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Research Article

Urbanity mapping reveals the complexity, diffuseness, diversity, and connectivity of urbanized areas

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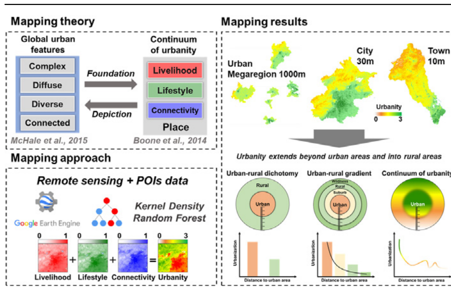
HIGHLIGHTS

- This study developed an integrative approach for continuum of urbanity mapping.
- Urbanity mapping discovers urbanized areas' complexity, diffuseness, diversity, and connectivity.
- Urbanity mapping captures the livelihoods, lifestyles, and connectivity.
- Urbanity extends beyond urban areas and into rural areas.

GRAPHICAL ABSTRACT



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ABSTRACT

There are urgent calls for new approaches to map the global urban conditions of complexity, diffuseness, diversity, and connectivity. However, existing methods mostly focus on mapping urbanized areas as bio physical entities. Here, based on the continuum of urbanity framework, we developed an approach for cross-scale urbanity mapping from town to city and urban megaregion with different spatial resolutions using the Google Earth Engine. This approach was developed based on multi-source remote sensing data, Points of Interest – Open Street Map (POIs-OSM) big data, and the random forest regression model. This approach is scale-independent and revealed significant spatial variations in urbanity, underscoring differences in urbanization patterns across megaregions and between urban and rural areas. Urbanity was observed transcending traditional urban boundaries, diffusing into rural settlements within non-urban locales. The finding of urbanity in rural communities far from urban areas challenges the gradient theory of urban-rural development and distribution. By mapping livelihoods, lifestyles, and connectivity simultaneously, urbanity maps present a more comprehensive characterization of the complexity, diffuseness, diversity, and connectivity of urbanized areas than that by land cover or population density alone. It helps enhance the understanding of urbanization beyond biophysical form. This approach can provide a multifaceted understanding of urbanization, and thereby insights on urban and regional sustainability.

1. Introduction

More than half of the world population now live in urban areas, with more people expecting to move to cities (Reia et al., 2022; Wahba Tadros et al., 2021). Over this process, landscapes became increasingly urbanized, affecting peri-urban, rural, and wilderness areas far from the urban core (van Vliet, 2019). Simultaneously, urbanized areas are becoming increasingly mixed and diffused due to rapid urbanization and the huge demand for infrastructures (Hutchings et al., 2022). These situations greatly challenge the understanding and continued application of the existing urban-rural dichotomy system to urbanized areas (Serra et al., 2014; Wang, 2022).

The urban-rural gradient (Mcdonnell and Pickett, 1990) or continuum (McKenzie, 1930) offers an instrumental approach to analyze dif-

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fused urbanized areas. This approach deviates from the urban-rural dichotomy and acknowledges the varied degrees of urbanization and their socio-ecological impacts in all regions (Halfacree, 2009; Padilla and Sutherland, 2019). Urbanization typically follows a discernible pattern of sequential changes along a gradient, including shifts in demographics, economic factors, administrative roles, and functions (Boone et al., 2014; Marcotullio and Solecki, 2013). However, relying solely on these gradient patterns may not capture the nuanced realities of contemporary urbanized areas. Due to urban expansion, sprawl, and escalating socio-economic infrastructural demands (Irwin and Bockstael, 2007; Pandey et al., 2022), the demarcations between various urbanized regions have blurred, showing complex, diffuse, diverse, and connected characteristics (McHale et al., 2015). For example, urban megaregions, which extend beyond traditional urban boundaries, consist of multiple urbanized zones (Pickett and Zhou, 2017). These zones are interconnected through extensive road networks facilitating material exchanges and infrastructure hubs enabling information transmission (Seto et al., 2012). Meanwhile, certain urban lifestyles are now emerging in rural landscapes, even before their transition to urban settings (Lennon and Berg, 2022; McGranahan et al., 2005). Urbanized areas no longer imply that they must be understood and characterized as biological or physical entities. Therefore, methods that map urbanized areas as biological or physical entities cannot capture the contemporary global urban conditions of complexity, diffuseness, connectivity, and diversity, which calls for new approaches.

The four characteristics of urbanized areas, namely complexity, dispersion, connectivity and diversity, can be reflected in one concept, the continuum of urbanity, a mixture of intersecting urban and rural areas (Boone et al., 2014). It is important to emphasize that the "continuum" is not a transect or linear gradient of change in real space. Instead, it is an urbanization characterized by a mix of livelihoods that enable people to support themselves, diverse lifestyles that embody consumption, culture, and creativity, and connectivity that links dispersed areas and is not confined by physical or administrative boundaries (Pickett and Zhou, 2017). Thus, unlike the 'visible' urbanization features (e.g., built-up land, population), with the framework of continuum of urbanity, urbanity is the 'invisible' and integrative urbanization feature including livelihoods, lifestyles, and connectivity (Boone et al., 2014; Montgomery, 1998). Therefore, urbanity defined here differs from that used in many previous studies portraying urbanity from the perspective of physical structures and forms, such as street networks and urban land use patterns, with the aim of revealing the diversity of inner-city spaces, enhancing the social vitality of urban spaces, and serving spatial design (Mohammed and Ukai, 2023; Yap et al., 2023; Ye et al., 2017). The continuum of urbanity provides a powerful framework for understanding contemporary global urbanization and is increasingly used in studies of urbanization and its social and ecological impacts (Nagendra et al., 2013; Seto and Reenberg, 2014; Zhou et al., 2021; Zhou et al., 2022). However, the application of continuum of urbanity has been hindered by the lack of methods and products for spatial quantification.

The integration of the increasingly available remotely sensed data and crowdsourcing big data provide opportunities to quantify the continuum of urbanity in a spatially explicit way. Remotely sensed data have long been used to map urbanized areas (Zhu et al., 2019), and quantify urbanization related indicators such as population density, and socio-economic profile of urbanized areas (Li et al., 2020; Wang et al., 2018; Zheng et al., 2023). Crowdsourcing big data has been increasingly used to measure urbanization (Cai et al., 2017; Herfort et al., 2023; Li et al., 2016; Xu et al., 2023). For instance, Points of Interest (POIs) cover a range of infrastructures and locations essential to livelihoods and lifestyles (Wang et al., 2022). Data from Open Street Map (OSM) about transportation facilities can be used to assess varied commuting patterns (Barrington Leigh and Millard Ball, 2020; Weiss et al., 2018). Therefore, combining remote sensing and big data has great potential to comprehensively portray urbanized regions and overcome data constraints in urbanization studies (Uhl et al., 2023; Ye et al., 2019).

Here, based on the continuum of urbanity framework, we developed an approach for cross-scale urbanity mapping from towns to cities and urban megaregions with different spatial resolutions using the Google Earth Engine. This approach was developed based on multi-source remote sensing data, Points of Interest – Open Street Map (POIs-OSM) big data, and the random forest regression model. By explicitly quantifying livelihoods, lifestyles, and connectivity, urbanity mapping helps enhance the understanding of urbanization on its socioeconomic characteristics, which is beyond the biophysical form. With the widely available remote sensing and big data, this approach provides researchers and policymakers with a multi-faceted understanding of urbanization, promoting urban sustainability, planning, and strategy development.

2. Materials and methods

2.1. Study areas and workflow

We mapped livelihood, lifestyle and connectivity and the combined characterization of urbanity areas at 1,000 m, 30 m and 10 m for the three scales of urban megaregion, city, and town, respectively. Urban megaregion is a large area formed by the intertwining of urban areas and their expanding suburbs, new urban settlements and new infrastructures, and it has been recognized as the primary urban form for the future of urbanization (Fang and Yu, 2017). In this study, the urban megaregion scale involves six regions, namely Beijing-Tianjin-Hebei (BTH), Yangtze River Delta (YRD), Wuhan (WH), Chengdu-Chongqing (CC), Changsha-Zhuzhou-Xiangtan (CZX), and Pearl River Delta (PRD) (Fig. 1(a)). These urban megaregions are the frontiers of China's urbanization, as they contain the major urban lands, populations, economies, and infrastructures across the country (Yu and Zhou, 2017). Second, we selected Beijing as the city scale study area (Fig. 1(b)), which serves as both the center of the BTH megaregion and China's political and cultural center. In 2020, Beijing comprised 16 districts with 21.8 million residents. It ranked second in GDP scale among major cities nationwide, following Shanghai. The annual GDP growth rate for Beijing was 1.2% (https://www.qianzhan.com/analyst/detail/220/211122-b2607781.html). Third, Yanqi town, a suburb of Beijing, was selected as the town scale study area (Fig. 1(c)). Yanqi town spans the urban boundary, with the southeastern side comprising flat urban areas. In contrast, most of the northwestern side comprises valleys and mountains, with many rural settlements nestled within the valleys. The town has gradually transitioned from agricultural production to non-agricultural tourism revenue generation. In the last decade, Yanqi town has boasted 108 resorts, 4 folk tourism professional villages at the municipal level, 485 folk households, and has received 1.58 million tourists, generating a comprehensive tourism revenue of 190 million CNY (http://www.bjhr.gov.cn/).

