Synergistic Classification of Multilevel Land Patches (SC-MLPs): Reducing Conflicts and Improving Mapping Results for Land Uses and Functional Spaces With Very-High-Resolution Satellite Imagery

Xiuyuan Zhang, Shuping Xiong, Xiaoyan Dong, and Shihong Du

***Abstract*— Land uses (e.g., commercial, residential, and industrial lands) and functional spaces (e.g., living, productive, and ecological spaces) are two-level landscape patches and totally work as basic units for urban planning. The two-level patches are interrelated and mutually binding, but existing mapping methods extracted them separately, leading to substantial conflicts and errors in their mapping results. Accordingly, this study proposes a synergistic classification of multilevel land patches (SC-MLPs). It considers a multitask learning strategy and proposes a novel correlation loss function to measure the correlations between land uses and functional spaces, which is expected to resolve conflicts and improve the accuracy of the two-level land patch mapping results. Consequently, land-use and functional-space maps of three major Chinese cities are generated, which generally have a high resolution of 2 m and high overall accuracies of 90.1% for land uses and 93.8% for functional spaces. Compared to state-of-the-art land-use and functional-space mapping methods, our results have not only higher accuracies but also a better consistency which is improved by 36%. Accordingly, the proposed SC-MLP can generate not only accurate but also consistent maps of land uses and functional spaces, which plays a fundamental role in land system research and urban planning.**

***Index Terms*— Land use, multitask learning production-living-ecological space, synergistic classification of multilevel land patches (SC-MLPs).**

I. Introduction

LAND system is generally composed of four levels (see Fig. 1), i.e., land covers, land uses, functional spaces, and urban-rural areas [1], [2]. The former two, i.e., land covers and uses, support micro planning which designs and spatially allocates diverse land elements [3], and the latter two, i.e., functional spaces and urban-rural areas, aim at macro control that decides whether micro planning may be granted [4], [5]. Accordingly, land uses and functional spaces are two key levels for planning, as their interactions directly influence both macro and micro planning, and play an important role in overall land planning [6], [7].

Land uses and functional spaces essentially divide the heterogeneous land into diverse landscape patches according to their structures, usages, and functions [8], [9]. On the one hand, land use refers to the purposes and activities through which people interact with land and terrestrial ecosystems [10], [11], [12], and involves the management and modification of the natural environment or wilderness into the built environment, such as residential, commercial, industrial, and farmland [13]. On the other hand, functional-space zoning, e.g., living, productive, and ecological (see Fig. 1), is a method of urban planning, and it specifies a variety of outright and conditional functions of land, which determines whether a land-use plan at the micro-level urban planning may be granted [14]. That is, the differing regulations in variant functional spaces may govern the density, size, layout, and types of land uses [15], [16], [17]. Accordingly, both land uses and functional spaces are fundamental to urban planning.

Previous studies generally mapped land uses and functional spaces separately, as they considered the two mapping tasks as two independent processes, which results in substantial conflicts between land-use and functional-space mapping results. For example, a zone is sorted into "residential land" in land-use mapping but a "productive space" in functional-space classification. It is a so-called inconsistency between the two mapping results and may result from data nonstationary and classification errors. The inconsistency, besides mapping errors, is also critical to urban planning because inconsistent land-use and functional-space maps extremely confuse planners and can lead to no decision. The inconsistency, however, has been totally ignored by previous studies and has become a bottleneck in applying remote sensing mapping results to urban planning.

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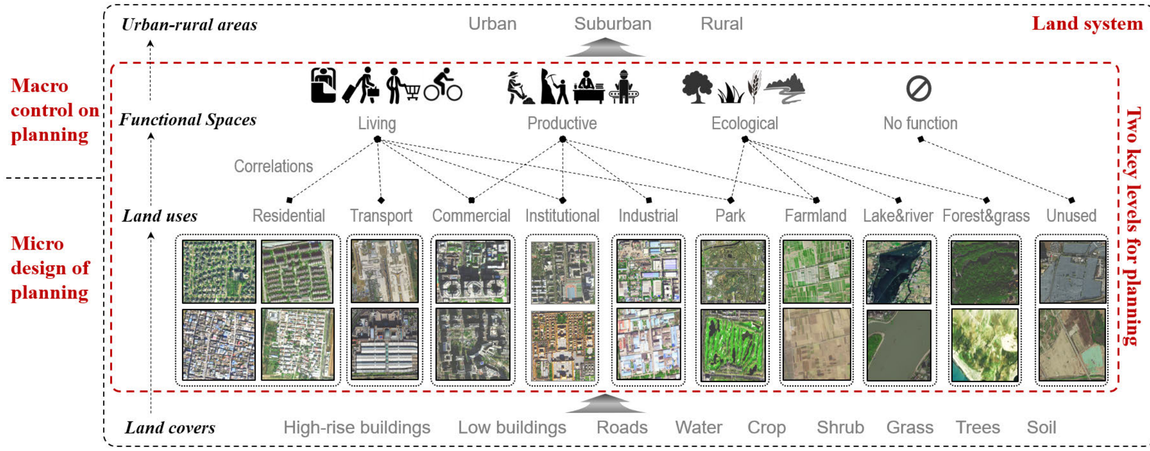

Fig. 1. Land system consisting of four levels, i.e., land covers, land uses, functional spaces, and urban-rural areas, where land covers and uses support micro design of planning, and functional spaces and urban-rural areas support macro control on planning. Accordingly, land uses and functional spaces are two key levels for planning, and their correlations are interactions between macro and micro planning, playing an important role in overall land planning.

Generally, consistent land-use and functional-space maps are hardly available for the following three reasons. First, the two-level land patches are extremely heterogeneous inside, as they can be composed of diverse land covers, e.g., road, soil, water, vegetation, and different buildings, with variant visual features [9], [18]. Second, their boundaries are ambiguous, because substantial land uses and functional spaces have similar visual clues and can be confusing on their boundaries, e.g., residential versus institutional [19], and most land uses and functional spaces have no physical enclosure. Third, land uses and functional spaces have strong correlations. As presented in Fig. 1, functional space can contain several kinds of land uses with compatible activities and services, and land use can correspond to one or two functional services [20], [21]. Accordingly, land uses and functional spaces both have three characteristics, i.e., heterogeneity, ambiguity, and correlation. The former two (i.e., heterogeneity and ambiguity) complicate land-use and functional-space classifications; while, the last one, i.e., correlation, can serve as a clue to resolve conflicts between two-level classifications and optimize their results (see Fig. 2). That is, land uses are basic units and fundamental to identifying functional spaces, and thus functional spaces can be extracted based on land uses; conversely, functional spaces are considered as backgrounds and contexts to improve land-use classifications, which are critical to resolving land uses' heterogeneity and ambiguity, as local contexts can reduce heterogeneity inside and improve distinguishability on the borders [22].

However, existing studies totally ignored the correlation and mapped land uses and functional spaces separately, resulting in substantial errors and conflicts in their mapping results (e.g., residential in land-use result but productive in functional-space result at the same location in the separated classifications). The previously separated classifications for only land uses or solely functional spaces are demonstrated as follows.

A. Land-Use Classification

Existing land-use classification methods can be sorted into two types. In the early stage, land uses were segmented by manually delineated road blocks [23], characterized by hand-crafted features, e.g., image features [24], visual indicators [25], [26], topic models [27], [28], and finally identified by traditional classifiers, e.g., K-nearest neighbors [24], random forest [29], [30], and support vector machine [31]. These methods cannot resolve the heterogeneity within land uses and are hard to produce accurate results for complex land uses, because they rely heavily on the qualities of hand-crafted features which can be highly heterogeneous and are easily mis-classified by the traditional classifiers. To resolve this issue, state-of-the-art deep learning methods have been widely applied to land-use classifications in recent several years [32], as deep learning methods can automatically extract robust, representative, and abstract features of land uses, reducing the heterogeneity and improving the classification accuracy [33], [34], [35]. However, deep-learning semantic segmentation methods, such as RefineNet, PSPNet, and DeepLabv3+ [36], [37], may exacerbate the ambiguity of land-use boundaries due to the deconvolution and upsampling processes [38], leading to inaccurate boundaries of land uses.

B. Functional-Space Classification

Compared to land-use classification, functional-space mapping is rarely studied, because functional space is a relatively new concept in the field of urban planning, and each functional space can have stronger heterogeneity inside and ambiguity on the boundary, compared to land uses; thus, it can be more challenging to extract and classify functional spaces [39]. Li and Fang [14] proposed the first classification system of productive-living-ecological spaces, and presented a quantitative identification method for these functional spaces, which relied heavily on a manually designed indicator, and required substantial field survey data, thus was not applied to large-scale functional-space mapping [22], [40], [41]. Duan et al. [42] argued that there were no standard indicators for quantitatively measuring productive-living-ecological functions, and thus using different indicators and different survey data can result in variant functional-space classification results. In a different way, recent studies have considered

