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Facilitating urban climate forecasts in rapidly urbanizing regions with land-use change modeling

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A B S T R A C T

The local climate zone (LCZ) mapping scheme classifies urban lands into multiple types according to their climate-relevant surface properties, enabling forecasts of changes in urban climate. However, stationary LCZ maps are insufficient for forecasts in the rapidly urbanizing regions, where there are frequent transitions among multiple urban lands and thus changing surface properties. To facilitate climate forecasts with these changing properties, we propose a new methodological framework to predict future LCZ maps using the Cellular Automata (CA) land-cover/land-use change (LCLUC) model. Different from most existing LCLUC studies that treat the urban area as homogeneous, our work is the first attempt to simulate the complex conversions among low-, mid- and high-rise urban lands defined in LCZ. To validate our method, we apply it in the Pearl River Delta (PRD) metropolitan area, China, a rapidly urbanizing region with more than 50 million residents. First, we use the World Urban Database and Portal Tool (WUDAPT) method to generate LCZ maps of the PRD region in 2009 and 2014, with satellite images. Then, we apply the CA model on the 2009 LCZ map to forecast 2014 one based on the LCLUC rules discovered by the data mining technique. The comparison between the forecasted and observed 2014 LCZ maps yields a kappa coefficient of 0.77 and an overall accuracy of 82%. Our method achieves satisfactory accuracies on the high- (84%) and low-rise (82%) urban lands while performing relatively poorly on the mid-rise (40%) lands. Our results demonstrate that the combination of the LCZ scheme and LCLUC modeling has the potential of capturing the structural changes within cities and providing the necessary input datasets for urban climate forecasts.

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1. Introduction

The local climate zones (LCZ) mapping scheme classifies urban lands into multiple types according to their climate-relevant properties, including the heights, spacing, materials, and functions of buildings, infrastructures, and vegetations (Stewart and Oke, 2012). Since these properties lead to different surface energy and water balances, the spatial pattern of multi-type urban lands determines the spatial distributions of heat, circulation, and thus, local climates. Used to parameterize urban lands in meteorological models, the surface properties information provided by LCZ mapping can substantially improve the models' abilities to simulate local weathers and climates in cities (Alexander et al., 2016, 2015; Brousse et al., 2016; Emmanuel and Krüger, 2012; Hammerberg et al., 2018). The improved skills of simulation suggest that integrating LCZ mapping and meteorological modeling has the potential to more reliably downscale forecasts of global climate change caused by greenhouse gases (GHG) emission. The downscaled forecasts provide critical information on changing urban climates, enabling us to better prepare for the climate impacts in urban areas (Knowlton et al., 2007).

However, urban climates are affected by not only the global emission of GHG but also the regional process of urbanization (Kalnay and Cai, 2003; Sun et al., 2016). In the next three decades, warming from urbanization is projected to be half as strong as that from GHG emission globally (Huang et al., 2019). Most of the LCZ mapping and meteorological modeling studies referenced above focused on cities in developed countries, which have experienced relatively slower urbanization. Therefore, they neglected the climate effects of the changing spatial patterns of LCZs caused by urbanization. Using the rapidly urbanizing coastal South China as an example, a recent study demonstrated the usefulness of LCZ mapping in investigating the climate effects of urbanization (Tse et al., 2018). By applying the same boundary conditions on different LCZ maps in the 1990s, 2000s, and 2010s, the study found that changing LCZ patterns warmed the air temperature and simultaneously reduced wind speed, significantly increasing the heat stress on urban residents.

Given that LCZ mapping provides the necessary information for studies on climate impacts from GHG and urbanization effects, it has the potential to facilitate urban climate forecasts. Historically, urban areas have warmed more significantly than the global mean due to the combination of GHG and urbanization effects (Stone, 2012). This severer warming trend is likely to continue in the coming decades as the world's urban population will rapidly increase to 6–7 billion, about two-thirds of the global population. Applying LCZ mapping to facilitate urban climate forecasts is critical to prepare for the climate changes in urban areas, where the majority of the world's population will live. However, since the spatial patterns of LCZ change drastically with urbanization, as demonstrated by (Tse et al., 2018), forecasting future urban climate requires predictions of future LCZ maps, especially in rapidly urbanizing regions.