Urbanization have been often characterized by confined biophysical factors, such as a higher proportion of built-up lands, a dense population distribution and a developed economy (Mahtta et al., 2022). However, urbanization is also a social process (Hahs, 2016; Murayama and Estoque, 2020), represented by, e.g., less agrarian livelihoods, increasing urban lifestyles, and increased connectivity. Such shifts can be attributed to different types of infrastructures (Gebreyes et al., 2020; Gutierrez-Velez et al., 2022; Hecht et al., 2015). Therefore, according to the continuum of urbanity framework, we argue that urbanity is an 'invisible' urbanization characteristic that synthetically describes livelihoods, lifestyles, and levels of connectivity that include the urban entity and its surrounding areas, which is more applicable to a holistic portrayal of urbanization in any part of the world (McHale et al., 2015). Furthermore, we argue that portraying urbanization anywhere requires adapting to different data sources and spatial scales. Consequently, we have developed a mapping workflow that adapts to three types of data sources and spatial scales based on the Google Earth Engine platform and a random forest model (Fig. 2). We referred to Rosier et al. (2022) study and used a unified mapping methodology in

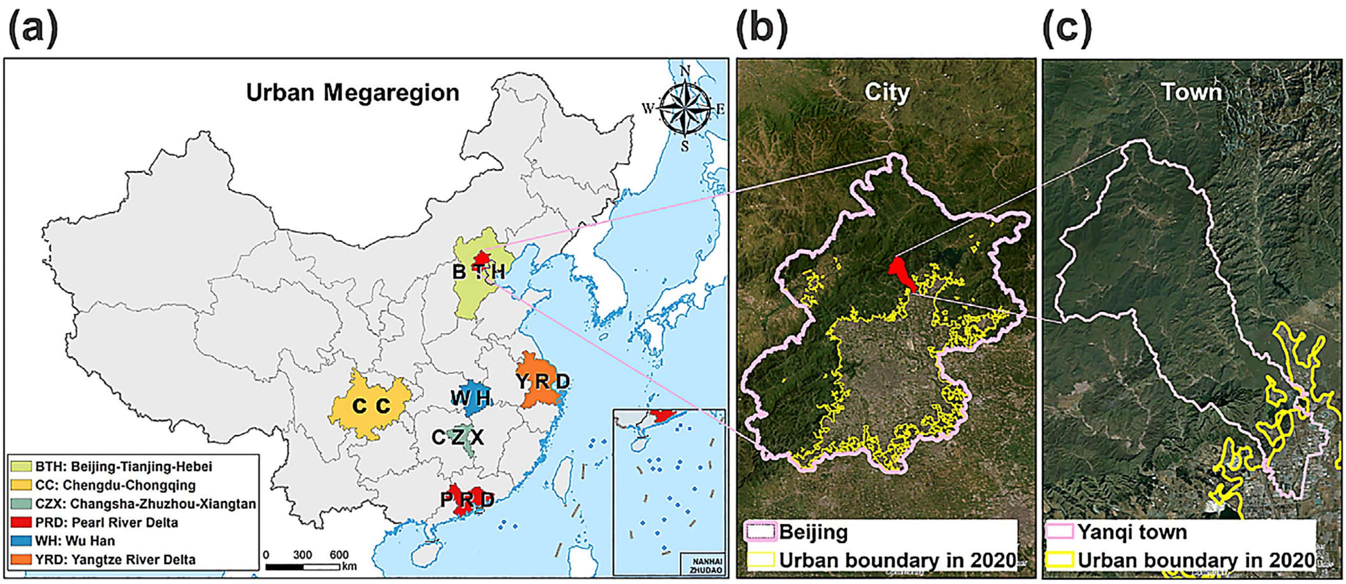

Fig. 1. Study areas: (a) six urban megaregions, (b) Beijing city, and (c) Yanqi town.

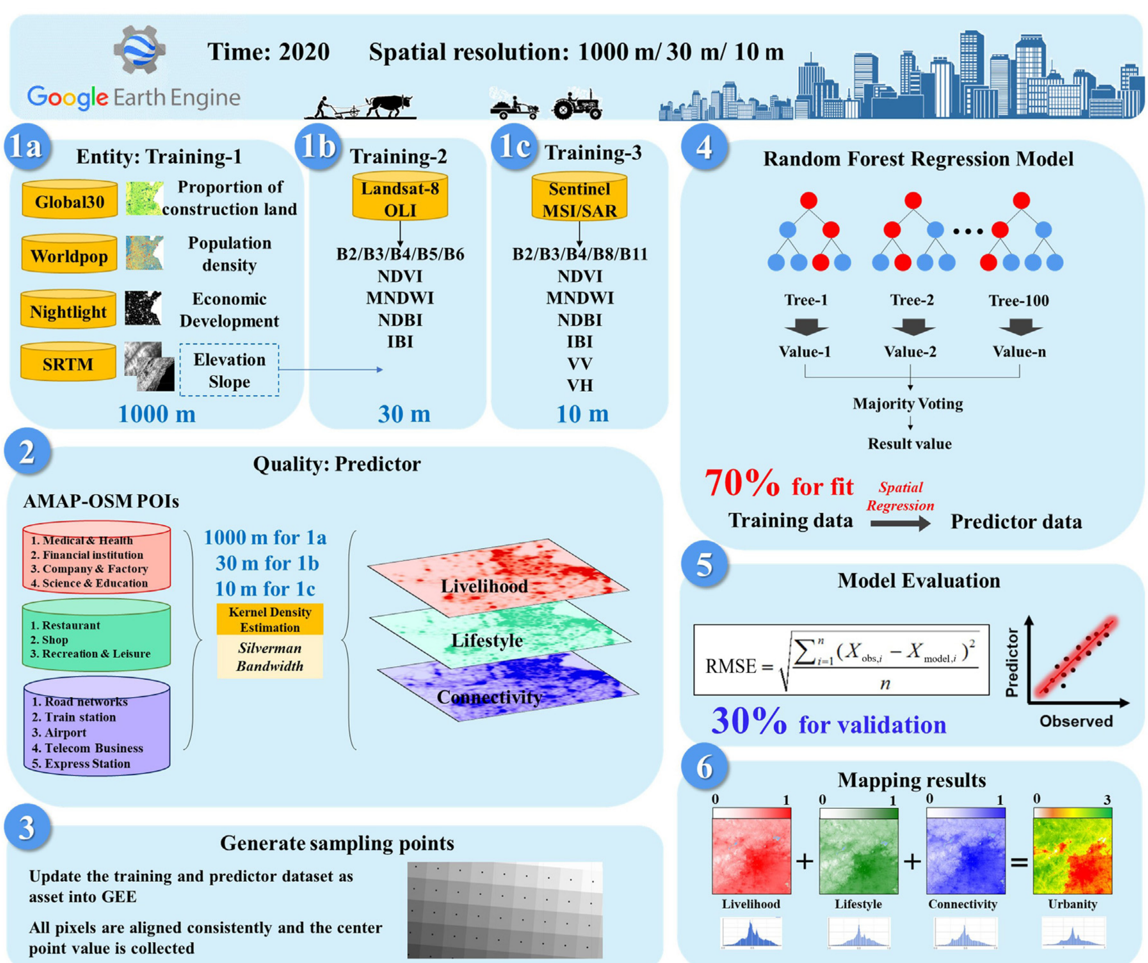

Fig. 2. Basic model workflow for mapping multi-scale urbanity in Google Earth Engine.