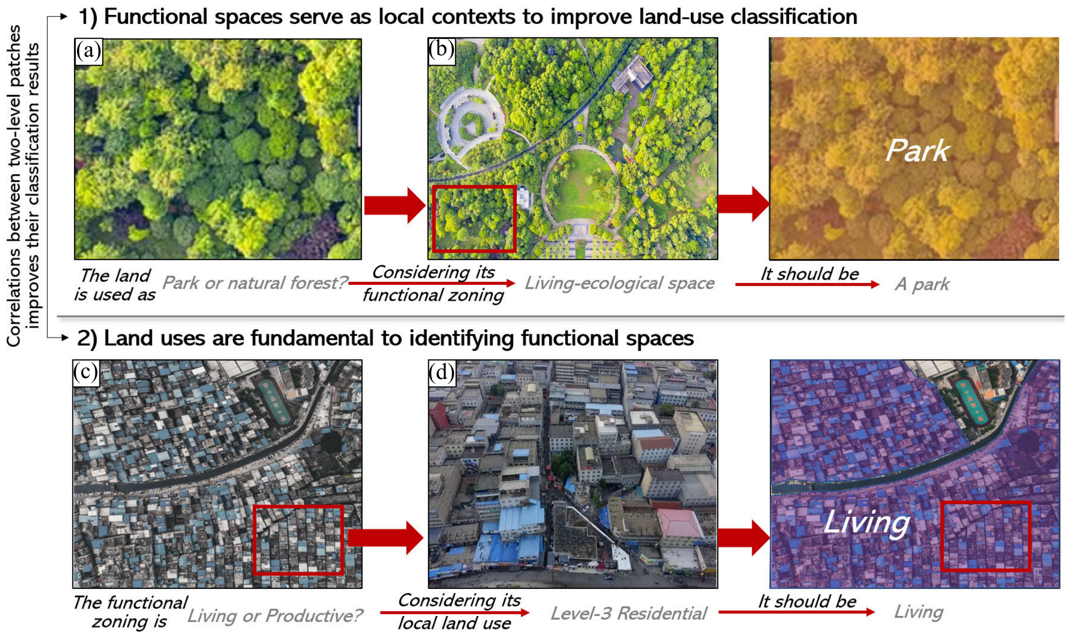

Fig. 2. Correlations between land uses and functional spaces serve as clues to improve their classification results. (a) Land patch can be recognized as a park or a forest, but considering its functional zoning as, (b) living-ecological space, it should be a park. On the other hand, (c) functional zone should be a living or productive space, but considering its (d) local shanty-town land use, it should be a living zone.

using very-high-resolution (VHR) images to extract functional spaces, as VHR images provide objective, comprehensive, and fine-scale land surface information, but there can be a significant semantic gap from image representations to functional spaces; thus, it is difficult to extract functional spaces directly from VHR images [43].

As demonstrated above, previous studies considered land-use and functional-space classifications as two independent processes and did not consider their correlations to improve their classification accuracies and consistency, which may lead to substantial mapping errors and conflicts, negatively affecting land system studies and extremely confusing urban planners. Accordingly, this study proposes a synergistic classification of multilevel land patches (SC-MLPs) which uses a multitask learning strategy to measure the correlation between land uses and functional spaces and classifies the two-level patches synergistically. Generally, the study makes three contributions: 1) it presents a hierarchical sampling method to generate differentiated samples of land uses and functional spaces for training SC-MLP, which is fundamental to improving the mapping accuracy and consistency; 2) it proposes a SC-MLP method which is the first model to extract functional spaces from satellite images and can improve classification accuracies for both land uses and functional spaces; and 3) the SC-MLP method furthermore improves consistency between land-use and functional-space mapping results by embedding a novel correlation loss function and a shared feature encoder. Accordingly, the SC-MLP is a novel method and totally different from existing separated land patch classifications; as proved by the study, the SC-MLP can produce not only accurate but also consistent classification results for different levels of land patches, directly contributing to land system research and urban planning.

II. Methodology

This study essentially aims to propose a novel method to map land uses and functional spaces simultaneously with VHR images and generate not only accurate but also consistent results for both patches. First, a category system and sampling strategy are demonstrated in Section II-A, which illustrates the concept baseline of the study and presents a hierarchical sampling method for land uses and functional spaces. Second, a SC-MLP approach is proposed in Section II-B, and it is the key of the study, which employs a multitask learning strategy to connect land-use to functional-space classifications and improve both results. Third, a method for evaluating classification results is demonstrated in Section II-C, where four indicators are considered to validate the effectiveness of our method.

A. Category System and Hierarchical Sampling Method of Land Uses and Functional Spaces

There are different categories of land uses and functional spaces, and it is very difficult to select representative samples for them from VHR imagery, especially for functional spaces which are composed of multiple land uses and have significant heterogeneity. Accordingly, this section aims to define category systems and present a hierarchical sampling method for both patches.

According to the code of urban land-use classification and planning (namely the standard hereafter) which was published by the Ministry of Housing and Urban-rural Development of China, land uses can be sorted into 12 categories (see Table I), including three kinds of residential, commercial, industrial, institutional, transport, park, unused, water, farmland, forest, and grass. According to the standard and previous studies [14], these land uses can be aggregated

TABLE I

CATEGORY SYSTEM ILLUSTRATING CORRELATIONS BETWEEN LAND USES AND FUNCTIONAL SPACES

Land uses	*Abbre.*	Descriptions	**Functional spaces**	*Abbre.*	Descriptions
Level 1-residential	*L1r*	Villa zones with loose building layout and high greening rates	**Living**	*L*	Land for people's residence, consumption, leisure and entertainment
Level 2-residential	*L2r*	Ordinary residential zones with basic infrastructures, regular layout			
Level 3-residential	*L3r*	Villages / shanty towns with old, low-rise buildings of high density, having a lot of ramps or dead ends and inadequate infrastructure			
Transport	*Tra*	Buses and subway stops, railways, and airport stations, streets, roads, and pipelines			
Industrial	*Ind*	Industrial, mining, and storage lands	**Productive**	*P*	Land for human production, commerce, public services and other productive activities
Forest & grass	*F&g*	Land covered with trees or grass	**Ecological**	*E*	Environments required for the survival and reproduction of species in a stable ecological system.
Water	*Wat*	Rivers, lakes, seas, reservoirs, and ponds			
Commercial	*Com*	Commercial offices, hotels, restaurants, shopping malls	**Living-productive**	*LP*	Land with both living and productive functions
Institutional	*Ins*	Public facilities, educational, and cultural areas			
Park	*Par*	Parks, zoos, and golf courses	**Living-ecological**	*LE*	Land with both living and ecological functions
Farmland	*Far*	Land used for cropping and farming, including farmland, paddy fields, irrigated land, orchard	**Productive-ecological**	*PE*	Land with both productive and ecological functions
Unused	*Unu*	Unused lands mainly containing bare soil	**No function**	*NF*	Land without function

into seven kinds of functional spaces, i.e., living, productive, ecological, living-productive, living-ecological, productive-ecological, and no function, where residential and transport are aggregated into living, industrial into productive, water, and forest and grass into ecological, commercial, and institutional into living-productive, park into living-ecological, farmland into productive-ecological, and unused into no function (see Table I). This is the first category system that associates land-use with functional-space categories and is the conceptual base of the study.

Based on the category system above, we can manually select and label samples for land uses and functional spaces. However, functional spaces are highly heterogeneous and abstract, and it is hard to collect their samples through visual interpretation. Accordingly, a hierarchical sampling method is proposed to generate functional-space samples based on land-use samples. The hierarchical sampling method is shown in Fig. 3.

First, a study area is segmented into patches with 1536 × 1536 pixels, and we label about 1/10 patches as samples, which should cover urban, suburban, and rural areas in a balanced way. Second, for each patch, two operators, i.e., Operator_1 and Operator_2, are invited to label land uses, and two sets of land-use samples, i.e., LU_1 and LU_2, can be generated. Third, based on the correlations between land uses and functional spaces (see Table I), LU_1 and LU_2 can be reclassified into seven functional-space categories, so that two sets of functional-space samples are obtained, i.e., FS_1 and FS_2. Fourth, LU_1 and FS_2 is associated and defined as a pair of samples, i.e., SP_1, and similarly another pair of samples, i.e., LU_2 and FS_1, is named as SP_2. For SP_1 or SP_2, its land-use and functional-space samples are generated independently, and using such pairs of samples can improve the consistency of land-use and functional-space mapping results. In detail, FS_2 is generated from LU_2, and can have few differences from LU_1, which can be used to calculate the correlation loss (see Section II-B) and improve the mapping consistency.

As demonstrated above, the correlations between land uses and functional spaces are defined in the category system, and it is employed to generate functional-space samples from land-use samples.

B. Synergistic Classification of Multilevel Land Patches (SC-MLPs)

1) Framework of SC-MLP: As demonstrated in Section I, land uses and functional spaces have strong heterogeneity inside and ambiguity on the boundary, especially since a functional space can cover a large area and contain diverse geographies; thus, it is considerably difficult to extract land uses and functional spaces from VHR images. Accordingly, the section aims to propose a novel classification method, namely SC-MLP (see Fig. 4). It uses a deep semantic segmentation approach to resolve heterogeneity and ambiguity of land uses and functional spaces, and employs a multitask learning framework to measure the correlations between land uses and

