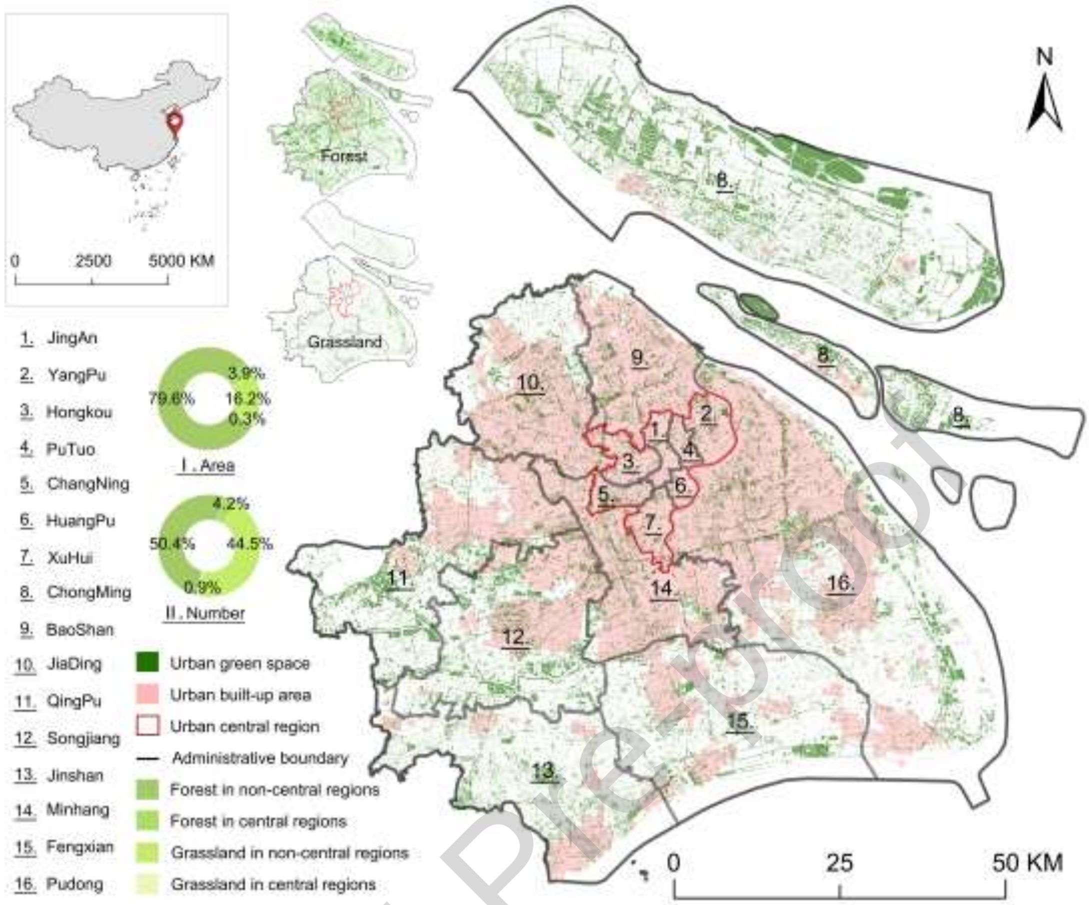

Fig. 1. The location, administrative composition of Shanghai City, and its forests and grasslands spatial distribution.

2.2.Methodology

2.2.1 Research framework

This study used Shanghai City as a case to explore the differences in exposure preference of urban residents between the urban forests and grasslands, then analyze the influence factors. A large dataset on locations of residents spanning one year was utilized to quantify the exposure preference of the residents for forests and grasslands at three different spatiotemporal scales. Based on this preference, we applied machine learning and Multi-Scale Geographically Weighted Regression (MGWR) to further investigate the socioeconomic features which influence the characteristics of exposure preference (Fig. 2). The following sections will describe the specific methods for each stage in detail.

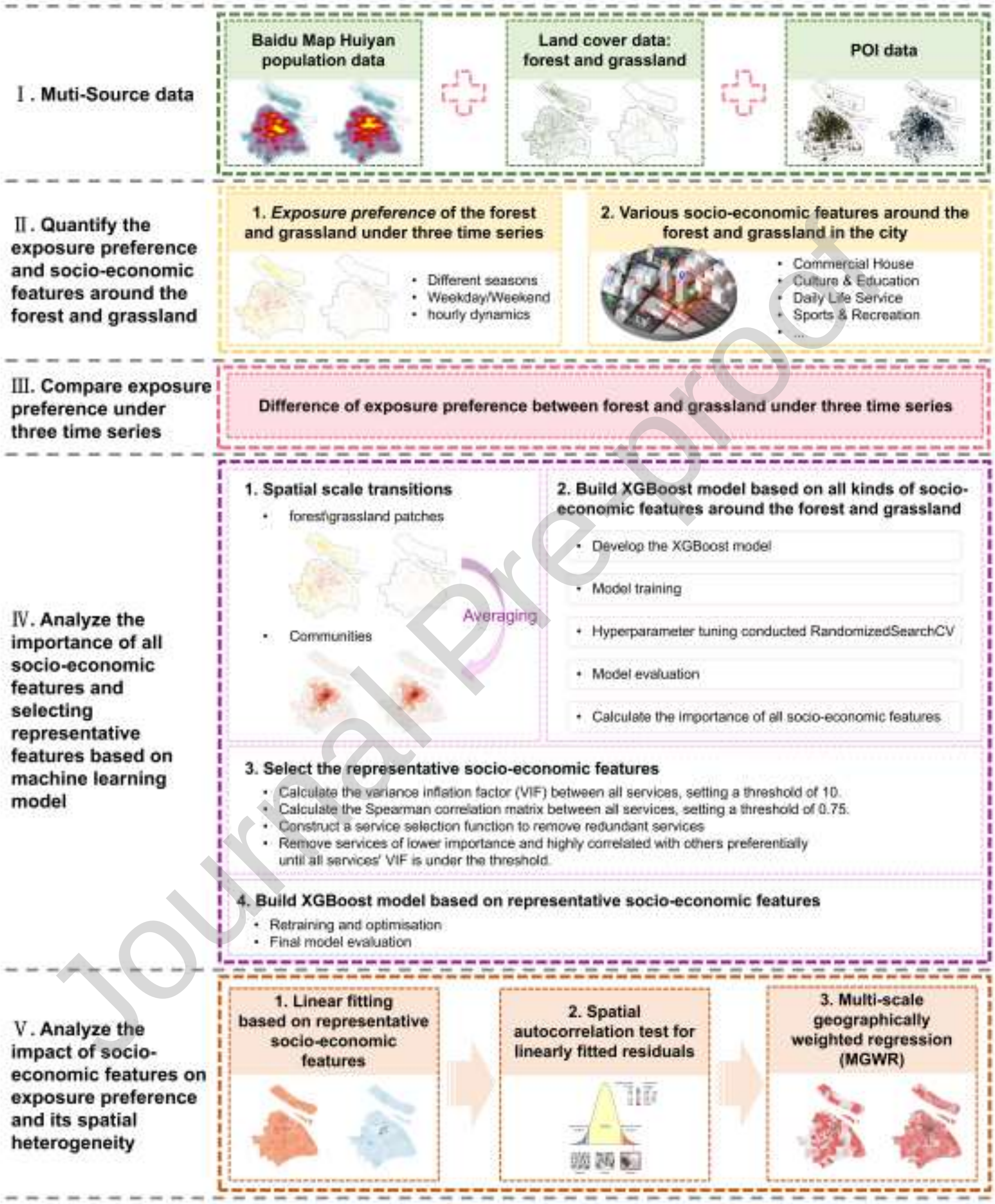

Fig. 2. Research technology flowchart.