Table 1
Data list.

Spatial Scales	Urban megaregion	City	Town	Resources
Resolution	1000 m	30 m	10 m	
Independent variables	*Proportion of built-up land*			*http://www.globallandcover.com*
	Population density			*https://www.worldpop.org/datacatalog*
	Nighttime lights			*http://geodata.nnu.edu.cn*
	Elevation			*https://www.usgs.gov*
	Slope			
		Elevation		
		Slope		
		B2/B3/B4/B5/B6		*Landsat 8 OLI SR*
		NDVI, MNDWI, NDBI, IBI		
			B2/B3/B4/B8/B11	*Sentinel MSI*
			NDVI, MNDWI, NDBI, IBI	
			VV and VH	*Sentinel SAR*
Dependent variables	*Livelihood: healthcare, financial institutions, businesses, factories, and scientific education.*			*POIs from AMapTM and OSM*
	Lifestyle: leisure and entertainment, shopping, and dining.			
	Connectivity: highways, primary, secondary, and tertiary roads, railways, train stations, airports, telecommunications outlets, and courier stations.			

Note: B2, B3, B4, B5, B6, B8, B11 represents different band image of Landsat and Sentinel.

three spatial tests to show that our urbanity is not scale-dependent (See appendix text S4 for details of the mapping flow). The complete code for this study and the mapping data source are located in Google Earth Enginewith the link to view the mapping process and results: https://code.earthengine.google.com/10b7b5af6ee8c1f9fd7d55d3a55db541

2.2. Materials

As shown in Table 1, at the urban megaregion scale, the urbanization indicators used for urbanity mapping include the proportion of built-up land, population density, nighttime lights, elevation, and slope. At the city and town scales, we select the main bands and surface indices in Landsat 8 and Sentinel MSI & SAR, respectively, as the independent variable input data sources (See appendix text S1, Fig. S1 and Fig. S2 for image and band processing). The input data for the dependent variable is the POIs-OSM data source). Furthermore, we used some existing spatial data on urbanization as auxiliary data for analysis, comparison, and validation (See appendix text S1, S2 and S3).

2.3. Methods

2.3.1. Kernel density estimation

The method employed in this study for kernel density estimation (Diggle, 1985) involves the calculation of bandwidth using the Silverman empirical bandwidth method (Zhou et al., 2019). Kernel density estimation is a statistical technique for estimating the probability density function. This method incorporates sample standard deviation, sample size, and dimensionality to estimate the bandwidth. By adapting to the variability of the data, this method effectively determines the optimal bandwidth, leading to more accurate results in kernel density estimation. By employing the Silverman empirical bandwidth method, we achieve a balance between smoothness and precision, resulting in reliable estimates of kernel density.

2.3.2. Random Forest regression

We utilized the non-parametric Random Forest (RF) algorithm for urbanity mapping. RF, an ensemble decision tree approach founded on bagging and random subspace, addresses the challenges associated with high-dimensional data and feature-instance ratios (Breiman, 2001). In step 4 of Fig. 2, we employed the spatial regression algorithm, specifically designed for continuous variables, and inputted the independent and dependent variables into the RF model to determine the spatial distribution of livelihood, lifestyle, and connectivity in three spatial scales (the regression parameters are shown in Fig. S3). Continuous adjustments were made to the hyperparameters and optimization was conducted on the model to achieve optimal accuracy. Additionally, we used 70% of the data for regression and 30% for accuracy validation.

2.3.3. Accuracy assessment

First, we used the Root Mean Square Error (RMSE) to test the goodness-of-fit of the RF regression. The RMSE is a popularly used statistical metric for assessing the accuracy of predictive models, especially in the context of continuous variables (Chai and Draxler, 2014). It offers an interpretable scale-based evaluation of a model's prediction accuracy by computing the square root of the mean of the squares of all the prediction errors. The prediction error is simply the difference between the actual observed values and the values predicted by the model. A lower RMSE value signifies better model performance, i.e., the model's predictions are closer to the observed data. Second, we evaluated the accuracy of the RF regression model by quantifying the correlation between observed and predicted outcomes (Khuri, 2013). This measure, known as the coefficient of determination (R^2), assesses the proportion of variance in the dependent variable explained by the model's independent variable(s). An R^2 value can range between 0 and 1, where values approaching 1 signify a higher degree of model fit, demonstrating that the model accounts for a larger proportion of the dependent variable's variance. Furthermore, we also compared the mapping results of urbanity with other remote sensing classification products for built-up land, such as Global Human Settlement Layer (GHSL) (Schiavina et al., 2022), Global Urban Boundary (GUB) (Li et al., 2020), ESA10 m land products (Zanaga et al., 2022), Urban Rural Catchment (URC) (Cattaneoet al., 2021), and Near real-time global 10 m land cover (Brown et al., 2022) (See appendix text S3).

3. Results

3.1. Mapping urbanity at the urban megaregion scale

The spatial regression analysis was performed on the variables of construction land proportion, population density, nighttime light intensity, and topography, utilizing a resolution of 1,000 m. The resultant R^2 values exceeded 0.85, and the RMSE of the training samples were

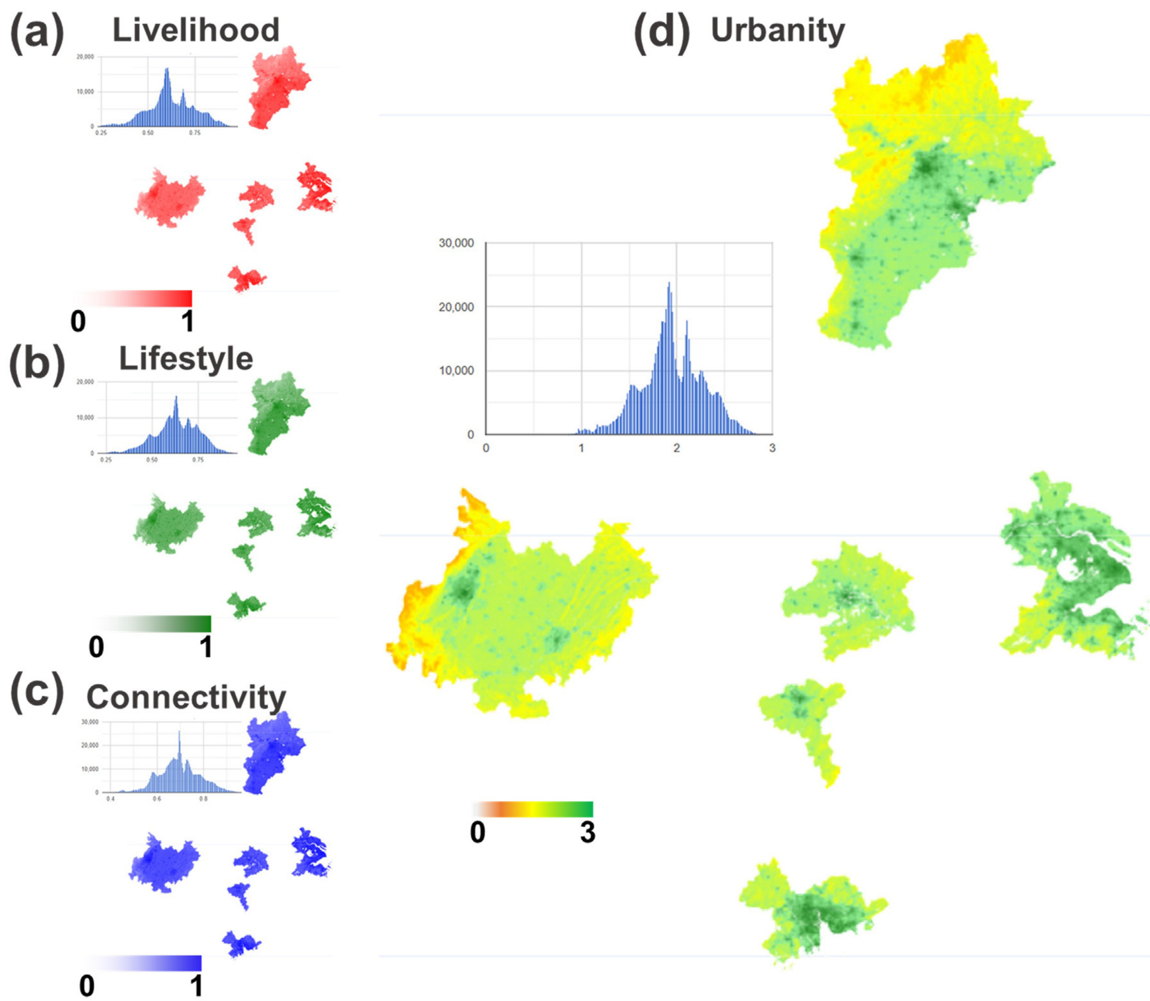

Fig. 3. Spatial distribution of Urbanity in six urban megaregions. (a) Livelihood, (b) lifestyle, and (c) connectivity, and their sums are characterized as (d) urbanity. Each histogram panel matches the distribution of 1,000 m pixels in space.

lower than those of the validation samples, which collectively attest to the robustness of our model (Fig. S4). The distribution of urbanity across urban megaregions exhibited a considerable degree of spatial variation (Fig. 3). The histograms representing livelihood, lifestyle, and connectivity demonstrate multiple peaks. More specifically, areas with better livelihood conditions were coded with increasingly red colors, while a greener color represented more diversity in lifestyle. Furthermore, stronger external connections were symbolized by bluer colors. These multiple peaks indicated a spatially intersecting distribution of areas with high and low values (Fig. 3(a), (b), (c)).