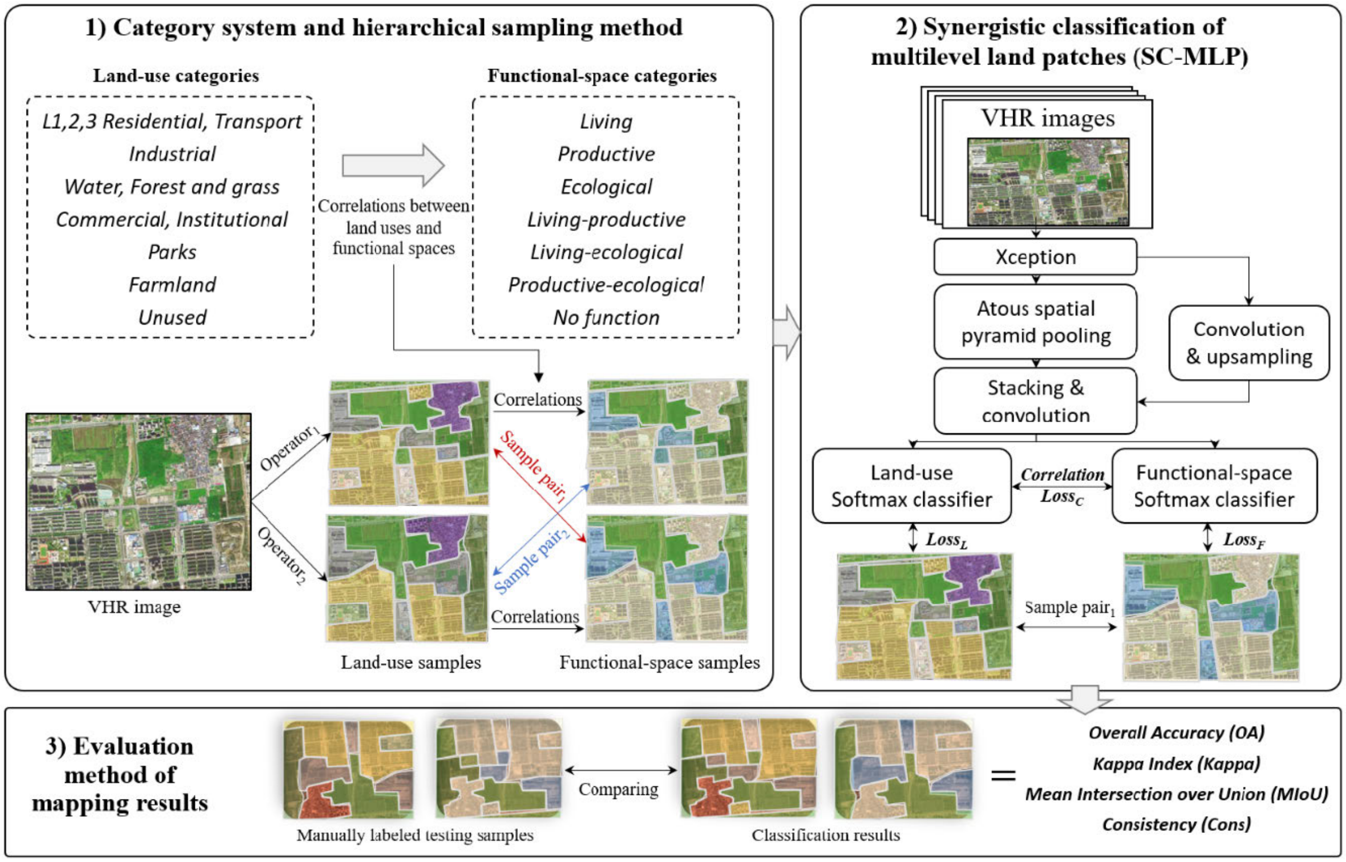

Fig. 3. Methodological framework including: 1) category system and hierarchical sampling method, 2) synergistic classification of multilevel land patches, and 3) evaluation method.

functional spaces, which is expected to reduce conflicts and improve their classification results.

As presented in Fig. 4, the SC-MLP consists of three parts: feature encoder, decoder, and synergistic classification, in which land-use and functional-space classifications share the same feature encoder and decoder that extract robust and common features for improving both accuracy and consistency of classification results. First, the feature encoder consists of an Xception [44] and an atrous spatial pyramid pooling (ASPP) [36], whose parameters are validated in our previous study [45] and presented in Fig. 4. The Xception contains a smaller number of parameters and has a better feature representation and generalization, compared to other backbones, and the ASPP has a larger receptive field and can extract multiscale features; thus, the feature encoder composed of Xception and ASPP can generate high-dimension feature maps which can be adaptive, robust, and representative, and are capable of resolving the heterogeneity of land-use and functional-space patches. Second, the decoder combines features generated from Xception and ASPP and up-samples them to restore patch sizes. Third, the synergistic classification is essentially a multitask learning method. It has two Softmax classifiers and three loss functions including the loss function of land-use classification (Loss_L), the loss function of functional-space classification (Loss_F), and the correlation loss function measuring the conflicts between land-use and functional-space classification results (Loss_C). These three loss functions can link land-use classification to functional-space one, where land-use classification results can bridge the gap from VHR images to functional spaces and reduce the strong heterogeneity inside functional spaces, while functional-space classification results serve as local contexts to resolve the heterogeneity and ambiguity of land uses; thus, these loss functions can improve both patches' classification results.

2) Three Loss Functions in SC-MLP: As illustrated in the last section, SC-MLP has three loss functions that are critical to improve land-use and functional-space classification results, and are keys to the model.

For Loss_L, it is defined by a cross-entropy loss. Each pixel's land-use classification result can be encoded as a possibility vector $\boldsymbol{L} = \{L_1, L_2, \ldots, L_{12}\}$, where $L_i (1 \le i \le 12)$ refers to the possibility that the pixel belongs to ith land-use category, and the corresponding ground truth in the training sample is encoded as a one-hot vector $\hat{L} = \hat{L}_i | 1 \le i \le 12\}$ with the labeled category set as 1 and others set as 0; thus, Loss_L can be calculated by $\text{Loss}_L = -\sum_{i=1}^{12} \hat{L}_i \log L_i$. The Loss_L essentially measures the difference between land-use classification results to training samples, with which SC-MLP can generate land-use classification results consistent with land-use samples.

For Loss_F, it is also defined by a cross-entropy loss. Each pixel's functional-space classification result can be encoded as a possibility vector $\boldsymbol{F} = \{F_j | 1 \le j \le 7\}$, where F_j refers to the possibility that the pixel belongs to jth functional-space category, and the corresponding training sample is encoded

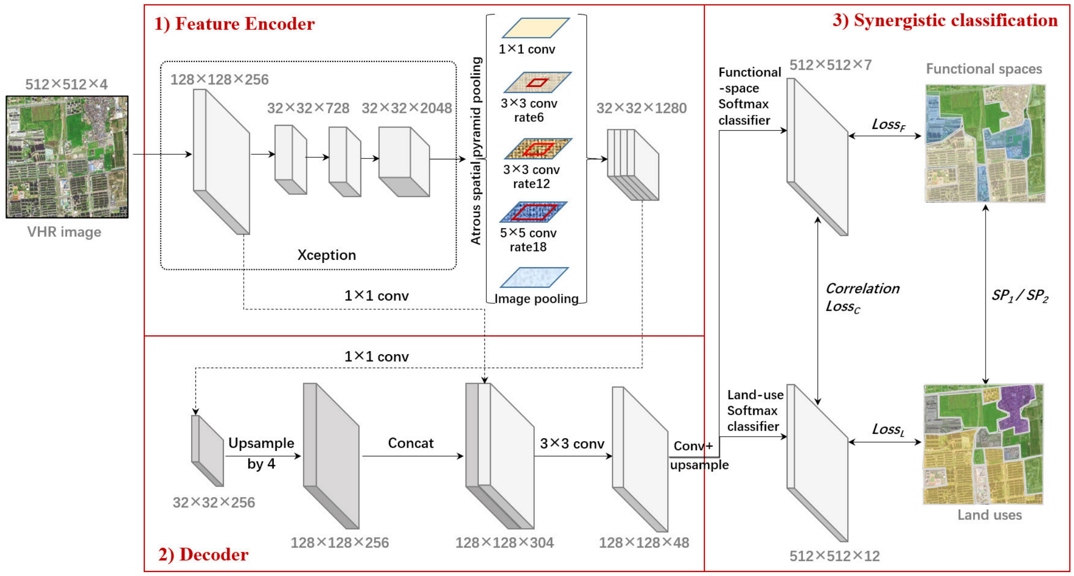

Fig. 4. Framework of synergistic classification of multilevel land patches (SC-MLPs), where land-use and functional-space classifications share the same feature encoder and decoder, and are controlled by three loss functions, i.e., Loss_L, Loss_F, and Loss_C.

as a one-hot vector $\hat{F} = \hat{F}_j|1 \leq j \leq 12\}$, thus Loss_F can be calculated by $\text{Loss}_F = -\sum_{j=1}^{7} \hat{F}_j \log F_j$. Similar to the Loss_L, the Loss_F measures the inconsistency between functional-space classification results and ground truths in training samples; using Loss_F can guarantee functional-space classification results in line with functional-space samples.

For Loss_C, it is the most significant innovation of SC-MLP and is measured by a weighted cross-entropy loss. First, the possibility vector in land-use classification results $\boldsymbol{L}$ can be transformed into a possibility vector of functional spaces $\boldsymbol{F'}$ according to the correlations between land uses and functional spaces (see Table I), which is demonstrated as follows:

$$F'_L = L_{L1r} + L_{L2r} + L_{L3r} + L_{\text{Tra}} \tag{1}$$
$$F'_P = L_{\text{Ind}} \tag{2}$$
$$F'_E = L_{F\&g} + L_{\text{Wat}} \tag{3}$$
$$F'_{\text{LP}} = L_{\text{Com}} + L_{\text{Int}} \tag{4}$$
$$F'_{\text{LE}} = L_{\text{Par}} \tag{5}$$
$$F'_{\text{PE}} = L_{\text{Far}} \tag{6}$$
$$F'_{\text{NF}} = L_{\text{Unu}} \tag{7}$$

where abbreviations are illustrated in Table I. Then, a weight matrix $\boldsymbol{W}$ (see Table II) is proposed to measure semantic similarities among functional-space categories. Finally, Loss_C can be calculated by $\text{Loss}_C = -\sum_{i=1}^{7}\sum_{j=i}^{7} F_i \times \log F'_j \times (1 - W_{ij})$. There can be two contributions to employing Loss_C in SC-MLP for identifying land uses and functional spaces. On the one hand, Loss_C measures conflicts between land uses and functional spaces not only by cross-entropy loss but also by considering their semantic similarities which are modeled by the weight matrix $\boldsymbol{W}$; on the other hand, Loss_C associates classification results of the two levels of patches and makes their categories and boundaries consistent. The three losses are finally integrated by a weighted average function $\text{Loss} = V_L \times \text{Loss}_L + V_F \times \text{Loss}_F + V_C \times \text{Loss}_C$, where V_L, V_F, V_C are weights of three losses, $V_L, V_F, V_C > 0$ and $V_L + V_F + V_C = 1$.

These three loss functions play different roles in land patch classification. Loss_L and Loss_F are used to recognize land uses and functional spaces, respectively; Loss_c align the two-level classification results.