2.2.2 Quantifying the exposure preference in forest and grassland

This study utilized Baidu Huiyan population data, which objectively reflects the effective exposure of residents (explained in more detail in section 2.3.1), to quantify the actual exposure characteristics of urban residents in urban forests and grasslands. Accordingly, two indicators were developed: the Exposure Intensity (*EI*) and the Exposure Density (*ED*). A higher *EI* and *ED* indicates that more people are exposed to the specific period or green type than to other periods or green types, reflecting a stronger Exposure Preference (*EP*). Exposure Intensity (*EI*) represents the intensity of population exposure within the service radius of UGS, measured by the number of people per hour within the service radius (p/h) as equation (1):

$$EI_i = (p_1 + p_2 + p_3 + ... + p_n) / n \qquad (1)$$

Where n denotes the number of recorded points within the service area of the green patch i, while p is the number of people at each recorded point.

Meanwhile, Exposure Density (*ED*) takes into account the area of each green patch and is measured by the number of people per unit area per hour (p/m^2 /h):

$$ED_i = EI_i / A_i \qquad (2)$$

where A_i refers to the area of the green patch i. According to our previous research, 1 km is the optimal service radius to determine whether the UGS' services in Shanghai are realized (Geng et al., 2024). Therefore, the service radius for the forest and grassland in the study was kept at 1 km. All recorded points within the 1 km radius of each green patch and the recorded number of people were considered.

The visualization of *EI* and *ED* in the forest and grassland across different spatiotemporal scales was achieved by ArcGIS. In analyzing the significance of differences in *EI* and *ED* between the forest and grassland, we first used the 'Nortest' package in R to determine that the data followed a non-normal distribution. Then, the

'Cliff's Delta' value was calculated to assess the extent of data overlap and to determine the necessity of further exploring significant differences. Finally, the 'Wilcox.test' package was applied to analyze the characteristics, differences, and significance of population exposure to the forest and grassland.

2.2.3 Analyzing socioeconomic features influencing exposure preference in forest and grassland

We counted the number of different types of Points of Interest (POIs) within the 1 km radius of the green patch to characterize its socioeconomic features (He et al., 2019; Geng et al., 2024). The specific POI types are detailed in Section 2.3.3. We established quantitative relationships between *EI*, *ED*, and socioeconomic features using machine learning at the green patch level. To analyze feature importance, we compared the performance of several models, including eXtreme Gradient Boosting (XGBoost) and Random Forest (Appendix A). Moreover, we removed redundant factor types from the 19 socioeconomic features and selected representative ones. First, collinearity among different features was analyzed, identifying those with high collinearity (VIF values greater than 10). Prioritizing the most important features, we focused on those with collinear relationships and removed the least important services, recalculating VIF values. This process was repeated, removing the least important features until no multicollinearity remained among the selected services. The model's R^2 and RMSE values were calculated finally to re-evaluate the predictive power of representative features. For the correlation analysis between the 19 socioeconomic features and *EI*, *ED*, considering the data distribution, we used Python's 'scipy.stats' library to calculate the Spearman correlation coefficient. The `variance_inflation_factor` function from the `statsmodels.stats.outliers_influence` module was employed for model selection and hyperparameter tuning in the machine learning modeling porcess. To investigate the socioeconomic drivers of residents' differentiated exposure preferences between forests and grasslands, we integrated machine learning (XGBoost) and Multi-Scale Geographically Weighted Regression (MGWR). MGWR captures spatial heterogeneity and localized patterns, complementing XGBoost's global feature importance by providing geographically varying regression coefficients (Li and Fotheringham, 2020). At the community level, we averaged *EI*, *ED*, and POI values to analyze socioeconomic mechanisms (Fig. 2). MGWR accounts for spatial autocorrelation, with Moran's I of residuals calculated using ArcGIS. MGWR 2.2 software was used to explore spatial characteristics, with outputs including adj-R^2, beta-values, t-values, and *P*-values.

This combined approach was selected based on three key considerations: Non-Linearity and High-Dimensional Interactions: XGBoost excels at capturing complex, non-linear relationships and hierarchical feature importance, critical for analyzing multifaceted drivers of exposure preferences (Li and Fotheringham, 2020). Spatial Heterogeneity and Scale Effects: MGWR complements XGBoost by revealing localized spatial variations and addressing spatial non-stationarity. MGWR accommodates multi-scale processes, aligning with our goal to uncover context-specific planning implications (Basu and Das, 2023). Methodological Synergy for Policy Insights: XGBoost quantifies overall feature importance, while MGWR maps localized effects, providing actionable insights for spatially targeted green space planning in Shanghai.

2.3.Research data

2.3.1 The information of multi-source data used in this research.

This study utilized multiple datasets for data analysis and visualization. Table 1 provides a detailed summary of the sources, specific details, and respective usages of these datasets within the study. More comprehensive descriptions of the data processing procedures have been elaborated in the corresponding sections of subsequent chapters.

Table. 1. Sources and details of multi-source data

Data nams	Source	Detail	Usage
Administrative boundary data	The National Catalogue Service For Geographic Information https://www.webmap.cn	Containing three levels of boundary: city, district, and community.	Support administrative unit-based indicator quantification.
Boundary of central regions	Shanghai civil affairs bureau https://mzj.sh.gov.cn	Containing Jing'an District and six other districts.	Delineate Shanghai's core urban area boundaries.
Boundary of built-up areas	The National Tibetan Plateau Data Center https://doi.org/10.11888/HumanNat.tpdc.272851	Extracted from the dataset of urban built-up areas in China (2020).	Depict urban built-up status of Shanghai Municipality.
Population location data	Baidu Huiyan https://huiyan.baidu.com/	672 hours, 720,233 location points, and 198,804,208 person-times of population data were collected.	Characterize effective dwell distribution of populations around green spaces.
Urban green space data	The European Space Agency (ESA) WorldCover 10 m 2020 product https://esa-worldcover.org/en	Extracted the woodland and shrub layer as forests, and kept the grassland layer as grassland.	Map the spatial distribution of forest and grassland space in Shanghai city.
POI data	Amap https://www.amap.com	24 categories of POI data were collected in 2023.	Quantify diverse socioeconomic activities proximal to green spaces.

2.3.2 Multi-temporal population location data

The multi-temporal population location data reflects effective dwell distributions around green spaces and outperforms social media check-in data in describing UGS usage (Lyu and Zhang, 2019). The data collection methodology of *Baidu Huiyan* is detailed in Appendix B. Based on the administrative boundaries of Shanghai, the population location data was summarized at three time scales: different seasons, workday/weekend, and hourly dynamics. The specific dates of the population data collection are shown in Table 2. Holidays and other special situations that could influence population distribution were excluded during the data collection.