In order to facilitate urban climate forecasts, we propose a new methodological framework to predict future LCZ maps, by using land-cover/land-use change (LCLUC) model. Unlike most existing LCLUC modeling and LCLUC-induced climate change studies that treat the urban area as homogeneous (Argüeso et al., 2015; Chen and Frauenfeld, 2016; Chen et al., 2014; Li et al., 2014; Liu et al., 2019), our work is the first attempt to simulate the conversions among multiple types of urban lands defined in the LCZ mapping

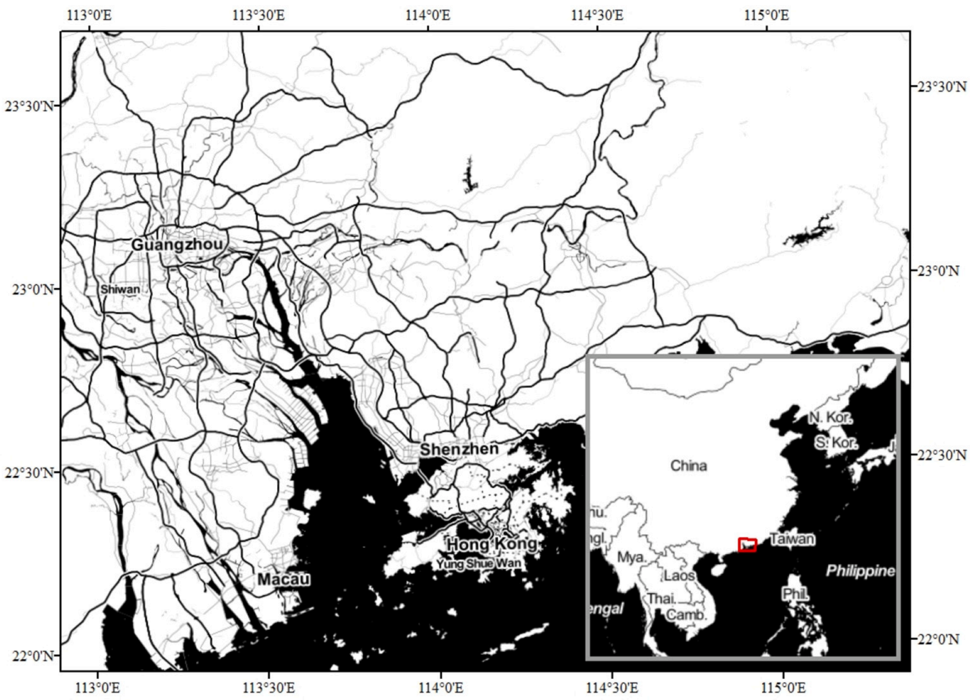

Fig. 1. Location of the Pearl River Delta region.

scheme. Despite the lack of LCLUC modeling studies, multi-type urban lands conversion has long been observed and theorized in urban studies by sociologists and economists (Alonso, 1964; Burgess, 1926). According to these theories, the spatial distributions of multi-type urban lands are determined by the bid rent curve, which is generated by the market competition for scarce land in a city. The urban land type that can afford the highest rent occupies the specific location. As the city grows, the bid rent curve shifts as demands increase, re-organizing locations of multi-type urban lands (Fujita, 1991). Being able to capture this re-organization process in the LCLUC model is the key to predicting LCZ maps and facilitating urban climates forecasts.

Here we apply the proposed methodology of integrating LCZ mapping and LCLUC modeling to simulate changes in the Pearl River Delta (PRD) metropolitan area in South China from 2009 to 2014. We generate the LCZ maps of PRD following the guidelines from the World Urban Database and Portal Tools (WUDAPT) (Bechtel et al., 2019). We simulate the changes in LCZ maps by using an LCLUC model: the Geographical Simulation and Optimization System – Future Land-use Simulation (GeoSOS-FLUS) model (Liu et al., 2017). The following sections will first provide more details on the study area and methods, and then present the results and discuss the implications.

2. Study area and data

The Pearl River Delta (PRD) metropolitan area, located in Guangdong Province of southern China, is among the fastest-growing urban areas in the world (Fig. 1). Ever since the establishment of the economic zone in 1978, this region has experienced double digits growth rates in both gross domestic production and urban population for decades. Recently, the RPD metropolitan area, with an urban population of over 50 million, overtook Tokyo to become the world's largest megacity (World Bank, 2015). The rapid growth of PRD is likely to continue in the future. The national and regional governments signed the framework agreement, in July 2017, to transform this region into the "Guangdong-Hong Kong-Macau Greater Bay Area," further emphasizing its significant role in China and worldwide (Bland, 2018). By applying the proposed method in PRD, we aim to exemplify its potentials in studying urban climates for other rapidly urbanizing regions.