The comprehensive representation of these three dimensions yielded a clear delineation of urbanized areas - a measure we term urbanity. Areas exhibiting higher urbanity - depicted in deep green colors - marked the physical urban boundaries and signaled superior livelihood, lifestyle, and connectivity. Conversely, areas colored yellow or orange corresponded to lower urbanity values, implying that while these locations may not be urbanized in a traditional sense, they still exhibit varying degrees of livelihoods, lifestyles, and connectivity. Our analysis of urbanity across various urban megaregions revealed substantial differences (Fig. S5). The YRD region demonstrated the highest median urbanity value (2.29), followed by the PRD region (2.12), WH (2.00), CZX (1.94), BTH (1.92), and CC (1.87). These urbanity rankings offer a comparative perspective on the degrees of urbanization across regions. Furthermore, they elucidate variations in the spatial distribution of livelihood, lifestyle, and connectivity among these six urban megaregions (Fig. S5). For instance, YRD and BTH regions show multiple consecutive high peaks in the histograms, indicating heterogeneous spatial distributions. In contrast, the PRD region shows a smoother distribution in high-value areas, suggesting lower spatial heterogeneity. On the other hand, the urbanity distribution in WH, CC, and CZX revealed a singular peak, implying a more uniform spatial distribution of urbanized areas.

In this study, we employed the urban-rural gradient tool from the Global Human Settlement Layer (GHSL) dataset to evaluate urbanity across various gradient type (Fig. 4). Our findings indicate a spread of urbanity into traditionally deemed rural areas. The GHSL system classifies the urbanization level into seven categories based on the integration of built-up land and population density indicators, and considers the urbanization level to be decreasing from the urban centre to very low density rural (Fig. 4(a)). However, the urbanity in the urban-rural gradient does not follow a linearly decreasing pattern of change; instead, the urbanity level rises sharply when transitioning from inside to outside of the urban area. The median values of urbanity are higher in both suburban (2.20) and rural (1.98) than in semi dense urban clusters (1.96). This suggests that while suburban and remote rural areas are lower urbanized areas in the traditional urban-rural gradient, from an urbanity perspective, suburban and rural areas not only share similar livelihoods, lifestyles, and connectivity characteristics with urban areas, but also have higher levels than urban areas. Moreover, the urbanity histograms for the seven gradient types disclosed a blend of both high and low values in rural locales, with dark green depicting high values

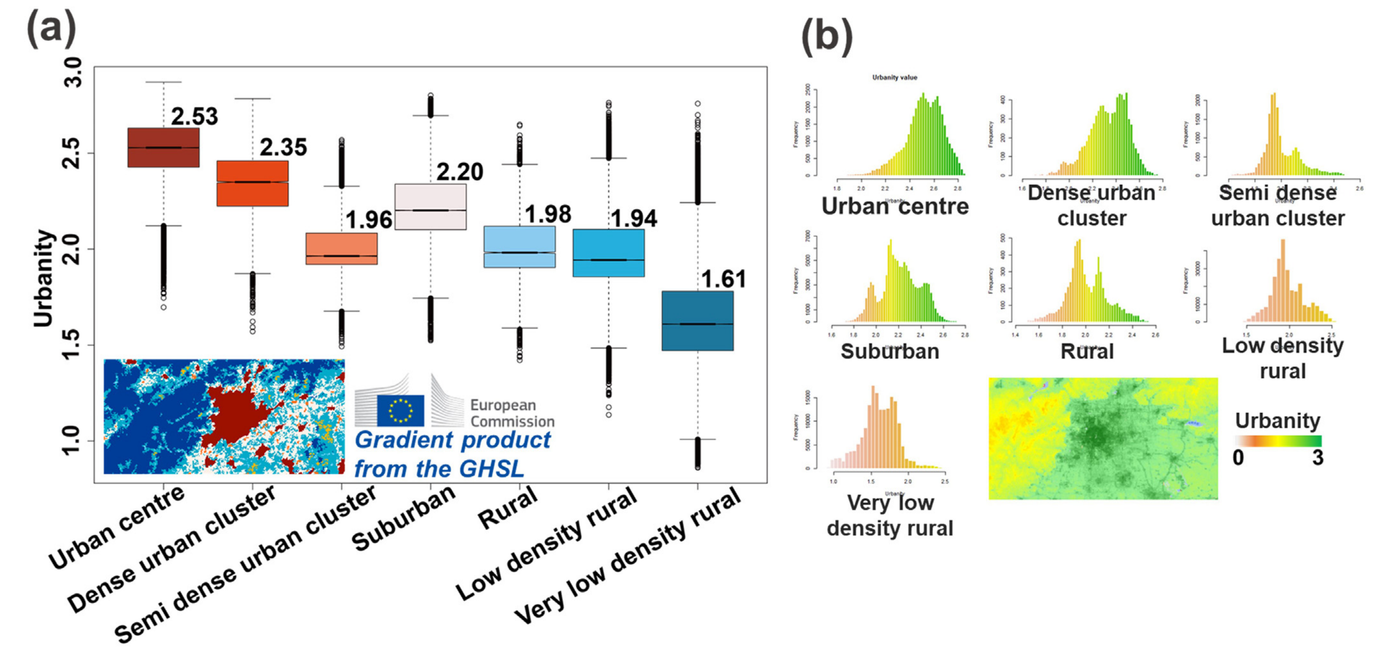

Fig. 4. Distribution of statistical urbanity in the urban-rural gradient of Global Human Settlement Layer (GHSL) (Schiavina et al., 2022). (a) Box plot and (b) histogram distribution of urbanity along the urban-rural gradient of GHSL. Bottom left is an example map of GHSL in the Beijing area. Bottom right is a map of urbanity in Beijing.

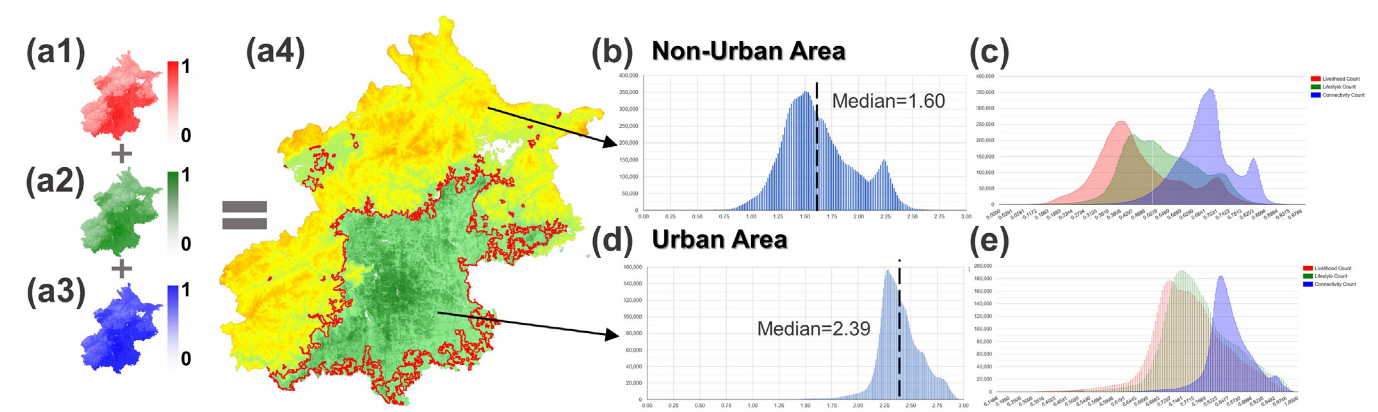

Fig. 5. Urbanity distribution in Beijing. (a1) Livelihood, (a2) lifestyle, (a3) connectivity, and their sums are characterized as (a4) urbanity. The red lines are derived from the Global Urban Boundary (GUB) in 2020 (Li et al., 2020). Outside the red boundary are (b) urbanity and histograms of the (c) three dimensions in the non-urban area. Inside the red boundary are (d) urbanity and histograms of the (e) three dimensions in the urban area.

and orange-yellow signifying low values. Despite the general decreasing trend, urbanity within the seven gradient types still exhibited multiple peak distributions, signaling its heterogeneity along the conventional urban-rural gradient. This observation underscores the complexity and diffuseness of urbanity even within the context of traditionally defined urban-rural gradients.