Table. 2. Time scales segmentation of Baidu Huiyan population data

	Workday	Weekend
Spring	Jan. 10, 2024; Jan. 11, 2024; Jan. 12, 2024; Jan. 15, 2024; Jan. 16, 2024	Jan. 13, 2024; Jan. 14, 2024
Summer	Apr. 10, 2023; Apr. 11, 2023; Apr. 12, 2023; Apr. 15, 2023; Apr. 16, 2023	Apr. 13, 2023; Apr. 14, 2023
Autumn	Jul. 10, 2023; Jul. 11, 2023; Jul. 12, 2023; Jul. 15, 2023; Jul. 16, 2023	Jul. 13, 2023 Jul. 14, 2023
Winter	Oct. 10, 2023; Oct. 11, 2023; Oct. 12, 2023; Oct. 15, 2023; Oct. 16, 2023	Oct. 13, 2023; Oct. 14, 2023

2.3.3 Forest and grassland data

The forest and grassland data for Shanghai were extracted from the European Space Agency's (ESA) 2020 Global Land Cover product. Based on the layer definitions of ESA products and the broad concept of urban forests, we merged the Tree Cover and Shrubland layers as the foundational dataset for forests in Shanghai, by ArcGIS's reclassification tool. According to data from the Shanghai Statistical Bureau (https://tjj.sh.gov.cn/), the green space area only increased by 5.2% between 2020 and 2023. Considering the policy on "zero growth" in construction land as outlined in the *Outline of Shanghai Master Plan* (2015-2040) and the slowed pace of urban development due to COVID-19, land use changes during this period have been minimal. Given the widely recognized quality of ESA data and the acceptable proportion of land use change, we used this dataset for subsequent analyses.

2.3.4 POI data

By utilizing POI data that captures socioeconomic activities, our study identifies the socioeconomic features surrounding different green space types. We manually screened the complete 2023 Shanghai POI dataset and excluded 5 categories: *Incidents and Events*, *Indoor facilities*, *Invented Data*, *Pass Facilities*, and *Place Name & Address*. These categories were removed because they either overlap semantically with other retained types or could introduce noise into our analysis of socioeconomic activities related to green space exposure. The retained 19 POI types comprehensively represent various aspects of urban socioeconomic activities, ensuring they capture the diverse social activities around green spaces that may influence residents' green space exposure preferences (Yao et al., 2022). Table 3 details the urban socioeconomic activities encapsulated within each feature and the POI classifications used to characterize them, following Amap's official criteria (Appendix C). The naming of socioeconomic features in the table adheres to Amap's big category of POI data, while the various urban socioeconomic activities are named according to their sub-category.

Table. 3. The 19 types of socioeconomic features and socioeconomic activities they contain.

Socioeconomic features	Code	Specific urban socioeconomic activities included
Commercial House	*CH*	Building, Industrial Park, Residential Area.
Sports & Recreation	*SR*	Recreation Center, Golf Related, Holiday & Nursing Resort, Recreation Place, Sports & Recreation Places, Sports Stadium, Theatre & Cinema.
Accommodation Service	*AS*	Hotel.
Governmental Organization & Social Group	*GOSG*	Democratic Party, Foreign Organization, Governmental Organization, Industrial and Commercial Taxation Institution, Public Security Organization, Social Group, Traffic Vehicle Management.

Transportation Service	*TS*	Airport Related, Border Crossing, Bus Station, Coach Station, Commuter Bus Station, Ferry Station, Light Rail Station, Loading & Unloading Area, Parking Lot, Port & Marina, Railway Station, Ropeway Station, Subway Station, Taxi.
Daily Life Service	*DLS*	Agency, Baby Service Place, Bath & Massage Center, Beauty and Hairdressing Store, Electric Bicycle Service Station, Funeral Facilities, Information Centre, Job Center, Laundry, Logistics Service, Lottery Store, Move Service, Photo Finishing, Post Office, Professional Service Firm, Repair Store, Shared Device, Telecom Office, Ticket Office, Travel Agency, Water Supply Service Office.
Shopping	*SH*	Clothing Store, Commercial Street, Comprehensive Market, Convenience Store, Franchise Store, Home Building Materials Market, Home Electronics Hypermarket, Personal Care Items Shop, Plants & Pet Market, Shopping Plaza, Special Trade House, Sports Store, Stationary Store, Supermarket.
Auto Service	*AUS*	Automobile Service, Battery Change Station, Car Wash, Charging and Power Swapping Station, Charging Station, Dedicated Charging Station, Filling Station, Other Energy Station, Used Automobile Dealer.
Food & Beverages	*FB*	Bakery, Chinese Food Restaurant, Coffee House, Dessert House, Fast Food Restaurant, Foreign Food Restaurant, Icecream Shop, Leisure Food Restaurant, Tea House.
Public Facility	*PF*	Emergency Shelter, Newsstand, Public Phone, Public Toilet.
Finance & Insurance Service	*FIS*	ATM, Bank, Finance & Insurance Service Institution, Finance Company, Insurance Company, Securities Company.
Tourist Attraction	*TA*	Park & Plaza, Park & Square, Scenery Spot.
Auto Dealers	*AD*	Various brand of auto sales.
Enterprises	*EN*	Company, Factory, Famous Enterprise; Farming，Forestry, Animal Husbandry and Fishery Base.
Medical Service	*MS*	Clinic, Disease Prevention Institution, Emergency Center, Hospital, Medical and Health Care Service Place, Pharmacy, Special Hospital, Veterinary Hospital.
Science/Culture & Education Service	*SCES*	Archives Hall, Art Gallery, Arts Organization, Convention & Exhibition Center, Cultural Palace, Driving School, Exhibition Hall, Library, Media Organization, Museum, Planetarium, Research Institution, School, Science & Technology Museum, Training Institution.

Road Furniture	*RF*	Service Area, Signpost, Toll Gate, Traffic Light, Warning Sign.
Auto Repair	*AR*	Various brand of auto repair.
Motorcycle Service	*MOS*	Motorcycle Repair, Motorcycle Sales.

3. Results

3.1.Exposure preference of the urban resident to the forest and grassland

The result revealed significant seasonal variations in exposure intensity (*EI*) and exposure density (*ED*) for both forests and grasslands.The average annual *EI* and *ED* in forests were 542.86 p/h and 2.69 p/m^2/h. The highest *EI* and *ED* for forests occurred in spring, with values of 654.17 p/h and 3.24 p/m^2/h, respectively, while the lowest values were in winter at 416.77 p/h and 2.07 p/m^2/h. On weekdays, the *EI* and *ED* in the forest were significantly higher than on weekends. The lowest *EI* and *ED* occurred at 4 am, with values of 114.01 p/h and 0.57 p/m^2/h in the forest. Then, *EI* and *ED* gradually increased, reaching the first peak at 11 am. A temporary decrease was observed midday, with a low point at 2 pm. This was followed by a rise to a second peak at 5 pm, which marked the highest *EI* and *ED* of the day. At that time, the *EI* and *ED* in the forest were 803.74 p/h and 3.98 p/m^2/h, respectively. After this peak, both *EI* and *ED* began to decline (Fig. 3). High *EI* and *ED* for forest patches were consistently observed in central urban areas and their surrounding edges on different time scales, with central regions of Shanghai showing higher values than non-central regions (Fig. 4). The average annual *EI* and *ED* in grasslands were 285.45 p/h and 1.95 p/m^2/h. The highest *EI* and *ED* for grassland were also in spring, at 344.64 p/h and 2.35 p/m^2/h, and lowest in winter at 216.40 p/h and 1.48 p/m^2/h. The variation trends of *EI* and *ED* in the grassland were consistent with forest at different time scales (Fig. 3). Likewise, the grassland located in the central regions had higher *EI* and *ED* (Fig. 4).