3) Applying SC-MLP to Land-Use and Functional-Space Mapping: This section illustrates the implementation of SC-MLP to land-use and functional-space mapping, including SC-MLP training, hyperparameter setting, and classification.

For training SC-MLP, VHR images, and hierarchical samples (see Section II-A) are first overlapped, where VHR images are put at the top, land-use samples in the middle, and functional-zone samples at the bottom. The overlapped layers are further clipped into image patches with 512 × 512 pixels, and the image patches with sample layers are fed into the SC-MLP and processed through a feature encoder, decoder, and synergistic classification. As a result, the possibility that a pixel belongs to different land uses and functional spaces can be calculated, i.e., $\boldsymbol{L}$ and $\boldsymbol{F}$, which are compared to the ground truth of training samples, i.e., SP_1 or SP_2, and used to calculate three losses, i.e., Loss_L, Loss_F, and Loss_C. Finally, the parameters in SC-MLP can be updated by Adam based on the three losses. This process is iterated until all three losses converge.

The hyperparameters in the process are documented as follows. For Xception, it contains three flows, i.e., entry, middle, and exit flows, whose output size is set as 32 × 32 with a dimension of 2048. For ASPP, it contains four dilated convolutions with different convolution kernels (1 × 1, 3 × 3, 3 × 3, 5 × 5) and dilated rates (1, 6, 12, 18); thus, it can extract features with different vision fields and at different scales. For Adam, its learning rate is set as 0.0002 for training. For SC-MLP, it is trained for 50 000 iterations. For loss calculation, the weights of the three losses are set as: $V_L = 0.3$, $V_F = 0.3$, and $V_C = 0.4$, respectively, which will be verified in Section III-E.

TABLE II
WEIGHT MATRIX $\boldsymbol{W}$ MEASURING SEMANTIC SIMILARITIES AMONG FUNCTIONAL-SPACE CATEGORIES

Functional-spaces	L	P	E	LP	LE	PE	NF
L	100%	0%	0%	50%	50%	0%	0%
P	0%	100%	0%	50%	0%	50%	0%
E	0%	0%	100%	0%	50%	50%	0%
LP	50%	50%	0%	100%	25%	25%	0%
LE	50%	0%	50%	25%	100%	25%	0%
PE	0%	50%	50%	25%	25%	100%	0%
NF	0%	0%	0%	0%	0%	0%	100%

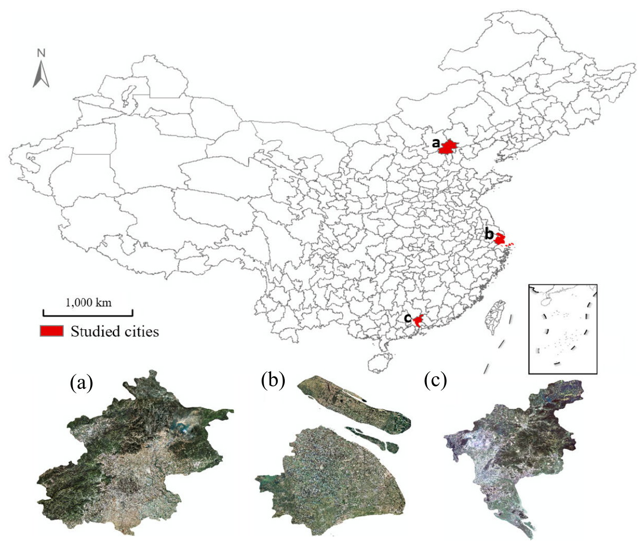

Fig. 5. Three studied cities for verifying the effectiveness of the proposed method, including (a) Beijing, (b) Shanghai, and (c) Guangzhou (GF-1 images in band combination 3/2/1, true color).

The hyperparameters are tuned based on approximately 80 000 validation samples in our previous study [46].

For classification, VHR images without sample are fed into the trained SC-MLP, and output possibility vectors of $\boldsymbol{L}$ and $\boldsymbol{F}$. Land-use classification result $\mathrm{LU} = \arg\max_{1\leq i\leq 12}(L_i)$ and functional-space result $\mathrm{FS} = \arg\max_{1\leq j\leq 7}(F_j)$ are assigned to each pixel. Consequently, land-use and functional-space mapping results can be generated.

C. Evaluation Method of Mapping Results

Four indicators are considered to evaluate land-use and functional-space classification results and validate the effectiveness of our method, including overall accuracy (OA), Kappa index (Kappa), mean intersection over union (MIoU), and consistency between land-use and functional-space classification results (Cons).

Using the hierarchical sampling method presented in Section II-A, N patches covering 1536×1536 pixels are manually labeled, and thus $9 \times 2 \times N = 18N$ pairs of samples can be generated, as each patch is clipped into nine samples with 512×512 pixels and is labeled twice by two operators, where a pair of samples contains both land-use and functional-space samples at the same location. We use $12N$ pairs of samples to train the SC-MLP and employ other $6N$ as test ones to measure the four indicators above and evaluate the mapping results.

The former three indicators, i.e., OA, Kappa, and MIoU, have been widely used in evaluating patch classification results. OA refers to the ratio of accurately classified pixels n_{accurate} to the total number of pixels of test samples n_{total}, and $\mathrm{OA} = (n_{\text{accurate}}/n_{\text{total}})$. Kappa can be calculated by $\mathrm{Kappa} = (\mathrm{OA} - \mathrm{OP})/(1 - \mathrm{OP})$, where $\mathrm{OP} = \sum_{i=1}^{K}((n_i^P \times n_i^S)/n_{\text{total}}^2)$, K is the number of considered categories, n_i^P denotes the number of pixels belonging to the ith category in classification results, and n_i^S is that in samples. MIoU calculates the mean ratio of intersection to the union of all categories, and $\mathrm{MIoU} = \sum_{i=1}^{K}(P_i \cap S_i/P_i \cup S_i)$, where P_i refers to the ith category classification results and S_i the ith category samples. The last indicator Cons is similar to MIoU, but it measures results' consistency between land-use and functional-space results, and it is calculated by $\mathrm{Cons} = \sum_{j=1}^{7}(P_j^F \cap P_j^{L2F}/P_j^F \cup P_j^{L2F})$, where P_j^F denotes the jth category of functional-space classification results, the L2F means the functional-space results transformed from land-use classification results by considering their correlations in Table I, and P_j^{L2F} is the probability of jth category of L2F.

OA measures overall classification results. Kappa and MIoU consider the classification result of each category from quantity and form perspectives, respectively. Cons are first proposed in the study and measure the consistency between land-use and functional-space classification results; the Cons are important for land system studies and planning, as inconsistent land-use and functional-space results will bring uncertainty and confusion to land system study and planning. Accordingly, the four indicators assess the classification results from different aspects and can make a comprehensive evaluation.

III. EXPERIMENTAL RESULTS AND ANALYSIS

A. Study Area and Used Data

This study selects three metropolises in China, including Beijing, Shanghai, and Guangzhou (see Fig. 5), as representative cases to verify the effectiveness of our method. There can be three reasons for choosing them. First, these big cities cover large areas (Beijing covers 16 410 km^2, Shanghai 6340 km^2, and Guangzhou 7434 km^2) and have much more complex landscape patterns and more diversity in land patches than small cities. Second, these cities are located in different

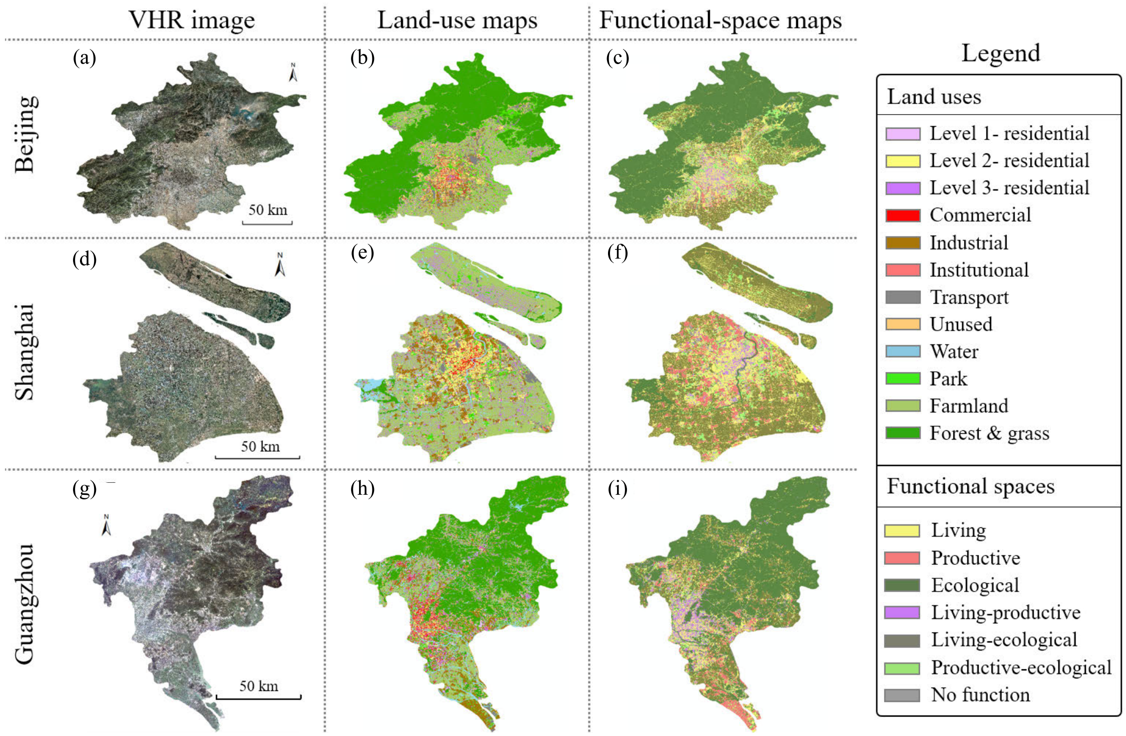

Fig. 6. Land-use and functional-space mapping results of the three cities by using SC-MLP. (a), (d), and (g) are VHR images of the three cities; (b), (e), and (h) are land-use mapping results; and (c), (f), and (i) are functional-space mapping results.

regions, i.e., Beijing in North China (around 40°N), Shanghai in the Middle East (around 31°N), and Guangzhou in South (around 23°N), and thus they can have distinct landforms, climates, and environments. Third, these cities have different development histories, cultures, and main functions, and thus have variant landscapes, forms, and plans. Accordingly, it is challenging for our method to accurately map the land uses and functional spaces in these cities.