3.2. Mapping urbanity at the city scale

We conducted a mapping of urbanity in Beijing at a 30-meter resolution for the year 2020, leveraging unclassified Landsat multispectral satellite imagery (Fig. 5). The ensuing model fit results showcased R^2 values exceeding 0.85, and RMSE for the training samples that was lower than that of the validation samples, reflecting a robust performance of the model overall (Fig. S6). This analysis drew a more distinct spatial structuring of livelihood, lifestyle, and connectivity. Urbanity, their combined representation, effectively outlined the extent of urbanization in Beijing, as evinced by the dark green areas. Drawing upon the urban and non-urban demarcations ascertained by the 2020 GUB, it was observed that the median urbanity was higher in urban zones compared to non-urban areas (2.39 versus 1.60) (Fig. 5(b) and (d)).

However, in the non-urban areas, a bimodal distribution was noted in the histograms of urbanity, livelihood, lifestyle, and connectivity (Fig. 5(b), (c), (d), (e)). These twin peaks corresponded to the orange-yellow regions and dark green areas distributed in valleys. This pattern implies that urbanity transcends the physical boundaries of traditional urban areas, suggesting the presence of potential urbanized areas nested within non-urban regions.

3.3. Mapping urbanity at the town scale

In the Yanqi town, the model demonstrated R^2 values of 0.92, 0.91, and 0.92 for livelihood, lifestyle, and connectivity, respectively. Furthermore, the RMSE for the training samples was smaller than that of the validation samples, denoting the model's proficient fitting performance (Fig. S7). Within Yanqi town, areas with high livelihood values were pre-

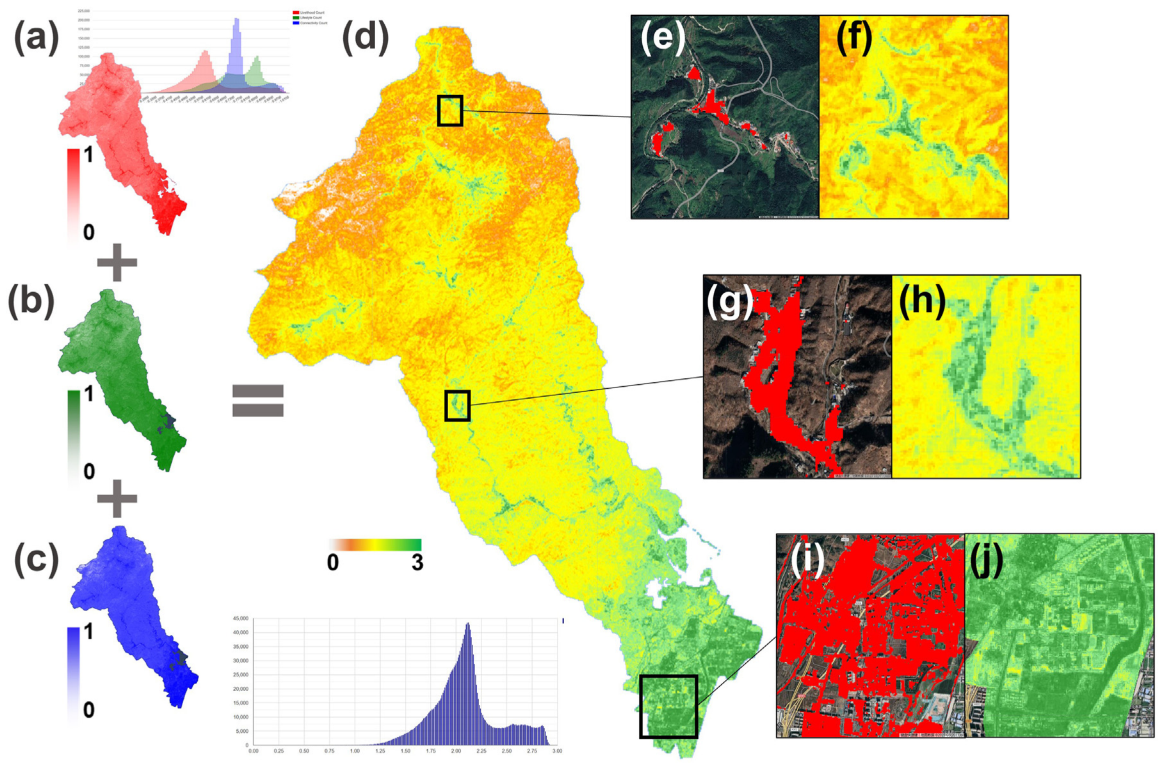

Fig. 6. Urbanity Distribution in Yanqi town. (a) Livelihood, (b) lifestyle, (c) connectivity, and their sums are characterized as (d) urbanity. The upper and lower panels are histograms of the three dimensions and urbanity. (e)-(j) Comparison of ESA 2020 10 m built-up land (Zanaga et al., 2022) with urbanity.

dominantly localized to the urban regions on the southeast side, while lifestyle and connectivity were more extensively distributed (Fig. 6(a), (b), (c)). Urbanity effectively delineated the spatial structure of the urbanized areas (Fig. 6(d)). Compared to binary land cover classifications, urbanity, with its continuous numerical values, revealed spatial heterogeneity in densely built-up land areas (Fig. 6(i) vs. (j)). The physical urban areas manifested a blend of high and low urbanity traits. Conversely, urbanity detected more nuanced potential urbanized regions within the river valleys, which are traditionally classified as non-urban areas. Conventional land cover classifications underestimated or even entirely overlooked these regions, leading to an under-extraction and under-detection of certain functional building zones (Fig. 6(e) vs. (f), (g) vs. (h)). Utilizing 80 m × 80 m sampling frames, we computed the median urbanity along the urban-rural distance gradient for six villages (Fig. S8). The analysis revealed that the remote villages in river valleys did not exhibit a lower urbanity, despite their distance from urban centers, further emphasizing the compatibilities and mixture of urbanity in urban and rural areas.

4. Discussion

4.1. Urbanity reaches beyond urban entities into rural areas

This study introduces the concept of ‘urbanity’ to define what constitutes an urbanized area, framing it as both socio-economic and physical characteristics—such as land, population, and nighttime light—as well as a mixture of livelihoods, lifestyles, and connectivity. Our research gains significant insights from incorporating the continuum of urbanity theory. According to this framework, irrespective of traditional ‘urban’ or ‘rural’ classifications, urbanity considers urbanized areas to be components of an integrated system (Fig. 7(e)).

Depicting urbanized regions depends on how urbanization is understood. The urban-rural dichotomy simplifies the spatial structure of urbanized areas, especially through the urban-rural household registration dichotomy that facilitates the classification and management of urban and rural populations (Bai et al., 2014) (Fig. 7 (a) and (b)). However, such understanding is insufficient for exploring the heterogeneity of urbanized areas and issues of sustainable development (McGranahan and Satterthwaite, 2014). The urban-rural gradient or continuum has made an important contribution to this (Dewey, 1960; Mcdonnell and Pickett, 1990), and many studies have argued that it is simpler and more reliable to characterize the continuum or dispersal categories of intra-urban and surrounding areas in terms of gradients (Fig. 7(c) and (d)) (Dawazhaxi et al., 2022; Kaminski et al., 2021). Nonetheless, the current increasingly dispersed and mixed urbanized areas are hardly sufficient for revealing spatial structure and specific features through gradients. Moreover, urbanization varies greatly across different regions of the globe, requiring the adoption of universal concepts to understand complex, diffuse, diverse, and connected urbanization systems (McHale et al., 2015).