When comparing the average levels across the entire city, the *EI* and *ED* in the forest were significantly higher than for the grassland at all times (P<0.001). Within central urban regions, grasslands have 15% higher *ED* than forests (13.60 p/m^2/h for grasslands and 11.83 p/m^2/h for forest, P<0.001). Additionally, fluctuations in *EI* within central regions were larger than in non-central regions, with values of 3009.99 p/h in the forest and 2539.78 p/h in the grassland within a day. The peak periods for *EI* and *ED* in central regions were extended by 1 hour, with the second peak occurring at 6 pm (Fig. 3). The green patches with a high *EI* and *ED* appear earlier in central regions in the morning, while disappearing earlier in non-central regions in the afternoon. Notably, large non-central forest patches at the outer edge of central regions maintained a higher *EI* during the day (8:00 AM to 7:00 PM). In the city's outskirts, *EI* and *ED* in the forest and grassland remained consistently low (Appendix D). Correlation analysis revealed significant positive associations between *EI* and *ED* for both forests (Spearman's *Rho* =0.73 at patch scale; *Rho*=0.998 at community scale) and grasslands (*Rho*=0.79 and *Rho*=0.98, respectively; P <0.001). Cliff's Delta analysis further confirmed distinct distributions between *EI* and *ED* across scales (Cliff's Delta >0.95, P <0.001). At the community scale, central urban grasslands exhibited 15% higher *ED* than forests (13.60 vs. 11.83 p/m^2/h, P <0.001), despite comparable *EI* values. Notably, patch-level correlations were weaker than community-level results, reflecting scale-dependent variations in exposure dynamics.

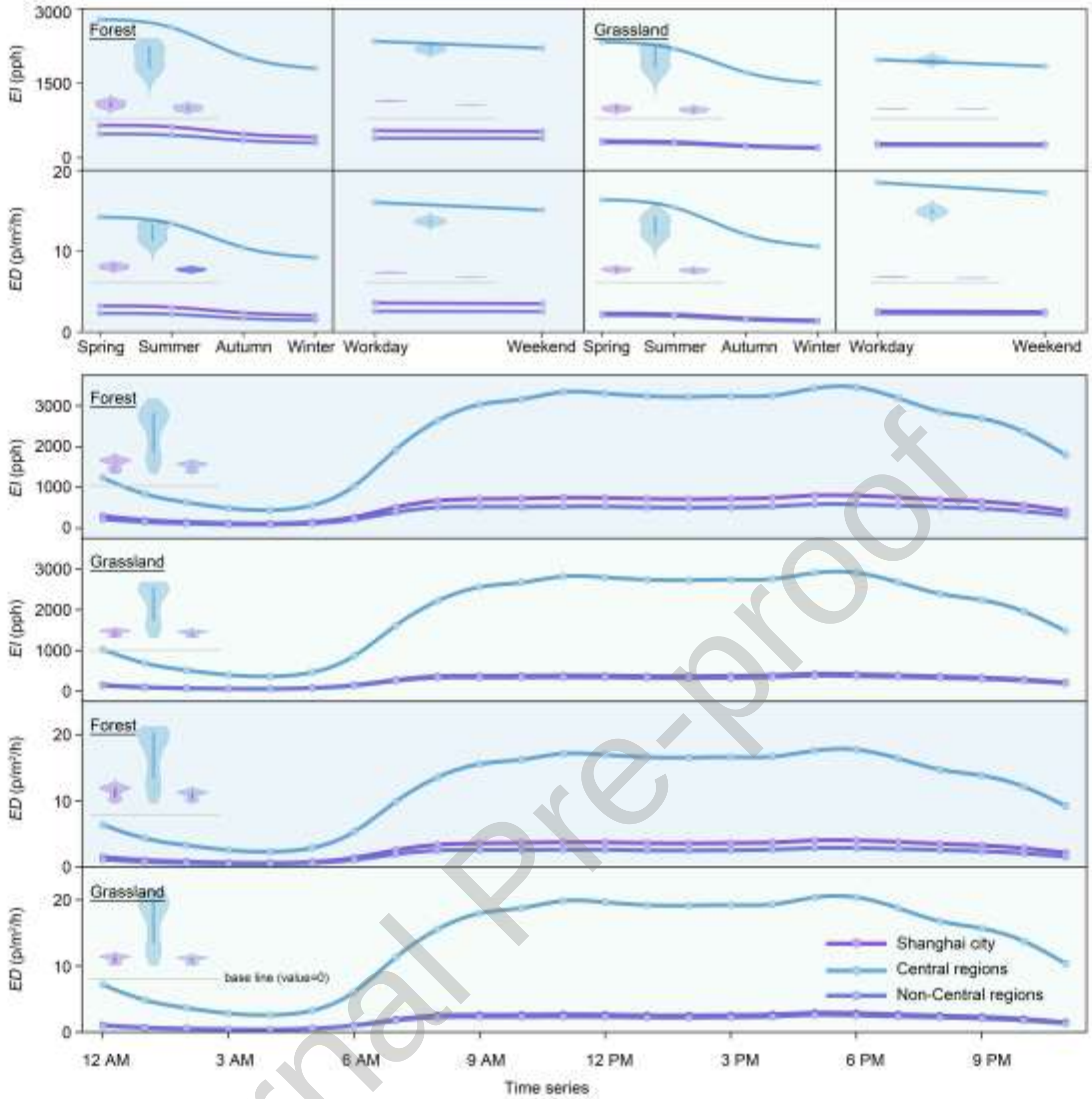

Fig. 3. Dynamic difference of forest and grassland's *EI* and *ED* in different time scales.