GF-1 satellite images covering the three cities are used, which were acquired in September 2015. Basically, the multispectral bands are merged with the panchromatic band to produce the pan-sharpened image [47] which has a very high resolution of 2 m and four bands (i.e., blue, green, red, and near-infrared). Furthermore, the images have been ortho-rectified to provide accurate image features for identifying land uses and functional spaces.

B. Land-Use and Functional-Space Mapping Results

Using the proposed hierarchical sampling method and SC-MLP, we produce land-use and functional-space maps for the three cities (see Fig. 6). In general, Fig. 6 clearly presents the spatial distributions of different land uses and functional spaces, and the mapping results have specialists compared to existing maps.

On the one hand, compared to existing high-resolution land-use maps, e.g., EULUC-China [48] which is generated based on Sentinel-2A/B with a 10 m resolution and based on street blocks restricted by regular shapes, our land-use results have a higher resolution of 2 m and can represent land uses with irregular shapes. On the other hand, compared to existing functional-space datasets, e.g., PLEL [49] with rough units of administrative districts and solely three categories, i.e., production, living, and ecological, our functional-space results have a much finer spatial resolution and consider seven functional categories. Accordingly, the mapping results are unique and contribute to fine-scale land surveys and plans, and the results can be freely available at https://geoscape.pku.edu.cn/.

Furthermore, nine representative regions in the three cities are selected to show the mapping results in detail (see Fig. 7). For Beijing, the first region is in the downtown and includes the Beijing North Railway Station [see Fig. 7(a)], the Beihai Park [see Fig. 7(b)], the Imperial Palace [see Fig. 7(c)], hutongs [see Fig. 7(d)], and the Beijing Railway Station [see Fig. 7(e)]; the second region is located in the northwest Beijing and contains the Summer Palace [see Fig. 7(f)], the Yuanmingyuan Park [see Fig. 7(g)], a campus [see Fig. 7(h)], the ZOL commercial zone [see Fig. 7(i)], and the Tsinghua University [see Fig. 7(j)]; the third region is located in the southeast Beijing and includes Beijing-Benz factory [see Fig. 7(k)] and Yizhuang commercial district [see Fig. 7(l)]. For Shanghai, the fourth region is located in the downtown and covers The Bund Commercial District [see Fig. 7(m)], the Lujiazui Commercial District [see Fig. 7(n)], Century Park [see Fig. 7(o)], and villas [see Fig. 7(p)]; the fifth region is located in the north Shanghai and covers golf course [see Fig. 7(q)], an airport [see Fig. 7(r)], the Baoshan Steel Industrial Zone [see Fig. 7(s)]; the sixth region is in the east Shanghai and contains a wildlife park [see Fig. 7(t)] and the Pentagon World Trade Plaza [see Fig. 7(u)]. For Guangzhou, the seventh region is in the downtown and includes the Tianhe Sports Center [see Fig. 7(w)] and two

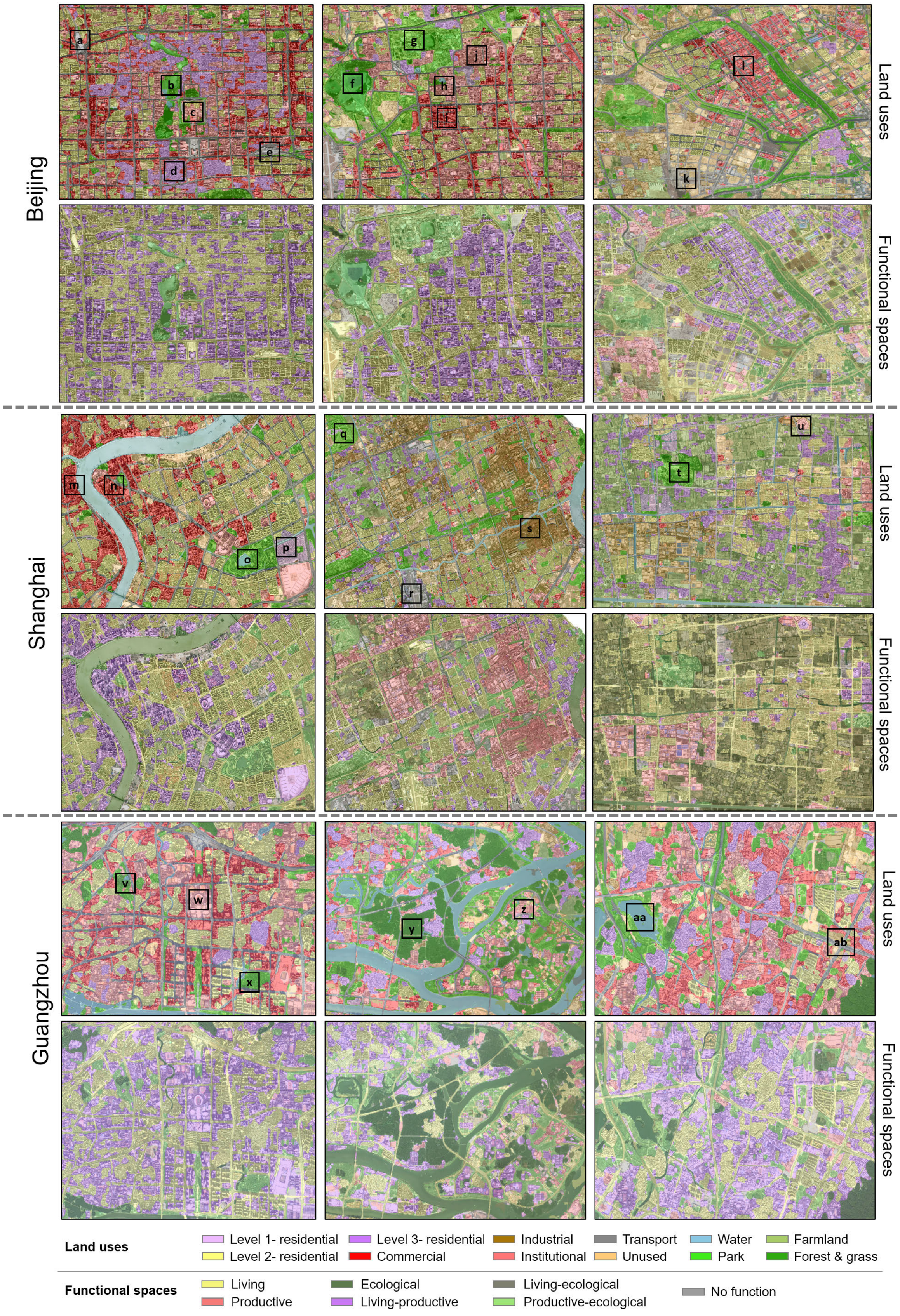

Fig. 7. Land-use and functional-space mapping results of representative areas in three cities, where classification results are 60% transparent and overlapped with VHR images. (a)–(l) are located in Beijing, (m)–(u) in Shanghai, and (v)–(ab) in Guangzhou.

TABLE III
COMPARISON BETWEEN SYNERGISTIC (SYC) AND SEPARATED (SEC) CLASSIFICATION RESULTS

Cities	Method	Results	*OA*↑	*Kappa*↑	*MIoU*↑	*Cons*↑
Beijing	SyC using $Loss_c$	Land-use	**90.3%±0.1%**	**0.82±0.002**	**0.64±0.005**	**0.74**
		Functional-space	**95.6%±0.3%**	**0.88±0.007**	**0.59±0.030**	
	SeC without $Loss_c$	Land-use	89.5%±0.4%	0.81±0.008	0.61±0.015	0.51
		Functional-space	90.2%±0.5%	0.81±0.014	0.58±0.041	
Shanghai	SyC using $Loss_c$	Land-use	**91.8%±0.1%**	**0.83±0.006**	**0.579±0.026**	**0.72**
		Functional-space	**94.0%±0.2%**	**0.87±0.011**	**0.62±0.021**	
	SeC without $Loss_c$	Land-use	91.6%±0.1%	0.82±0.017	0.577±0.037	0.59
		Functional-space	91.2%±0.3%	0.85±0.016	0.58±0.030	
Guangzhou	SyC using $Loss_c$	Land-use	**88.3%±0.1%**	**0.80±0.013**	**0.58±0.013**	**0.69**
		Functional-space	**91.7%±0.1%**	**0.84±0.014**	**0.60±0.025**	
	SeC without $Loss_c$	Land-use	87.6%±0.3%	0.79±0.021	0.56±0.021	0.48
		Functional-space	87.0%±0.3%	0.80±0.037	0.51±0.062	

parks [see Fig. 7(v) and (x)]; the eighth region is in southeast Guangzhou and covers the Sun Yat-sen University [see Fig. 7(y)] and a wetland park [see Fig. 7(z)]; the ninth region is in the northeast Guangzhou and contains a park [see Fig. 7(aa)] and an expressway [see Fig. 7(ab)]. All these scenes are accurately identified in the land-use and functional-space mapping results. For example, the hutongs in Fig. 7(d) are correctly recognized as level-3 residential land and living space in land-use and functional-space maps, respectively; and the Yumingyuan Park of Fig. 7(g) is identified as park and living-ecological in the two-level mapping results.