The continuum of urbanity provides a new perspective on this. All places are an intertwined collection of urban and rural areas, and urbanization extends beyond physical boundaries, dispersing and integrating with surrounding areas (Fig. 7 (e) and (f)). Each place mixes different levels of livelihoods, lifestyles, and connectivity, which adds diverse socioeconomic attributes to the existing biophysical spatial structure. Furthermore, each place is linked to each other by connectivity (e.g., roads, delivery points) to compose an area of urbanity. Thus, urbanization in some places is no longer on a downward trend from the inside to the outside of the city but rather a mix of different livelihoods, lifestyles, and connectivity diffused anywhere (Fig. 8). For example, at the megaregion scale, where both the suburban and rural categories have higher levels of urbanity than the semi-dense urban clusters (Fig. 8 (a) and (b)). At the city scale, inner-city residential community and urban village share similar livelihoods, lifestyles and connectivity characteristics with rural community located away from urban areas (Fig. 8 (c) and (d)). Moreover, at the town scale, although remote villages in the valley are farther away from the down town, their degree of urbanity does not decline

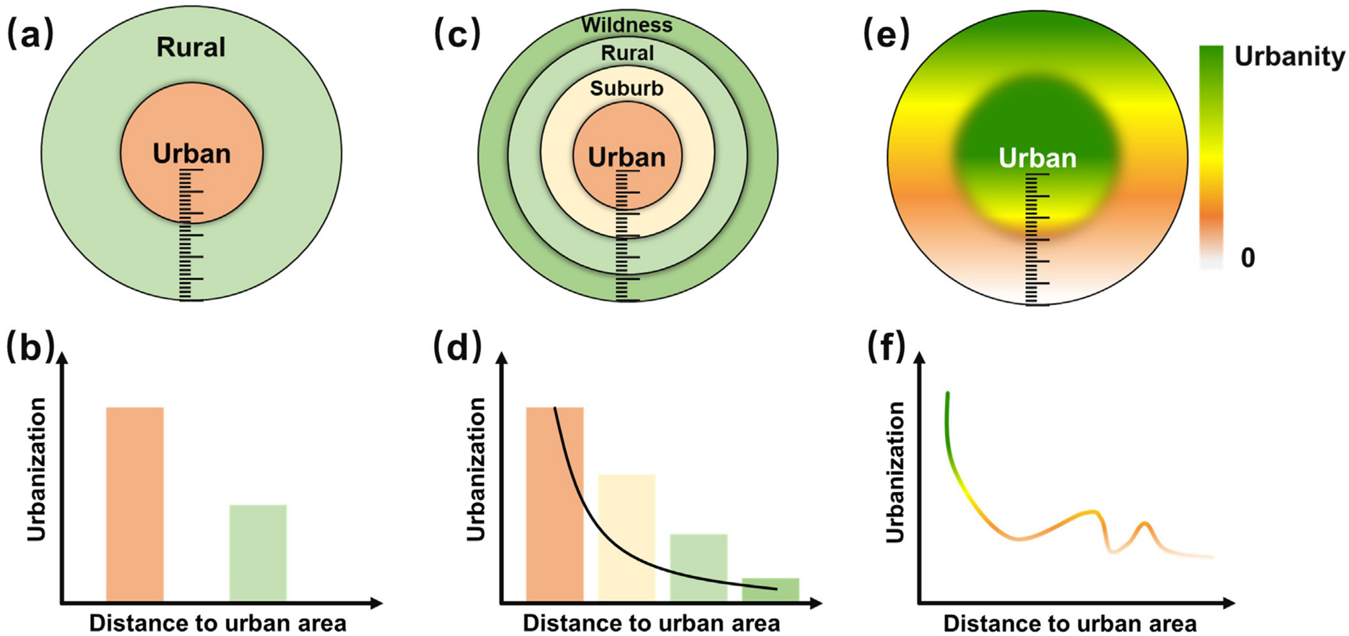

Fig. 7. Understanding the three patterns of urbanized areas. (a) The urban-rural dichotomy separates (b) the urban and rural area. (c) The urban-rural gradient or continuum shapes (d) a decreasing degree of urbanization from the urban interior to the exterior. (e) The continuum of urbanity represents a complexity, diffuseness, connectivity, and diversity urbanized area. (f) Places distant from urban areas have similar and mixed livelihoods, lifestyles, and connectivity as those close to urban areas.

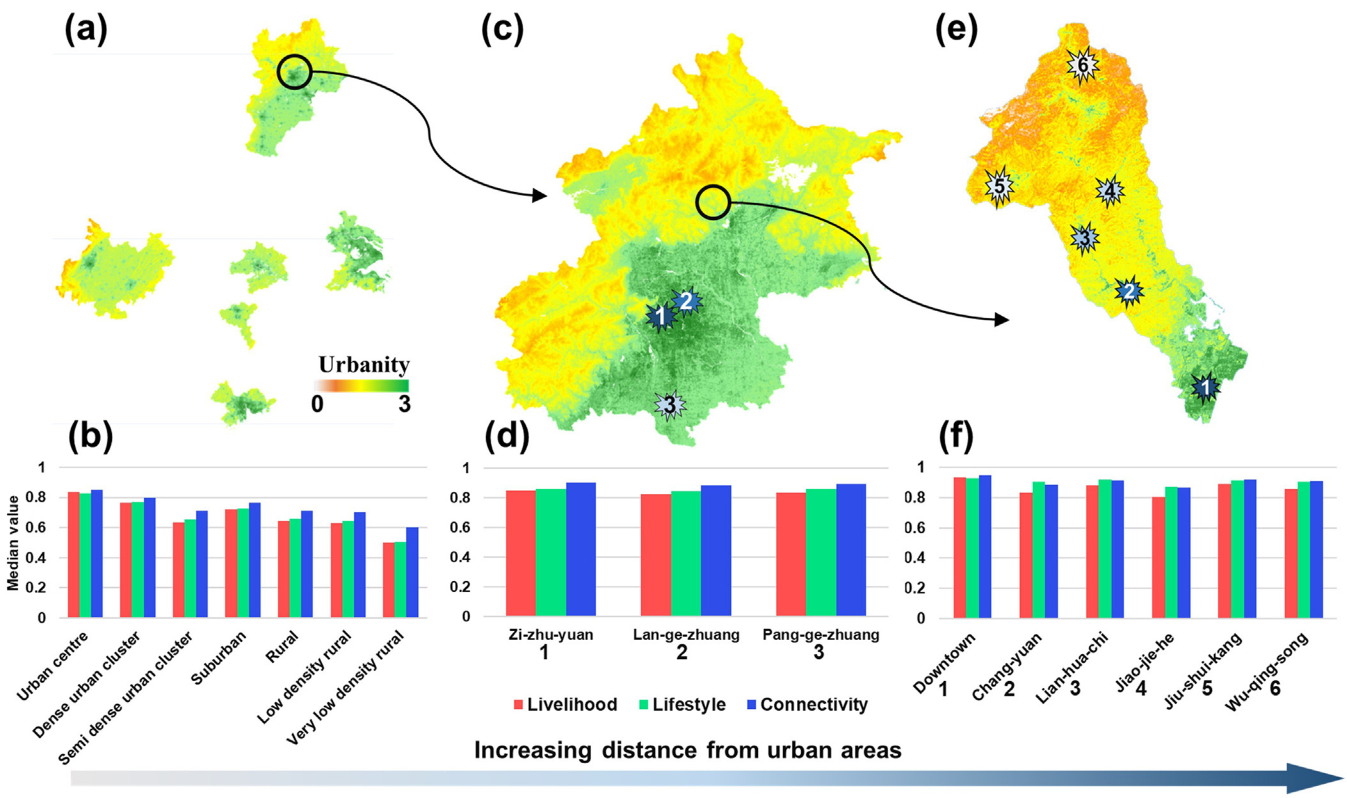

Fig. 8. Distribution characteristics of livelihoods, lifestyles, and connectivity with increasing distance from urban areas at three scales (a) and (b) are distributed characteristics of livelihoods, lifestyles, and connectivity across the urban-rural gradient at the urban megaregion scale; (c) and (d) are livelihoods, lifestyles, and connectivity characteristics of the three urban and rural communities at the city scale. No. 1 represents an inner-city community (Zi-zhu-yuan), No. 2 represents an urban village (Lan-ge-zhuang) and No. 3 represents a rural community in the suburbs (Pang-ge-zhuang). (e) and (f) are livelihoods, lifestyles, and connectivity characteristics of urban and rural communities at the town scale. No. 1 to No. 6 represent communities that are gradually moving away from the urban area.