The input data of local climate zones (LCZ) maps are developed using the World Urban Database and Portal Tools (WUDAPT) level 0 method (Bechtel et al., 2019). The LCZ scheme classifies land-cover/use into 17 categories, ten of which are built-up urban lands, and the rest are natural types. Since some meteorological models do not support the full 17 LCZ categories, we also remap them into the simplified LCZ (SLCZ) categories, which have three types of urban lands (Tse et al., 2018). The correspondences between LCZs and SLCZs are listed in Table 1. While the 10-type urban lands in LCZ include more nuances like pervious/impervious covers ratios, construction materials, and functions, the 3-type urban lands in SLCZ only reflect variations in density: low-rise, mid-rise, and high-rise. The results on both LCZ and SLCZ will be presented and discussed in the following sections.

To estimate the suitability for different land-uses, we include eight geographical factors (Appendix). Three factors related to physical geography—elevation, slope, and aspect—determine the difficulties of developing urban lands on a particular location. The remaining five factors related to economic geography—distances to city centers, town centers, railway stations, highways, and roads—determine whether a location is desirable for urban development.

3. Methods

The land-cover/land-use change (LULCC) model is used to simulate and to estimate future LCZ maps based on the historical pattern

Table 1
Correspondence between Local Climate Zone (LCZ) categories and the Simplified LCZ (SLCZ) categories and the accuracies achieved by the LCLUC model.

Local Climate Zone (LCZ) Categories			Simplified LCZ (SLCZ) Categories		
LCZ Code	Description	Accuracy	SLCZ Code	Description	Accuracy
LCZ 1	Compact High-rise	28%	SLCZ 1	Urban (High-rise)	84%
LCZ 4	Open High-rise	44%			
LCZ 2	Compact Mid-rise	21%	SLCZ 3	Urban (Mid-rise)	40%
LCZ 5	Open Mid-rise	21%			
LCZ 3	Compact Low-rise	55%	SLCZ 6	Urban (Low-rise)	82%
LCZ 6	Open Low-rise	24%			
LCZ 7	Lightweight Low-rise	29%			
LCZ 8	Large Low-rise	56%			
LCZ 9	Sparsely Built	12%			
LCZ 10	Heavy Industry	29%			
LCZ 101	Dense Trees	79%	SLCZ 11	Mixed Forest	22%
LCZ 102	Scattered Trees	30%			
LCZ 103	Bush, Scrub	46%	SLCZ 13	Shrubland	77%
LCZ 104	Low Plant	65%	SLCZ 14	Cropland/Grassland Mosaic	50%
LCZ 105	Bare Rock or Paved	29%	SLCZ 9	Barren or Sparsely Vegetated	70%
LCZ 106	Bare Soil or Sand	10%			
LCZ 107	Water bodies	–	SLCZ 17	Water bodies	–
Overall		70%			82%

and the interaction between multiple land-uses. In this study, we employ the Geographical Simulation and Optimization System (GeoSOS) – the Future Land-use Simulation (FLUS) model (Liu et al., 2017). This model is capable of discovering probabilities of land-uses to occur from historical LULCC states and combining these probabilities with neighborhood influences among land-uses, in order to predict plausible future land-uses interactions and changes. It has been successfully applied to simulating urban dynamics and expansion, and as well as predicting urban development and landscape changes in China (Chen et al., 2014; Liu et al., 2017). In these previous applications of GeoSOS-FLUS, there is only one type of urban land, to which other land-uses can be converted to. Our work is the first to apply GeoSOS-FLUS in simulating the complex conversions between multiple types of urban lands based on the LCZ framework.

Fig. 2 shows the flowchart of the LCLUC model. Firstly, a data mining technique, the Artificial Neural Network (ANN), is applied to discover the probability of occurrence of various land-uses from the current LCZ and SLCZ maps, according to geographical factors such as slopes, access to transportation and distances from city centers. Using samples from the current land-uses, ANN fits a non-linear function that maps multiple inputs—geographical factors—to multiple outputs—the occurrence probabilities of LCZ/SLCZ land-use types. Secondly, the trends of LULCC with socioeconomic developments are analyzed and extrapolated to predict future land-use demands. Finally, the Cellular Automata (CA) model is used to simulate land-uses conversions based on the probability of occurrence and neighborhood influences repeatedly, until land-uses demands are met. In the CA model, a pixel is more likely to be converted to land-use k, if the occurrence probability for k is higher and there are more grid cells of k in the 3 by 3 neighborhood. During each iteration of land-use conversions, an inertia mechanism increases the likelihood of converting to land-use k, if the current number of grid cells of k is lower than the demand; vice versa, this mechanism makes converting to k less likely, if the number of k already exceeds the demand. The future maps are then generated by the CA model.