Here, we want to explain the reason why the SC-MLP can produce such accurate results. Taking the park in Fig. 7(t) as an example, it can be easily misrecognized as farmland according to its spectrum, texture, and location, but it is accurately identified by SC-MLP by considering its function, i.e., living-ecological. Furthermore, the productive space in Fig. 7(s) has an ambiguous boundary and is confused with surrounding living and living-productive spaces, but it is correctly identified by SC-MLP considering its land-use type, i.e., industrial. Accordingly, the synergistic classification strategy in SC-MLP can avoid many misclassifications and improve classification accuracy and consistency. Summarized above, the SC-MLP method can produce fine-grained, accurate, and consistent land-patch mapping results, which are different from existing land-use and functional-space datasets, and contribute to fine-scale and real-time land system studies and urban plans.

C. Comparison Between Synergistic and Separated Classifications

Aiming at verifying the effectiveness and advances of synergistic classification (SyC) by using SC-MLP, ablation experiments are performed by comparing SC-MLP's results to traditional separated classification (SeC) results. Specifically, the separated classification differs from SC-MLP in that SeC does not use the correlation loss, i.e., Loss_c, in Section II-B during training, so SeC classifies land uses and functional spaces independently and totally ignores their correlations while classification. Essentially, SeC represents a widely used mapping strategy of land-use and functional-space mapping, which is considered a benchmark to compare with the SyC proposed in the study.

Four indicators, i.e., OA, Kappa, MIoU, and Cons (see Section II-C), are measured by threefold cross-validation and employed to quantitatively assess the classification results. As presented in Table III, SyC which considers correlations between land uses and functional spaces outperforms SeC which ignores patch correlations. Generally, compared to SeC, SyC produces more accurate land-use and functional-space results with higher OA, Kappa, and MIoU, and SyC's results are more consistent, while land-use and functional-space results have higher Cons. This is attributed to the usage of Loss_c which measures correlations between two-level patches and improves their results. Using Loss_c can slightly improve land-use results, whose OA is increased by 0.5%, Kappa by 0.01, and MIoU by 0.02 on average. Using Loss_c can significantly improve functional-space results, with their OA increased by 9.5%, Kappa by 0.05 on average, and MIoU by 0.05. Most importantly, considering Loss_c can greatly improve the consistency between two-level patches' results with their Cons increased by 0.19 (improved by 36%), contributing to multilevel land surveys and plans that require high consistency between land uses and functional spaces.

Apart from the quantitative evaluation, we also compare SyC and SeC results by visual interpretation. For land-use classification results, a campus [see Fig. 8(a)], a commercial [see Fig. 8(b)], level-3 and level-2 residential [see Fig. 8(c) and (d)], and an unused [see Fig. 8(e)] lands in Beijing are broken in SeC results but are completely extracted in SyC results. In Shanghai, a level-2 residential district [see Fig. 8(f)] is wrongly identified as level-1, and an industrial zone [see Fig. 8(g)] is misclassified into institutional in SeC results; in Guangzhou, level-3 residential [see Fig. 8(h)] and transport lands [see Fig. 8(i)] are misclassified into commercial zones in SeC results; however, they accurately classified in SyC results. For functional-space classification results, a living [see Fig. 8(j)] and a living-productive [see Fig. 8(k)] spaces in Beijing are misidentified as no function and productive spaces in SeC results, but they are correctly identified in SyC results. In Shanghai, two living spaces [see Fig. 8(l) and (m)] are wrongly classified into living-ecological and living-productive

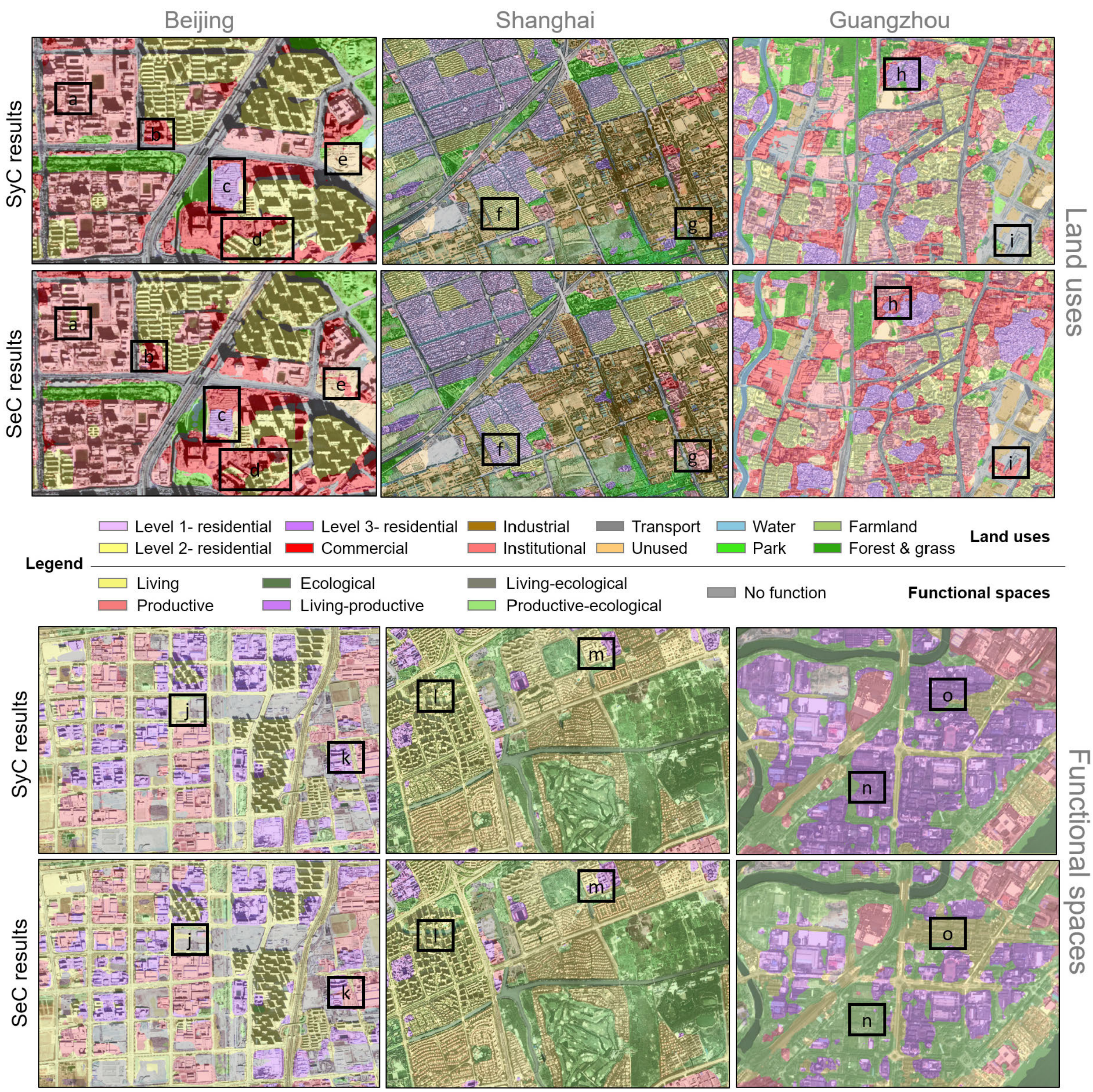

Fig. 8. Comparisons between synergistic classification (SyC) and separated classification (SeC) results for land uses and functional spaces in six representative scenes, where classification results are 60% transparent and overlapped with VHR images.

spaces; in Guangzhou, two living-productive spaces [see Fig. 8(n) and (o)] are misclassified as living-ecological and living spaces; their SyC results, however, are accurate. Accordingly, the SyC classification results outperform SeC for two-level patches in the three cities.

Furthermore, we want to compare the two strategies from the principle perspective. Taking the level-3 residential area in Fig. 8(c) as an example, it can be recognized as residential or commercial lands according to its visual clues, but it should be the former one considering its functional-space category, i.e., living space; thus, functional spaces can serve as local and semantic contexts to improve land-use classification results. In addition, Fig. 8(m) can be sorted into living or living-productive spaces considering its features and surroundings, but it should be a living space, as it is labeled as a residential area in the land-use results. It is evidence that SyC measuring the correlation between land uses and functional spaces can produce more accurate and consistent results than SeC.

D. Different Linking Rules Between Land Uses and Functional Spaces Applied to SC-MLP

As verified in the comparison experiment in the last section, the correlation between land uses and functional spaces measured by the $Loss_c$ is critical for extracting the two levels

TABLE IV
COMPARING TWO CORRELATION LOSSES (Loss_C VERSUS Loss'_C) APPLIED TO SC-MLP

Cities	Method	Results	*OA*↑	*Kappa*↑	*MIoU*↑	*Cons*↑
Beijing	SyC using $Loss_c$	Land-use	**90.3%±0.1%**	**0.82±0.002**	**0.64±0.005**	**0.74**
		Functional-space	**95.6%±0.3%**	**0.88±0.007**	**0.59±0.030**	
	SeC without $Loss_c$	Land-use	89.5%±0.4%	0.81±0.008	0.61±0.015	0.51
		Functional-space	90.2%±0.5%	0.81±0.014	0.58±0.041	
Shanghai	SyC using $Loss_c$	Land-use	**91.8%±0.1%**	**0.83±0.006**	**0.579±0.026**	**0.72**
		Functional-space	**94.0%±0.2%**	**0.87±0.011**	**0.62±0.021**	
	SeC without $Loss_c$	Land-use	91.6%±0.1%	0.82±0.017	0.577±0.037	0.59
		Functional-space	91.2%±0.3%	0.85±0.016	0.58±0.030	
Guangzhou	SyC using $Loss_c$	Land-use	**88.3%±0.1%**	**0.80±0.013**	**0.58±0.013**	**0.69**
		Functional-space	**91.7%±0.1%**	**0.84±0.014**	**0.60±0.025**	
	SeC without $Loss_c$	Land-use	87.6%±0.3%	0.79±0.021	0.56±0.021	0.48
		Functional-space	87.0%±0.3%	0.80±0.037	0.51±0.062	