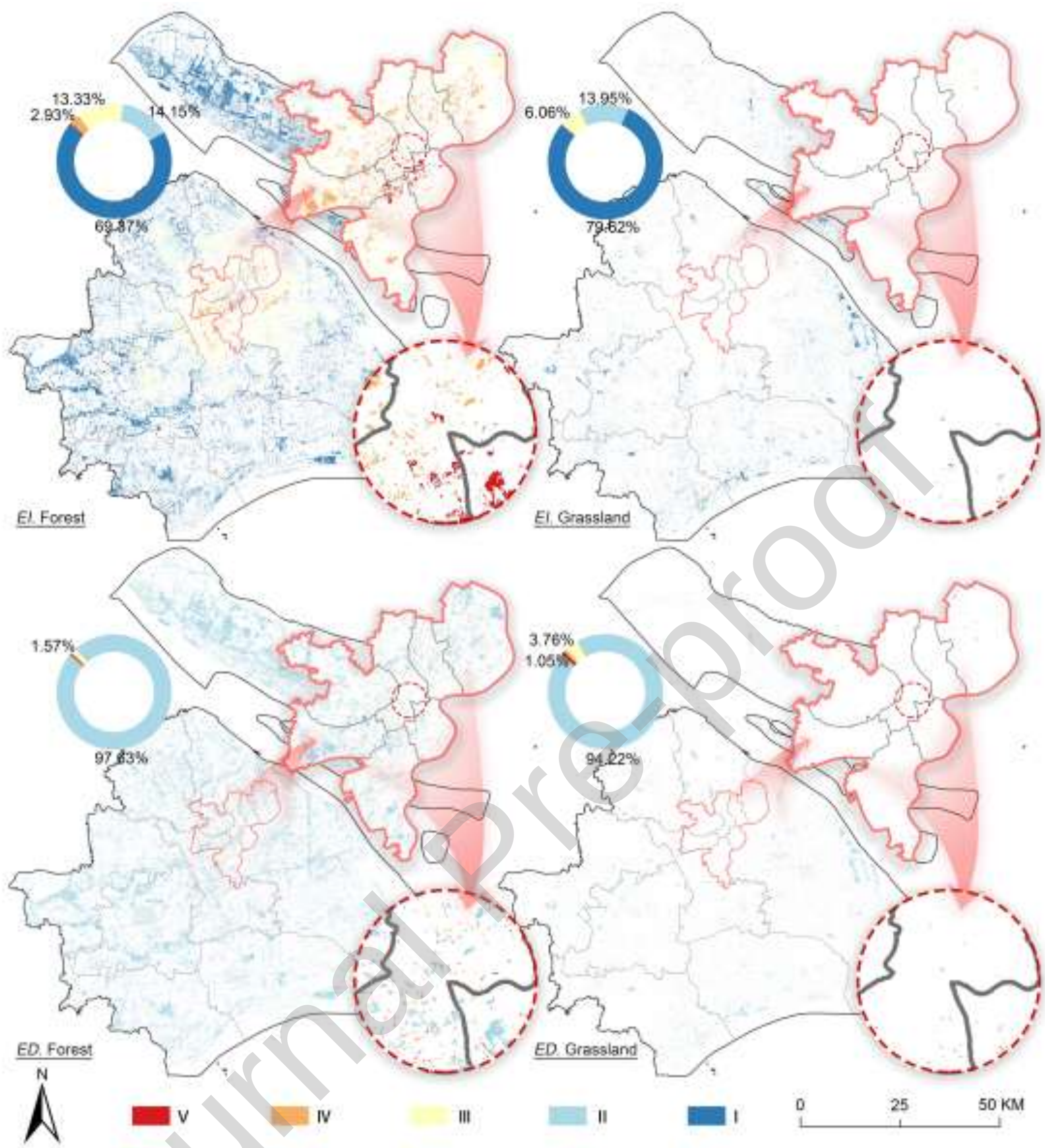

Fig. 4. Spatial difference of the average annual *EI* and *ED* in forest and grassland. Among them, *EI* is categorized into five grades according to 0-500, 500-1000, 1000-2500, 2500-5000, and greater than 5000; *ED* is categorized into five grades according to 0, 0-1, 1-3, 3-5, and greater than 5. The higher the class, the larger the *EI* and *ED* of the green patch. The annular pie chart shows the area proportion of green space patches at different grades.

3.2.Impact of socioeconomic features to exposure preference in the forest and grassland

Commercial House and *Sports & Recreation* (see Table 3 for detailed characteristics) were the first and second most important socioeconomic features contributing to a high *EI* in the forest, with a relative importance of 0.592 and 0.178. *Accommodation Service* and *Government Organisation & Social Groups* were the third and fourth most important socioeconomic features for forests *EI* (with a relative importance of 0.065 and 0.055). *Commercial House* and *Daily Life Service* were the first and second most important features contributing to high *ED*, with an importance value of 0.344 and 0.209 (Fig.5a). The two most important socioeconomic features contributing to a high *EI* in grasslands were the same as in forests (with a relative importance of 0.435 and 0.301), but the third and fourth most important features in grasslands were *Shopping* and *Transportation Service* (with a relative importance of 0.067 and 0.052). *Sports & Recreation* and *Commercial House* were the first and second most important socioeconomic features contributing to high *ED*, with importance values of 0.157 and 0.098, respectively (Fig.5a).

The number of 19 socioeconomic features within the service radius of the forest and grass space had a significant correlation with the *EI* and *ED* of the population in the space. Only *Road Furniture* had a significant negative correlation with the two indicators, but the correlation was low. The other 18 types of socioeconomic features all showed strong and significant positive correlations (Fig.5b). The same socioeconomic features varied in importance rankings and importance values for contributing to the high *EI* and *ED* in the forest and grassland. For example, *Accommodation Service* is the third most important socioeconomic feature for forests' *EI*, but only ranked eighth in importance for grasslands' *EI*. While *Commercial House* has the highest importance for *EI* for both the forest and grassland, there is a difference in its importance for both indicators, 0.592 and 0.435, respectively (Fig.5a).

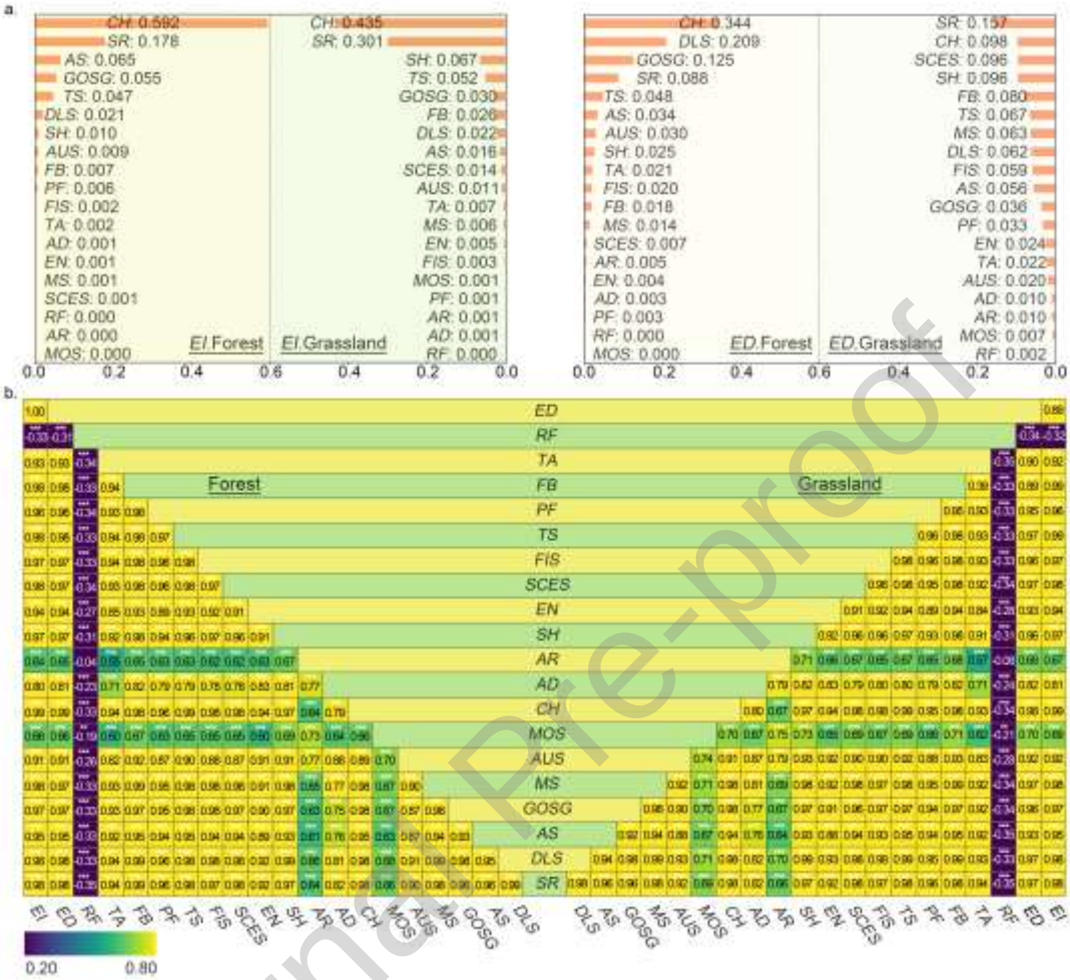

Fig. 5. a: The importance of all socioeconomic features to *EI* and *ED* for forest and grassland by XGBoost model. b: Spearman correlation matrix between each feature and *EI* and *ED* in community level. *** for $P < 0.001$, and ** for $P < 0.01$.