In simulating the conversions among LCZs, the GeoSOS-FLUS has two important advantages over other widely used LCLUC models, such as SLEUTH, CLUE-S, and CLUMondo. First, unlike the SLEUTH model (Clarke et al., 1997; Votsis, 2017) which can only simulate the expansion of one types of urban land, GeoSOS-FLUS is capable of simulating the conversions among multiple types of land-use and thus can be applied to simulate multiple urban lands defined in the LCZ framework. Second, unlike the CLUE-S (Verburg et al., 2002) and CLUMondo (Ornetsmüller et al., 2016) models which estimate the occurrence probability separately for each land-use type, GeoSOS-FLUS uses ANN to analyze occurrences of multiple types simultaneously and thus can capture the competition among different land-uses. The comparative analysis in (Liu et al., 2017) demonstrated that GeoSOS-FLUS can achieve higher accuracy than CLUE-S in simulating the conversions of multiple land-uses, which only includes one type of urban land. Although both models have the potential to simulate multiple urban land-uses as defined in the LCZ framework, we choose GeoSOS-FLUS because it represents the state-of-the-art multi-type LCLUC modeling.

To assess the accuracy of the GeoSOS-FLUS model, we validated it on the LCZ and SLCZ maps of PRD in 2009 and 2014. In the validation process, the maps in 2009 are used as the current state to predict those in 2014, which is then compared with the observed ones in 2014. Since the land-use demands in 2014 are already known, we skipped the second step of demand trend analysis in the validation. Here, this paper focuses on examining whether LCLUC modeling is capable of forecasting the evolution of LCZ/SLCZ maps. To examine the capabilities of LCLUC modeling, we need to compare the "forecasted" maps in 2014 with the observed maps in the same period. Simulations beyond 2014 are not shown or analyzed here because they cannot indicate the reliability of the proposed methodology. After demonstrating the reliability, this methodology can be potentially used in forecasting future evolution of multi-type urban land-uses that can influence local urban climates.

4. Results

The land-cover/land-use change (LCLUC) model is able to simulate changes from 2009 to 2014 with higher accuracy on the 8-category simplified local climate zone (SLCZ) map than on the 17-category local climate zone (LCZ) map. The overall accuracy achieved on the SLCZ map is 82%, about 12% higher than that on the LCZ map (70%). This difference in accuracy is more prominent, however,

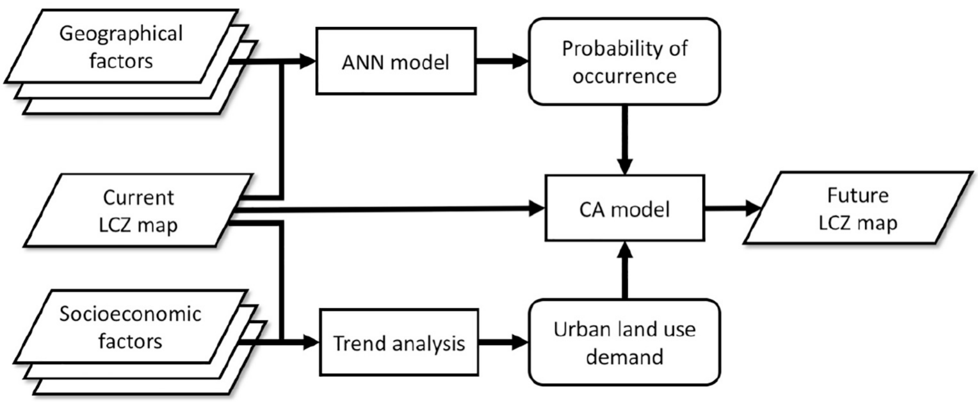

Fig. 2. Flowchart of the proposed methodology.

regarding urban lands (Table 1). Accuracies are lower than 50% for both high- and low-rise urban lands in the simulation of LCZ but are higher than 80% for those in SLCZ. Although the LCLUC model performs poorly on mid-rise urban lands in both cases, the accuracy achieved on the SLCZ mid-rise category (40%) is about twice as high as those on LCZ (21% for both open and compact mid-rise). Our results show that the LCLUC model is insufficient to simulate the complex transitions among full 17 categories of LCZ, but is sophisticated enough to simulate those among the eight categories in SLCZ. Given the higher reliability of simulating SLCZ, we will provide more details on the SLCZ simulation.