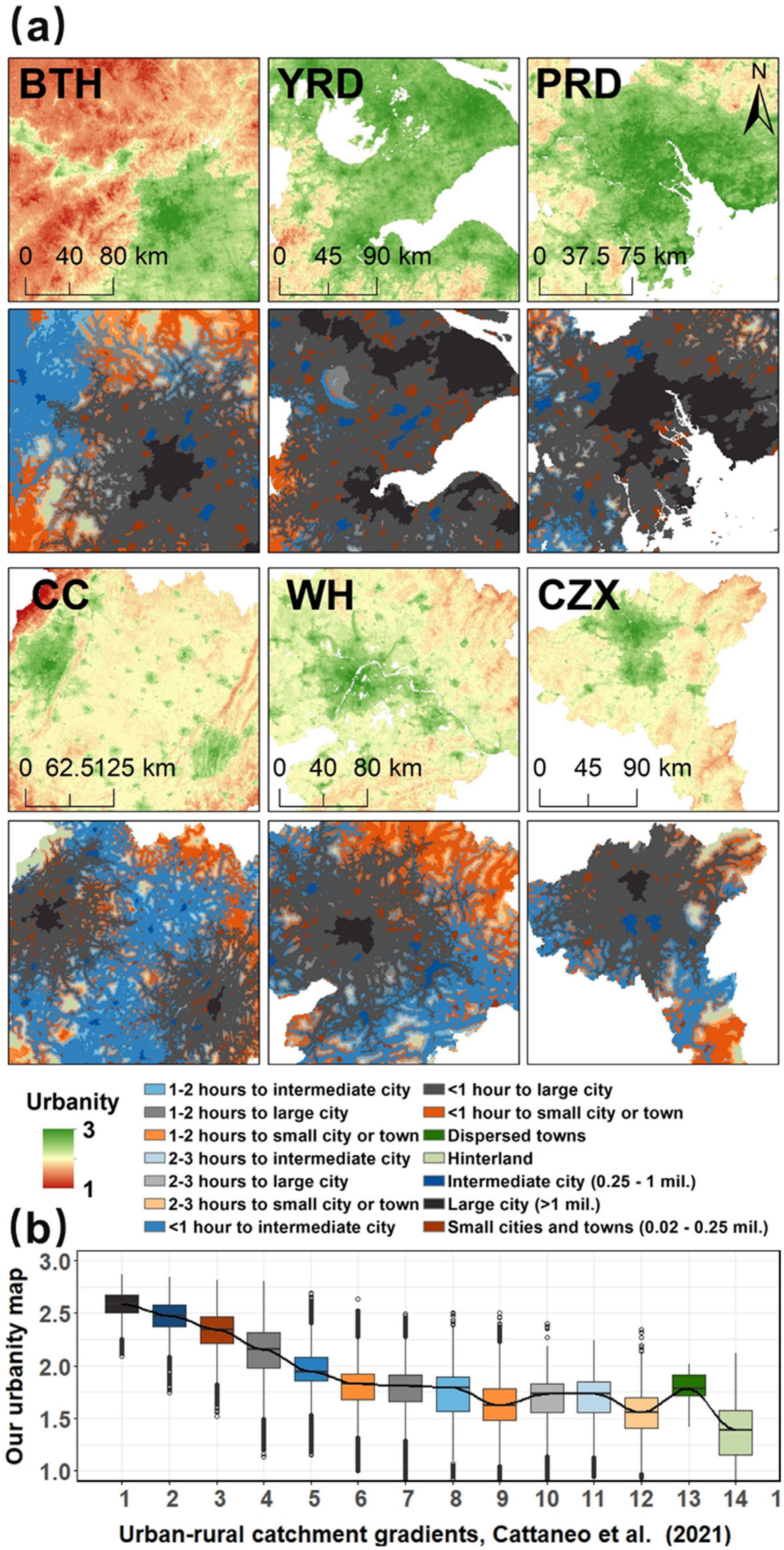

Fig. 9. (a) Comparison urbanity with the urban-rural catchment map (Cattaneoet al., 2021) at the 1,000 m resolution, in six urban megaregions. (b) Relationship between urbanity and urban-rural catchment map. *Note*: BTH, Beijing-Tianjin-Hebei; YRD, Yangtze River Delta; PRD, Pearl River Delta; CC, Chengdu-Chongqing; WH, Wuhan; CZX, Changsha-Zhuzhou-Xiangtan.

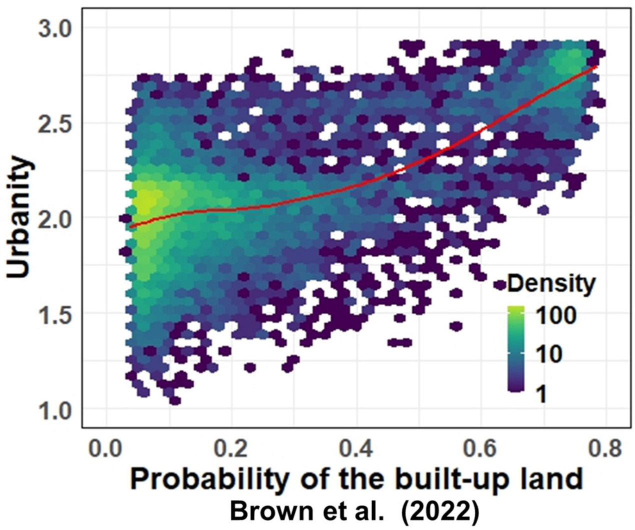

Fig. 10. Relationship between urbanity and dynamic built-up land at the 10 m resolution (Brown et al., 2022), in the Yanqi town. The fitting method for the curves is the Generalized Additive Model (GAM) (Hastie, 1990), which solves the fitting problem when there is a highly nonlinear relationship between the response variable and the explanatory variables, and has an outstanding ability to fit non-monotonic relationships. In the area of low probability of built-up land, the slope of the fitted curve is larger, indicating a higher urbanity.

with distance, but rather has the same level of urbanity as the downtown (Fig. 8 (e) and (f)). Therefore, this mapping method is not scale-dependent and reveals the common fact that urbanity reaches beyond traditional urban entity areas and diffuses into rural areas at different spatial scales. Although the urban-rural dichotomy and the urban-rural gradient consider rural areas as "visible" non-urbanized areas, urbanity demonstrates that rural areas can be also characterized by similar livelihoods, lifestyles, and connectivity as urban areas. In addition, this study provides the first visualization of the spatial distribution of continuum of urbanity and supports sociologists' view that "although cities are the characteristic sites of urbanism, people's lifestyles are not confined to urban areas" (Pahl, 2008; Wirth, 1938). This 'invisible' character of urbanization tells us that the effects of urbanization should not be limited to urban entities, but that their surrounding rural areas also benefit from urbanization and contribute to sustainable development (McHale et al., 2013).

The urbanity reveals complex, diffuse, diverse and connected urbanized areas. For example, in six urban megaregions, urbanity reflects different urbanization patterns and spatial heterogeneity (Fig. S5). In Beijing city, while the physical extent of urbanization has been defined by the city boundary (GUB), urbanity demonstrates that livelihoods, lifestyles, and connectivity like those in urban areas still exist in the valleys of non-urban areas. Furthermore, in Yanqi town, we paid closer attention to the spatial structure of urbanized areas within the urban area and each rural community (Fig. 6). Rural communities and settlements in the valleys cover the low-rise brick or concrete structures and two main roads. However, these simple buildings can provide places for livelihoods (rural enterprises), diverse lifestyle locations (tourist shops), and connectivity networks (roads leading to the urban area and courier points for material exchange).