TABLE V
COMPARING TWO CORRELATION LOSSES (Loss_C VESUS Loss'_C) APPLIED TO SC-MLP

Cities	Functional-space results	*OA*↑	*Kappa*↑	*MIoU*↑
Beijing	By using $Loss_c$ (soft link)	**95.6%±0.3%**	**0.88±0.007**	**0.59±0.030**
	By reclassification (hard link)	88.5%±0.3%	0.80±0.006	0.52±0.008
Shanghai	By using $Loss_c$ (soft link)	**94.0%±0.2%**	**0.87±0.011**	**0.62±0.021**
	By reclassification (hard link)	91.4%±0.1%	0.81±0.009	0.54±0.032
Guangzhou	By using $Loss_c$ (soft link)	**91.7%±0.1%**	**0.84±0.014**	**0.60±0.025**
	By reclassification (hard link)	85.5%±0.3%	0.77±0.026	0.49±0.018

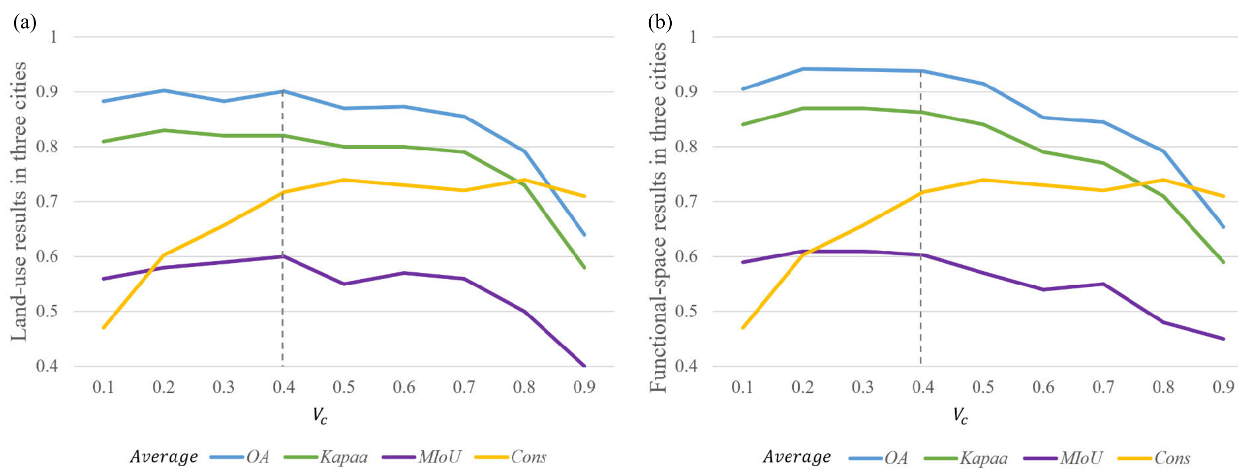

Fig. 9. Dynamic changes in (a) land-use and (b) functional-space results of the three cities with the increasing V_C, where four measures including OA, Kappa, MIoU, and Cons are considered.

of patches, but the Loss_c can have different measurements. Accordingly, this section analyzes the impact of using different Loss_c measurements and different linking rules on the land-use and functional-space classification results.

In Section II-B, the correlation Loss_c is measured by $\text{Loss}_C = -\sum_{i=1}^{7}\sum_{j=i}^{7} F_i \times \log F'_j \times (1 - W_{ij})$, which considers semantic similarities (i.e., W_{ij}) among functional-space categories. Differently, ignoring the semantic similarities, Loss_c can be calculated by an ordinary cross-entropy loss, i.e., $\text{Loss}'_C = -\sum_{i=1}^{7} F_i \times \log F'_i$. The two measurements, i.e., Loss_C and Loss'_C, are compared here, with respect to both land-use and functional-space classification results. As presented in Table IV, Loss_C produces more accurate results in most cases with higher and more stationary OA, Kappa, and MIoU, but Loss'_C generates more consistent results for two-level patches with higher Cons. Accordingly, Loss_C and Loss'_C satisfy different demands, as Loss_C is applied to accurate mapping but Loss'_C experts in synergistic multilevel-patch mapping and analysis.

Despite using correlation losses, we can link land-use results to functional spaces directly by reclassification using the correlations in Table I. That is, we can first generate land-use results by SeC in Section III-C, and then reclassify the land uses into functional spaces. Here, we compare the two linking rules, i.e., using Loss_C (soft link) versus direct reclassification (hard link). As shown in Table V, using Loss_C outperforms reclassification in extracting functional spaces, because reclassification results of functional spaces are totally dependent on the land-use results which, however, have some errors and can further influence functional-space results. On the contrary, SC-MLP links land uses to functional spaces using Loss_C, which can reduce the interferences of mutual misclassifications and improve both land-use and functional space results simultaneously. In a word, the reclassification is a hard connection between land uses and functional spaces, and errors will be directly transferred; while using Loss_C is a soft connection that can reduce error transmission.

In summary, this section compares different linking rules and strategies in synergistic land-use and functional-space classifications. Generally, using correlation losses is better than direct reclassification, but selecting Loss_C or Loss'_C depends on the demand. Loss_C will be used if accurate mapping results are required, but Loss'_C will be employed while performing a synergistic land analysis and planning, e.g., a territory development plan. Furthermore, the correlation losses and linking strategies are still open, which can be purposefully designed for other mapping tasks.

E. Impacts of Loss Weights on SC-MLP Results

As illustrated in Section II-B, three losses, i.e., Loss_L, Loss_F, and Loss_C, have three weights, i.e., V_L, V_F, and V_C, in measuring the integrated loss. However, these weights have different impacts on SC-MLP results, which will be analyzed in the section.

It is assumed that land-use and functional-space classifications are considered equally important and should have the same weights, that is, $V_L = V_F = (1/2)(1-V_C)$. Accordingly, a set of isometric progressive V_C, i.e., $V_C = 0.1, 0.2, 0.3, \ldots, 0.9$, are considered to analyze the weights' impacts on SC-MLP results. As presented in Fig. 9, with increasing V_C, OA, Kappa, and MIoU of SC-MLP's land-use and functional-space results first ascend when $V_C < 0.2$, and then drop down when $V_C > 0.4$, because when V_C becomes larger, the training samples of land uses and functional spaces will play a lesser role in the classification; while, Cons generally go up but level off after $V_C = 0.4$, because increasing V_C makes patch classification results more consistent, but it is difficult to further improve the consistency due to the decreases in classification accuracies. Overall, $V_C = 0.4$ and $V_L = V_F = 0.3$ produces both accurate and consistent results for land uses and functional spaces, and thus they are employed in the experiments.

In this case, V_C is larger than V_L and V_F, indicating that the proposed correlation Loss_C are more important than traditional loss functions, i.e., Loss_L and Loss_F. Accordingly, correlations should be considered in multilevel land patch classifications.

F. Spatial Patterns of Land Uses and Functional Spaces

The generated land-use and functional-space classification results in Section III-C can be applied to spatial landscape pattern analysis in different cities.

Generally, the two-level patches in Beijing are totally distributed in a radial pattern, those in Shanghai are distributed along the river, while those in Guangzhou are distributed along the mountain. For land uses, the three cities have similar patterns of land-use distributions in urban areas [see Fig. 10(e)–(g)], where urban areas are segmented by global urban boundaries (GUBs) [50]: commercial, institutional, and level-2 residential lands are mostly located in downtown areas; industrial lands are usually distributed in suburban areas; parks, level-1, and level-3 residential lands are scattered across cities. However, these cities have different land-use patterns in suburbs (see Fig. 6), as suburbs in Shanghai are mainly covered by farmland, those in Guangzhou are forest, and those in Beijing are mixed by farmland and forest. For functional spaces, the productive and living-related spaces in the three cities have similar spatial patterns, but ecological and productive-ecological spaces have significant differences in these cities [see Fig. 10(h)–(j)], as Guangzhou has a large area of ecological spaces, but Shanghai has large productive-ecological areas in suburbs.

The proportions of diverse land uses and functional spaces are calculated to quantitatively measure landscape patterns in these cities (see Fig. 10). For land uses, Beijing and Guangzhou have similar proportions of land uses from the whole city perspective [see Fig. 10(a)], but Shanghai has a different land-use pattern with a larger proportion of farmland (45.4%). Their differences will stand out [see Fig. 10(b)] solely considering urban areas which are extracted by GUB data, where Beijing has larger proportions of transport (16.6%), parks (13.1%), and unused lands (10.4%) compared to other cities, Guangzhou has larger proportions of forest (10.9%) and commercial land (5.9%), while Shanghai has larger proportions of industrial (17.5%) and level-2 residential lands (13.9%). For functional spaces, Beijing and Guangzhou have similar functional-space patterns from the whole city perspective [see Fig. 10(c)]. Differently, Shanghai has a lager productive-ecological space which accounts for almost half the administrative area, and Shanghai's living space accounts for 1/4 of the city. From the urban area point of view [see Fig. 10(d)], Shanghai has the largest productive related spaces; Guangzhou has the largest proportion of ecological space (17.4%), 8.4 and 5.2 times those in Beijing and Shanghai; Beijing has a larger proportion of living space (42.9%).

Accordingly, the generated land-use and functional-space results are applied to landscape pattern analysis and potentially contribute to land system research.