The representative socioeconomic features influencing *EI* and *ED* of the urban forest are *Commercial House* and *Road Furniture*. The representative features for the grassland's *EI* are *Commercial House* and *Road Furniture*, while for *ED*, the key features are *Sports & Recreation* and *Road Furniture* (Fig. 6a). The XGBoost results demonstrate that the representative socioeconomic features retained their predictive ability for *EI* and *ED* in the forest and grassland (Fig. 6b). The R^2 values for both the training and testing phases of the *EI* and *ED* models applied to the forest exposure were 0.99 and 0.76, respectively. For the grassland exposure, the *EI* model achieved R^2 values of 0.92 for training and 0.86 for testing, while the *ED* model reported values of 0.91 for training and also 0.86 for testing.

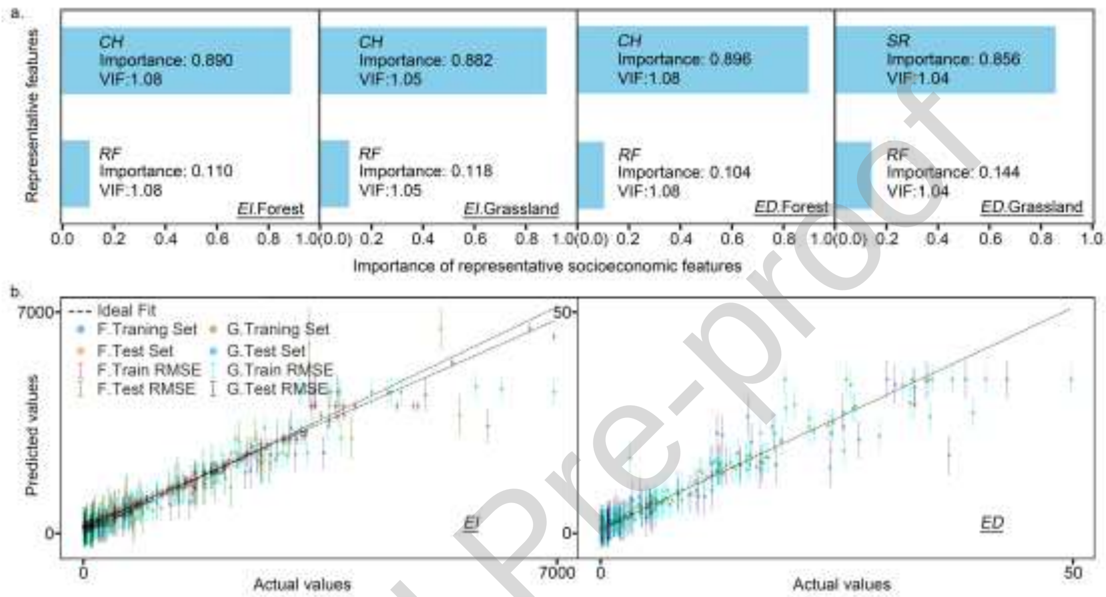

Fig. 6. a: Importance of representative socioeconomic features on *EI* and *ED* in the forest and grassland by XGBoost model. b: Observed and predicted value of *EI* and *ED* based on representative socioeconomic features of forest and grassland.

The MGWR results at the community level showed that the adj-R^2 values for the forest *EI* and *ED* were 0.837 and 0.797, respectively, while for the grassland *EI* and *ED*, the adj-R^2 values were 0.827 and 0.819. The positive influence of *Commercial House* on *EI* and *ED* in the forest displayed a relatively consistent spatial distribution (Fig. 7). The forests where *EI* and *ED* were highly affected by *Commercial House* were mainly located in the core communities of central regions, as well as in non-central regions like Pudong, Jiading, Jinshan, and Minhang. The negative impact of *Road Furniture* on *EI* and *ED* in the forest was not significant at the community scale (Fig.

8). The spatial characteristics of *Commercial House*'s positive influence on the grassland *EI* were similar to its influence on forest *EI*. The spatial distribution of communities whose grassland *ED* was positively influenced by *Sports & Recreation* was more concentrated. *Road Furniture* can have a significant negative impact on the grassland *ED* of each community. The communities more negatively impacted by *Road Furniture* are mainly located on the outer edges of central regions, while communities within the central regions were less impacted (Fig. 8).