4.2. Comparison with other urbanized maps

Comparisons between our urbanity maps and other studies showed the coexistence of consistency and variability. Within the six urban megaregions, we have shown that rural areas also reflect urbanity through the urban-rural gradient of (Schiavina et al., 2022), which we also compare with the urban-rural catchment of (Cattaneoet al., 2021) (Fig. 9(a)). Although urbanity exhibited a linear decrease with urban-rural catchment. Higher urbanity was, however, found in small towns dispersed in the peri-urban area, as well as in places far from the city (Fig. 9(b)). Additionally, in terms of the comparison of fine-scale maps, the probability of built-up land mapped by Brown et al. (2022) presented a linear relationship with urbanity in general (Fig. 10). However, locally, places covered with a few built-up lands have a higher urbanity, indicating that urbanity represents potentially urbanized areas. Comparison with the built-up land product from Zanaga et al. (2022) also suggests that urbanity can highlight more heterogeneous urbanized areas (Fig. 6 (e)-(j)). The three study cases, as well as the results of the comparisons between maps, demonstrate the sensitivity of urbanity mapping to spatial scales and multi-source remote sensing data. Therefore, the urbanity mapping approach we developed can be used as an analytical study to support urbanization within different spatial scales.

4.3. Mapping applications

For a long time, urbanization has been recognized as one of the primary drivers of social and environmental problems, thus posing a significant barrier to sustainable development (Pauleit et al., 2021). However, urbanization can also present opportunities for achieving sustainability (Childers et al., 2014; Pickett and Zhou, 2017; Seto et al., 2012). In this regard, our mapping results can be linked to the established Sustainable Development Goals (SDGs). For instance, livelihood corresponds to SDG 8.2, representing diversified employment, technology, and innovation; lifestyle corresponds to SDG 8.4, representing patterns of material consumption; connectivity corresponds to SDG 11.2, representing affordable and sustainable transportation systems (Fig. 11(c)). These three dimensions, as pathways to regional sustainability, aim to enhance well-being and social equity for people in any location (Boone et al., 2014; Pandey et al., 2022; Seto et al., 2017).

A major challenge is that while urban entity areas are considered representative of urbanization and are widely noted for the ecological effects that exist, but potentially urbanized areas beyond urban entities also have many ecological impacts as well (Hubacek et al., 2009; Hutchings et al., 2022; van Vliet, 2019; Wang et al., 2012; Yang et al., 2024). These places are gradually becoming dominated by non-agricultural production as they develop socio-economically and may have the same livelihoods, lifestyles, and connectivity as the physical urban areas, thus having an impact on the local ecosystem (Dawazhaxi et al., 2023). Therefore, portraying livelihoods, lifestyles, and connectivity in rural areas is the primary objective, which in turn explores the impact of urbanity in rural areas on the ecological environment (Fig. 11(d)). For example, urbanization provides a protective role for vegetation and alleviates damage to ecosystems from human activities by improving people's life quality and commute conditions (Li et al., 2017; Wang et al., 2012; Zhang et al., 2022a; Zhou et al., 2022). This will be one of the prospects for the application of this research and data.

4.4. Research gaps and prospects

Our work has thus far built upon the continuum of urbanity framework, fostering a comprehensive understanding of urbanized areas, and developing a multi-spatial scale adaptable methodology for urbanity mapping. Nevertheless, this study has some limitations. (1) Our data sources present an area of challenge. The POIs delineating livelihoods, lifestyles, and connectivity were chosen based on reference materials and a priori knowledge, introducing a substantial degree of subjectivity into our study. This can potentially influence the scientific legitimacy of characterizing specific lifestyles or livelihoods. (2) On the mapping methodology front, the third step in our workflow entails using each cell from each type of kernel density raster as a sampling point, as opposed to using the actual POIs' locations. This choice could affect the precision of our random forest spatial regression. However, it also circumvents the

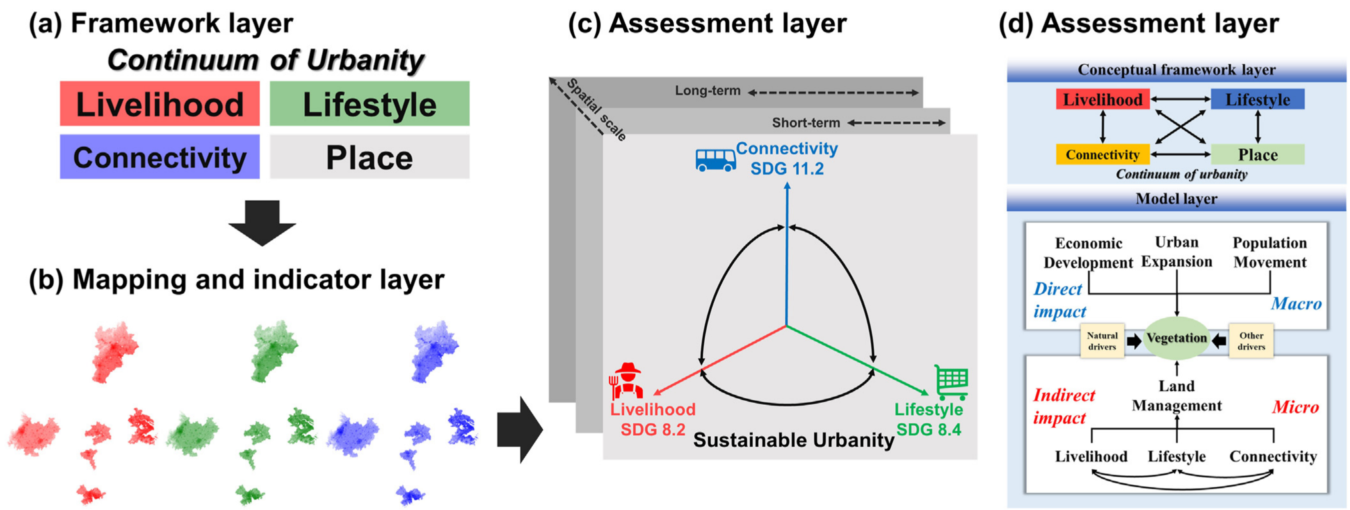

Fig. 11. Prospects for the application of urbanity mapping. (a) Based on the continuum of urbanity theory to (b) mapping the three dimensions of urbanity. (c) Converting the three dimensions of urbanity into SDGs for a holistic assessment of sustainable urbanity. (d) Exploring the indirect impacts of urbanization on ecosystem change in rural areas. Many studies have investigated the direct impacts of urban expansion, economic development and population movement on vegetation based on macroscopic data, but the indirect impacts remain unclear, especially the mechanisms of effects at the microscopic level (van Vliet, 2019; Zhang et al., 2022b). Thus, spatial data on the three dimensions of urbanity can support this by portraying the livelihoods, lifestyles, and connectivity of each place, thus exploring the indirect effects at fine scales.

data leakage issue associated with numerous real POIs, thereby reinforcing the spatial privacy protection for geographic big data. (3) This study employs the principle of distance decay in the kernel density method to measure the urbanization characteristics represented by the POI, which is challenging to directly validate the accuracy of the measurements. Therefore, in addition to making comparisons with similar products, there is a need to further develop methods that can enhance the robustness of the analysis. (4) The computational memory constraints of Google Earth Engine posed another limitation. As a result, we had to streamline our data sampling parameters during the regression results calculation and default the tilescale to a range between 5 and 8. This has implications for the final regression results and their validation accuracy. (5) Our study suffered from a lack of time series data related to POIs. As such, we were unable to track the temporal pattern of urbanity. Moving forward, we anticipate addressing these gaps. Our focus is to extend the urbanity maps to global scales and long time series and to explore their variation in different socio-economic and physical geographic contexts. Additionally, we will use urbanity maps as one of the drivers of vegetation change to explore the effects of urbanization on ecosystems in non-urban areas.

5. Conclusions

Combining remote sensing and POIs-OSM big data, we have developed urbanity mapping methods that can be adapted to multi-spatial scales. Our study shows that urbanity extends beyond physical urban boundaries and spreads into surrounding towns and rural areas. In addition, urbanity mapping elucidates the variability of urbanization patterns, revealing complexity, diffuseness, diversity, and connectivity urbanized areas in terms of livelihoods, lifestyles, and connectivity. Moreover, we do not disprove the products of other urban-rural gradients; rather, we hope to integrate these data into a tool for a holistic understanding of urbanized areas and their characteristics. As escalating urbanization, gaining insight into the essence of urbanization becomes imperative in steering sustainable development and equitable urban planning and policymaking. Our research provides academics and policymakers with an extensive dataset, in conjunction with a multifaceted comprehension of urbanization, which empowers evidence-based decision making and strategic planning.

Declaration of Competing interests

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

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.geosus.2024.03.004.

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