IV. Discussions

A. Pros and Cons of SC-MLP

As demonstrated in Section I, there have been plenty of land-use classification methods emerging in the past ten years [23], [27], [28], [34] but a few functional-space classifications have just emerged in recent years [42], [51], [52]. All these methods separate land-use and functional-space classifications and do not consider their correlations, resulting in many errors and conflicts [14], [49], [53]. Differently, this study proposes an SC-MLP to link the two-level land patch mapping and

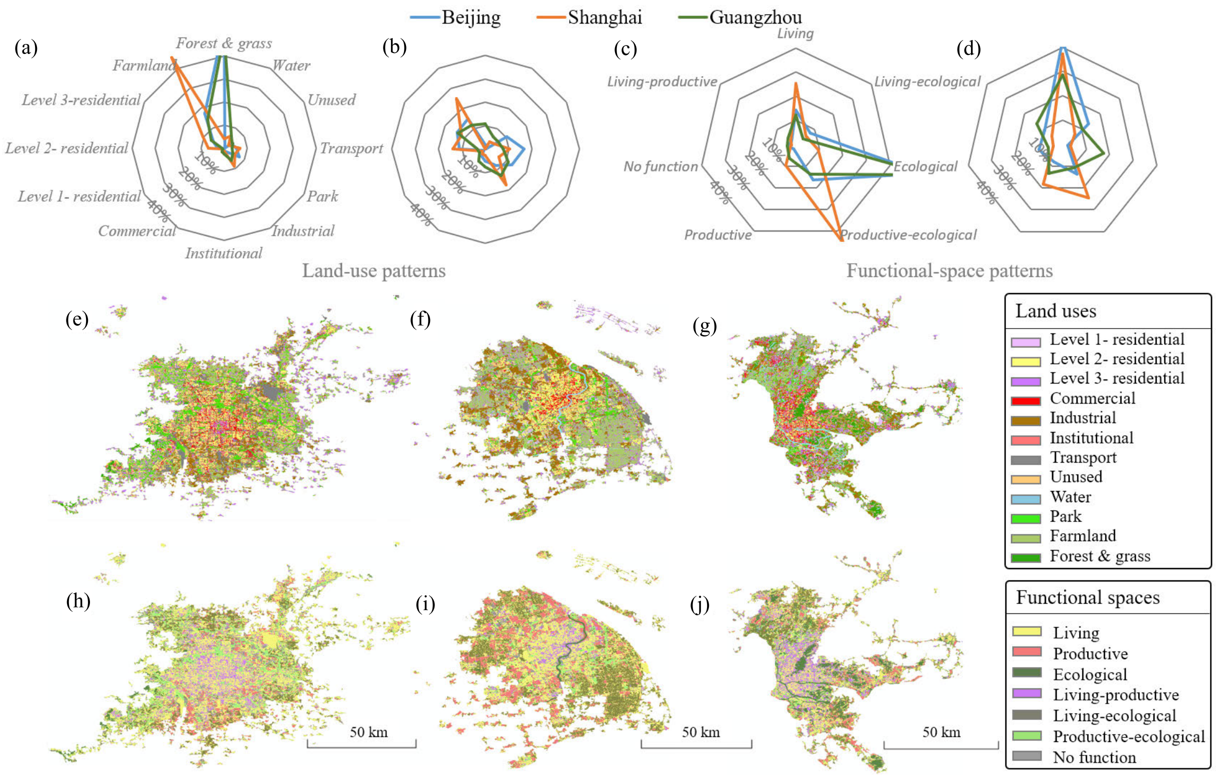

Fig. 10. Land-use and functional-space proportions in three cities: (a) land-use proportions of the three cities, (b) land-use proportions in the urban areas of these cities, where urban areas are delineated by global urban boundary (GUB) data, (c) functional-space proportions of these cities, and (d) functional-space proportions in these cities' urban areas. (e)–(j) represents spatial land-use and functional-space patterns in the urban areas.

identify them synergistically. The section aims to discuss the pros and cons of the proposed SC-MLP, compared to existing land patch mapping and analysis work.

SC-MLP generally has four advantages. First, it produces more accurate classification results for both land uses and functional spaces. Previous methods did not consider correlations between two land patches which led to inaccurate results, but SC-MLP considers land uses as basic components to reduce heterogeneity of functional spaces and improves functional-space classification results (see Fig. 2 and Table III), and furthermore SC-MLP employs functional-space categories as local contexts to improve land-use classification results (see Table III). Second, SC-MLP generates more consistent results for both patches. Previous methods perform land-use and functional-space classifications separately, whose results are independent and have substantial conflicts. Differently, SC-MLP characterizes land uses and functional spaces by a shared feature encoder and a shared decoder, also considers a correlation loss while training, and can classify land uses and functional spaces simultaneously; thus, SC-MLP results are much more consistent (see Section III-C). Third, SC-MLP can produce VHR land patch mapping results. Existing land-use and functional-space maps often have relatively rough resolutions, e.g., 10 m of EULUC-China and 30 m of GlobeLand30, which cannot support fine-grained land survey and analysis, while SC-MLP results have a high resolution of 2 m and is more suitable for land surveys at the fine scale. Fourth, SC-MLP has the potential to be a new paradigm of multilevel remote sensing image classification. SC-MLP can be applied to multilevel classification tasks, e.g., land cover and land use mapping, population and gross domestic product mapping, and so on, if their correlations can be measured and defined. In summary, SC-MLP can produce fine-grained, accurate, and consistent land patch maps, and thus contributes to a wide range of multilevel image classifications.

Apart from the excellent performance of SC-MLP, it also has three limitations. First, SC-MLP qualitatively recognizes seven functional-space categories but cannot quantify the main function of a patch. For example, SC-MLP can identify a park as a living-ecological space, but cannot distinguish which is its main function, living or ecological. Second, SC-MLP is verified to be applied to VHR satellite images (at meter-level resolution), as they can represent the internal textures and structures of land patches, but SC-MLP's adaptability to other resolutions of remote sensing imagery has not been discussed. Third, although the category system and correlation rules defined in SC-MLP are validated as effective in China, their adaptabilities to different countries need further verification [41].

B. Insights Into SC-MLP's Contributions to Land System Study and Overall Planning

Apart from the direct application to multilevel land patch mapping and spatial landscape pattern analysis, SC-MLP and its results have great potential for land system study [54], [55] and overall land planning [4], [56].

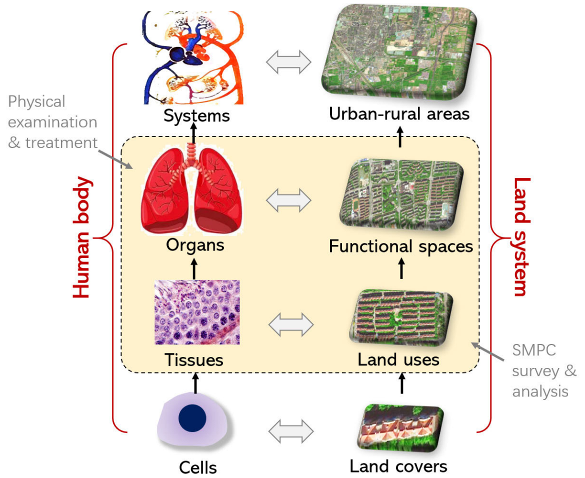

Fig. 11. Land system can be analogous to a human body. Physical examination and treatment mainly target tissues and organs, while synergistic multilevel patch classification targets land uses and functional spaces, as well as their correlations, and the two levels are the most important in land system studies.

First, as presented in Fig. 1, the land system can be generally composed of four levels, including: 1) land cover, 2) land use, 3) functional space, and 4) urban-rural area [57], [58], [59]. Land covers are indivisible and basic units of the land [60], and usually include buildings, impervious ground, trees, and soil; thus, they are analogous to human cells which are the basic components of the human body (see Fig. 11). Land uses, e.g., commercial, residential, and industrial lands, can consist of multiple land covers with variant features [61], [62], and they can be regarded as tissues which have certain structures. Functional spaces combine diverse land uses and refer to living, productive, and ecological spaces in the study, but more generally they refer to main functional zones in city planning and are analogous to organs with specific functions [63]. Urban-rural areas compose the whole city and can be regarded as body systems. In analogy to life science research, land system research should consider the component relations among these four levels to understand the compositions, structures, and functional services at different levels of land systems. Previous studies, however, separate the four levels, ignore their correlations, and cannot understand the whole land system [32], [64]. Although SC-MLP does not measure these four levels totally, it takes one step forward and connects the two middle levels of land use and functional space, whose results contributes to learning functional spaces' compositions and internal structures, as well as land uses' spatial distributions and functional contexts; thus, it plays an important role in land system studies.

Second, overall land planning, e.g., territorial spatial planning strategy in China, aims at the unity of main functional, land-use, and urban-rural planning [65]. The current status of functional spaces influences the division of main functional zones, which further constrains land-use planning and forms a new status of land uses and functional spaces [66]. Accordingly, overall land planning needs coordinating land uses and functional spaces [4]. However, existing land-use and functional-space mapping results have substantial errors and conflicts, and cannot satisfy overall land planning [62], [67]. SC-MLP produces not only accurate but also consistent results for both land uses and functional spaces, and can resolve their conflicts, significantly contributing to overall land planning. In summary, SC-MLP results can potentially contribute to land system study and overall land planning which will be the focus of our future study.

V. CONCLUSION

Previous studies ignored correlations between land uses and functional spaces, and extracted them separately, resulting in substantial errors and conflicts in both patches' classification results. To resolve this issue, the study proposed an SC-MLP method, which measures the two-level patches' correlations and produces not only accurate but also consistent mapping results. Accordingly, SC-MLP is a novel method for multilevel land patch classification and is totally different from existing separated classifications.

Compared to separated classification: 1) SC-MLP improves land patch classification accuracies, especially for functional spaces whose OA are improved by 9.5% in three case cities; 2) SC-MLP further improves the consistency between land-use and functional-space results with Cons, an indicator for measuring consistency, increased by 0.19 (improved by 36%), indicating that the conflicts between the two-level land patch mapping results are significantly reduced; and 3) SC-MLP generates accurate and consistent land patch maps for three major Chinese cities with a high resolution, high accuracies, and high consistencies, and the generated maps are applied to exploring the differences in spatial landscape pattern of cities (see Fig. 10).

In the future, we will further resolve the technical issues raised in Section IV-A and update the land patch dataset supporting multilevel land studies, plans, and policies.

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