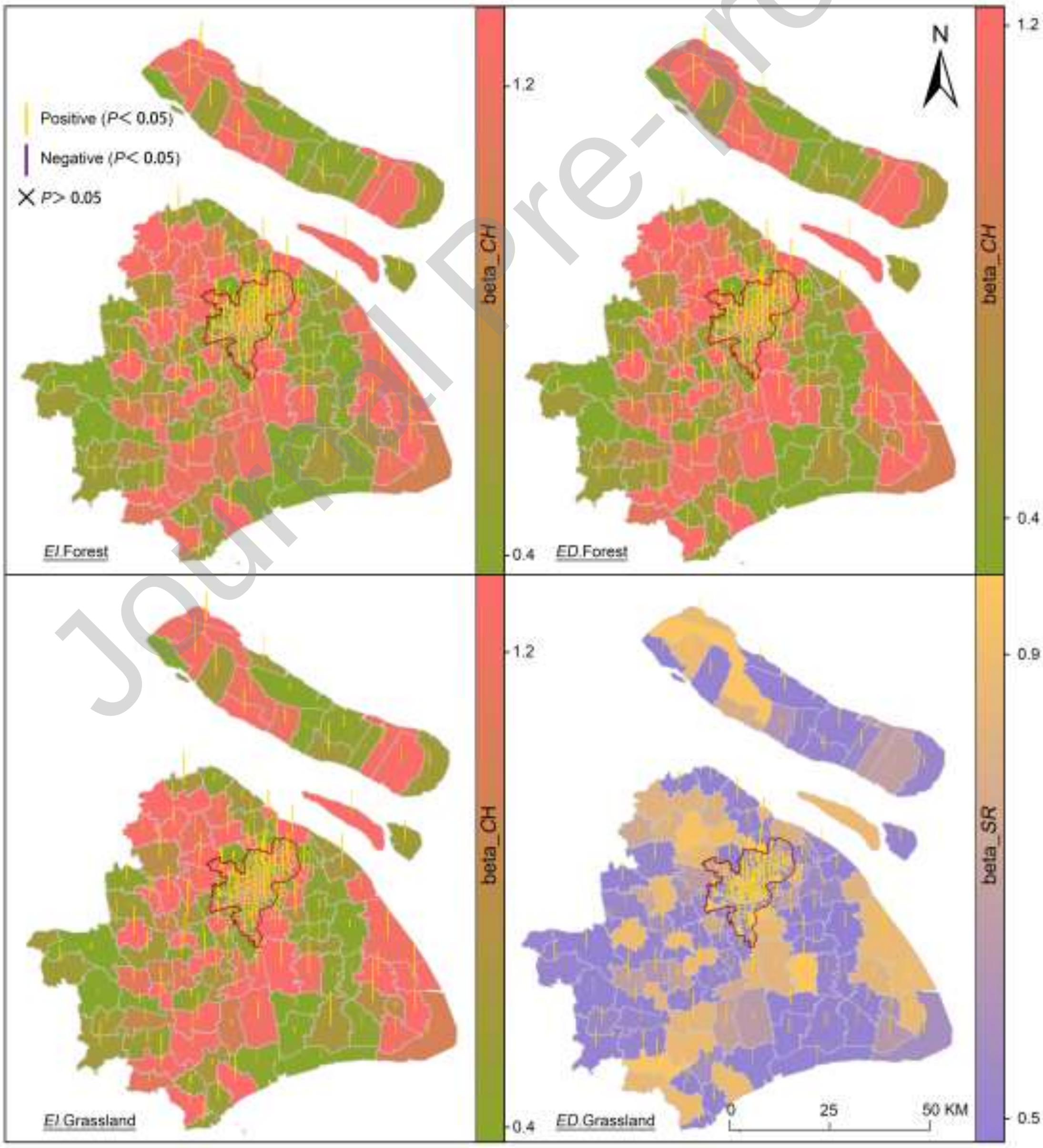

Fig. 7. MGWR between *EI*, *ED*, and *Commercial House, Sports & Recreation*. The estimated coefficient (beta-value) determines the color of the community patch; the larger the beta value, the stronger the effect of the feature depicted. The t-value determines the length of the color line at the center of each community patch; the higher the t-value, the longer the color line and the stronger the correlation. Different color of the line represents different correlations. The same below.

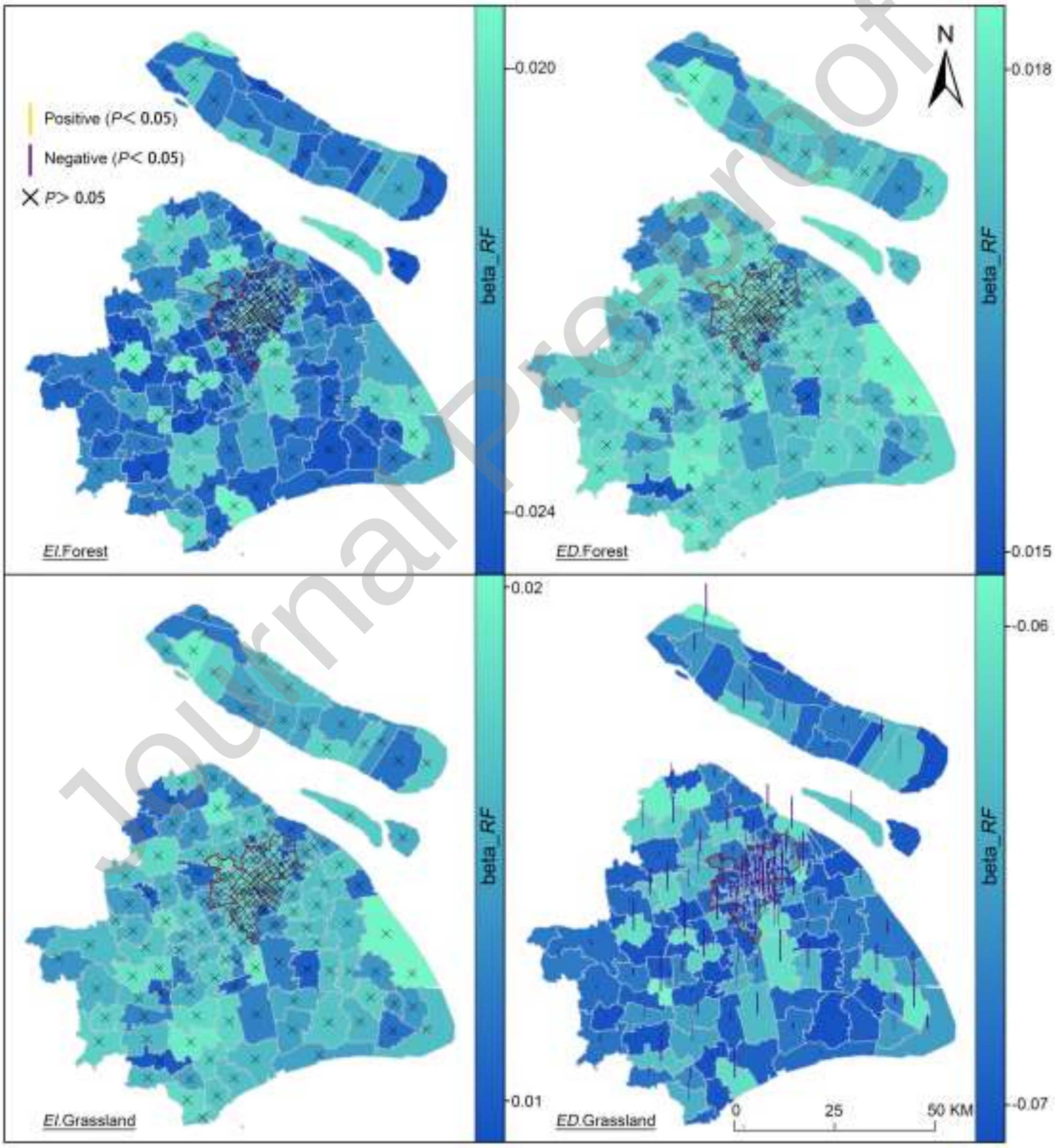

Fig. 8. MGWR between *EI*, *ED*, and *Road Furniture*.

4. Discussion

4.1. Differences in urban residents' exposure preference in the forest and grassland and their implications for management

The seasonal pattern in exposure intensity (*EI*) and exposure density (*ED*) aligns with the climatic characteristics of Shanghai, where spring offers mild temperatures and abundant vegetation, attracting more residents to green spaces. In contrast, winter's colder weather and reduced vegetation activity likely discourage outdoor activities. These cyclical fluctuations necessitate adaptive strategies that address both ecological cycles and human behavioral patterns (Kabisch and Haase, 2014). For instance, spring and autumn could be prioritized for organizing outdoor events or enhancing recreational facilities in green spaces, while winter may require strategies to mitigate reduced exposure, such as introducing winter-themed activities or improving accessibility in colder months (Bedimo-Rung et al., 2005). This dual temporal-spatial approach, grounded in dynamic resource allocation theory (Andersson et al., 2019), transforms observed exposure rhythms into actionable management frameworks.

The richer landscape types and more varied space structure of the forest support the diverse activity needs of residents, leading to a higher exposure preference for the forest by keeping higher mean *EI* and *ED* (Hoyle et al., 2019; Lehto et al., 2024). As a mega-city, the home-work separation in Shanghai forces urban residents to engage in long-distance and extensive commuting activities on weekdays, causing substantial fluctuations in exposure patterns in central regions within a day (Wang et al., 2022). The massive commuting activity within the service radius of the forest and grassland further reflects the high population exposure on weekdays. Lin et al. (2023) termed this non-staying green exposure that accompanies commuting activities as passive exposure, in which residents can also obtain the benefits provided by the forest and grassland. Our study also found that evening exposure peaks in central regions were delayed by one hour (from 5 pm to 6 pm). In addition to commuting activities, the concentration and diversity of socioeconomic and cultural activities in the central region are one of the factors that may contribute to the higher population exposure in the central forest and grass in the evening (Wang et al., 2022).

Compact spatial design contributes to the multifunctional attributes of grasslands in central regions, the scattered and fragmented distribution also maximizes their utilization efficiency. Given the high density and compactness of central regions, people prefer open grasslands over forests that can block sunlight, which may explain why the mean *ED* is significantly higher for grasslands than for forests within urban central regions (Lo and Jim, 2012). Considering municipal decisions on green infrastructure are highly cost-driven (Van Oijstaeijen et al., 2022), the higher daily maintenance costs for grasslands compared to forests make them a more luxurious green resource, leading to over 98% of Shanghai's grasslands being located in economically robust central regions (Smardon, 1988). Meanwhile, non-central regions tend to favor lower-maintenance forests, their higher *EI* dominance in suburbs highlights their capacity to absorb dispersed visitation. The complementary roles of *EI* (visitation magnitude) and *ED* (spatial efficiency) address distinct planning challenges and reveal localized mismatches. Our *EI*-*ED* decoupling phenomenon in suburbs demands a paradigm shift toward spatially optimized greening. This reconciles the 'quantity-quality paradox' in Shanghai's land-constrained context by aligning *EI* with infrastructure investments (e.g., expanding access to high-*EI* forests) and *ED* with spatial optimization (e.g., redesigning overcrowded grasslands), policymakers can resolve the tension between green coverage and utilization efficiency in land-constrained cities.

4.2. Potential impacts of socioeconomic features on urban residents' exposure preference in forests and grasslands

The compact and diverse socioeconomic features around the green patches in the central region steadily increased their *EI* and *ED* (Lyu and Zhang, 2019). Our multi-method framework (integrating MGWR and XGBoost) highlights spatial heterogeneity that *Commercial House*'s positive impact on forest exposure is spatially concentrated in central communities (Fig. 7), underscoring the value of multi-method approaches in bridging global patterns and local dynamics. Jim and Chen's (2010) hedonic analysis demonstrated market-driven valuation hierarchies: proximity to neighbourhood parks commanded 16.88% residential price premiums in Hong Kong surpassing harbour views (5.1%). This price capitalization effect creates economic incentives for developers to internalize green amenities in high-value locations. Similarly, co-location with *Science/Culture & Education Service* (e.g., museums, schools) elevates green exposure rates, as specialized venues attract polycentric flows (Schläpfer et al., 2021).

In contrast to conventional urban planning assumptions that a well-connected urban road system promotes green accessibility, our study revealed that *Road Furniture* is negatively correlated with green exposure. To explain our findings, it is critical to interpret *Road Furniture* as a proxy for broader spatial-environmental characteristics rather than isolated objects like traffic lights. Specifically, the *Road Furniture* category represents key transportation networks and nodes characterized by high traffic flow, noise pollution, and psychological stressors such as perceived safety risks. The grassland, lacking visual shading, makes *Road Furniture* more negatively impactful on grassland exposure preference than the forest (Margaritis and Kang, 2017). This finding reflects behavioral preferences that traffic-related stressors reduce residents' willingness to linger in adjacent green spaces rather than negate the ecological value of those designed primarily for environmental protection (Huai and Van de Voorde, 2022). The negative correlation between *Road Furniture* and green exposure underscores the importance of spatially separating high-traffic areas from leisure-oriented green infrastructure. Green space planning must align with site-specific objectives: ecological buffers prioritize environmental services, while recreational green spaces require design strategies that address human behavioral preferences. For recreational green spaces like community parks, minimizing direct adjacency to major roads is critical to optimize user experience (Arsalan et al., 2024).

4.3.Limitations and recommendations for improvement

While the ESA WorldCover database provides accurate spatial delineation of broad land cover classes (e.g., forests, grasslands), it oversimplifies the complexity of urban green infrastructure. The dataset failed to indicate UGS quality, which may significantly influence residents' exposure preferences. Second, unlike direct methods such as surveys or interviews, our population-level analysis based on big data does not account for individual differences (e.g., gender, age, socioeconomic status), potentially masking heterogeneous preferences. Third, the buffer-based calculation of exposure intensity, though standardized for spatial comparability, may not fully reflect residents' actual visitation patterns, which involve dynamic mobility trajectories rather than static proximity. Fourth, while our combined use of XGBoost and MGWR effectively addressed global variable importance and local spatial heterogeneity, this two-step approach may sacrifice some computational efficiency and synergistic insights compared to integrated spatial machine learning frameworks (e.g., geographically weighted random forest, GWRF).

Future studies could address these limitations through three key improvements. First, integrating multi-source databases to complement refined assessments of how green space quality affects exposure preferences. Second, combining internet big data with representative surveys or interviews to capture individual-level sociodemographic nuances and validate population-wide patterns. Third, incorporate mobile positioning data (e.g., GPS trajectories or LBS check-ins) to track purposeful visits, distinguish them from passive exposures, and refine the assessment of real-world mobility-usage relationships. Additionally, emerging spatial machine learning techniques to better reconcile global interpretability and localized adaptability, and offer more parsimonious solutions for modeling complex human-environment interactions.

5. **Conclusions**

This study reveals distinct exposure preferences (*EP*) between urban forests and grasslands in Shanghai, directly addressing the two research questions. First, spatial analysis reveals that grasslands achieve higher exposure density (*ED*) in central urban areas, efficiently serving dense populations through frequent short visits, whereas forests dominate in exposure intensity (*EI*) citywide, particularly in suburbs as destinations for large-scale recreational activities. Second, machine learning-MGWR synthesis identifies multiscale socioeconomic drivers-commercial-residential activities and sports-recreation facilities enhance forest/grassland exposure through functional synergy, whereas transportation infrastructure suppresses visitation. These findings achieve three stated objectives: 1) establishing the *EI*/*ED* dual-metric framework for green exposure assessment, 2) decoding context-specific drivers via spatial-machine learning hybrid modeling, and 3) providing empirical support for sustainable urban planning under land constraints. The results advocate three paradigm shifts: climate- and temporal-responsive management grounded in population exposure dynamics, context-functional design synthesizing user features with site-specific demands, and exposure optimization guided by human-environment interaction patterns. This evidence-based approach offers actionable strategies for balancing green space accessibility and ecological functionality during urban intensification.

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Declaration of interests statement

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.

Highlights:

- Forests have a higher exposure intensity than grasslands in Shanghai.
- Exposure to forests is higher at the city edge, while exposure to grasslands is higher in the city center.
- Spatial proximity to busy roads reduces residents' exposure to forest and grassland.
- Spatial proximity to dwellings contributes to higher forest and grassland exposure.