The simulation of conversions among SLCZs is based on the occurrence probabilities of land-covers/land-uses learned by an artificial neural network (ANN). Such probabilities of high-, low- and mid-rise urban lands are largely determined by distances to city centers, highways, and roads. Fig. 3 shows the probabilities of these three types of urban lands occurring as an RGB composite image, with high-rise as red, low-rise as green, and mid-rise as blue. High-rise urban lands are more likely to occur near city centers, where the agglomeration benefits drive up land prices and thus increase densities. Occurrence probabilities of low-rise urban lands are higher in locations that are farther away from city centers but are still close to the transportation networks (along roads and highways). In these peripheral locations, rural lands can be urbanized because of accessibility to the transportation network, and urban lands are less dense because of lower land prices. The mid-rise urban lands tend to occur in between low- and high-rise urban lands because the land prices, and thus densities, gradually increase from peripheries to the city centers. The occurrence probabilities learned by ANN largely match the bid-rent theory of urban land-use (Alonso, 1964; Fujita, 1991), which predicts the center-periphery density gradient.

With occurrence probabilities learned from the observed SLCZ map, the LCLUC model can correctly simulate the periphery-center spatial pattern of high-, mid- and low-rise urban lands (Fig. 4). However, there is a considerable variation in the accuracies among these three urban lands in SLCZ (Table 2). The accuracies of the high- (84%) and low-rise (82%) urban lands are substantially higher compared to that of the mid-rise (40%) urban lands. About 60% of the observed mid-rise urban lands are incorrectly simulated as high-rise and low-rise urban lands. Note that these two types of errors have comparable likelihoods: 27% for mid-rise as high-rise and 33% for mid-rise as low-rise. Such simulation errors are equally likely to occur when mid-rise urban lands are converted from low-rise, and to high-rise, urban lands.

5. Discussion

Our work is the first attempt to simulate the complex conversions among multiple types of urban lands defined in the local climate zone (LCZ) scheme by using an LCLUC model. Our results show that the simulation on the simplified local climate zone (SLCZ) map,

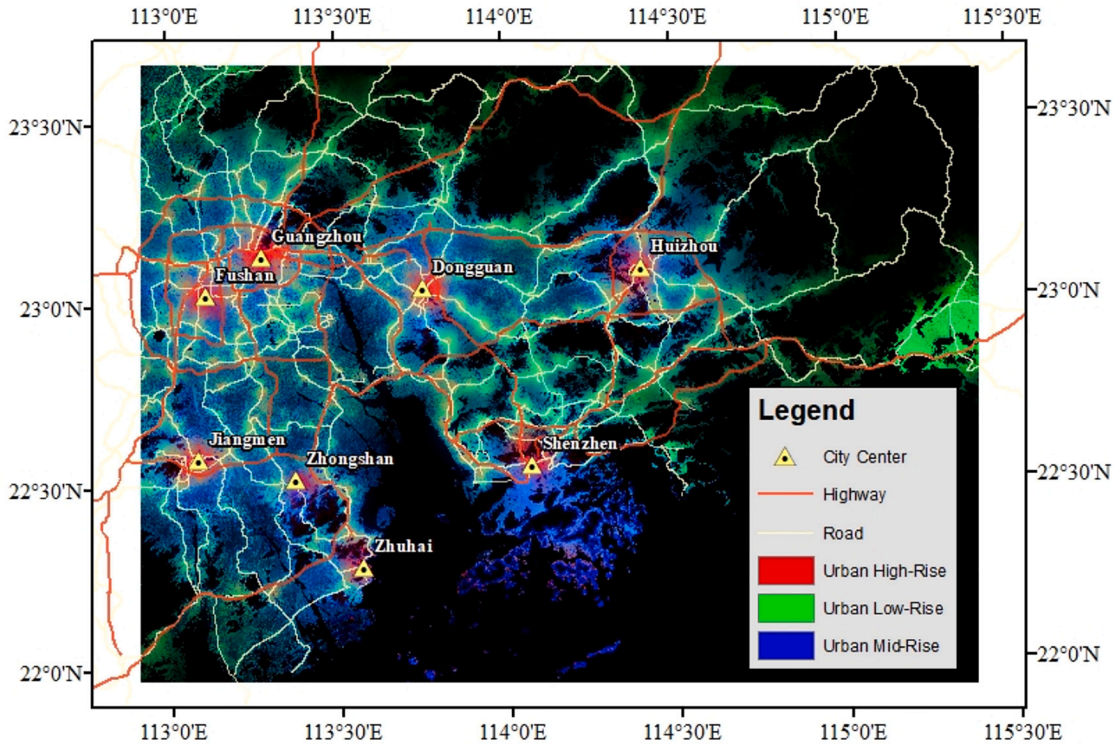

Fig. 3. Probabilities of occurrence of three types of urban lands in the Simplified Local Climate Zone categories. RGB color composite: probabilities of high-rise (red), low-rise (green) and mid-rise (blue) urban lands. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

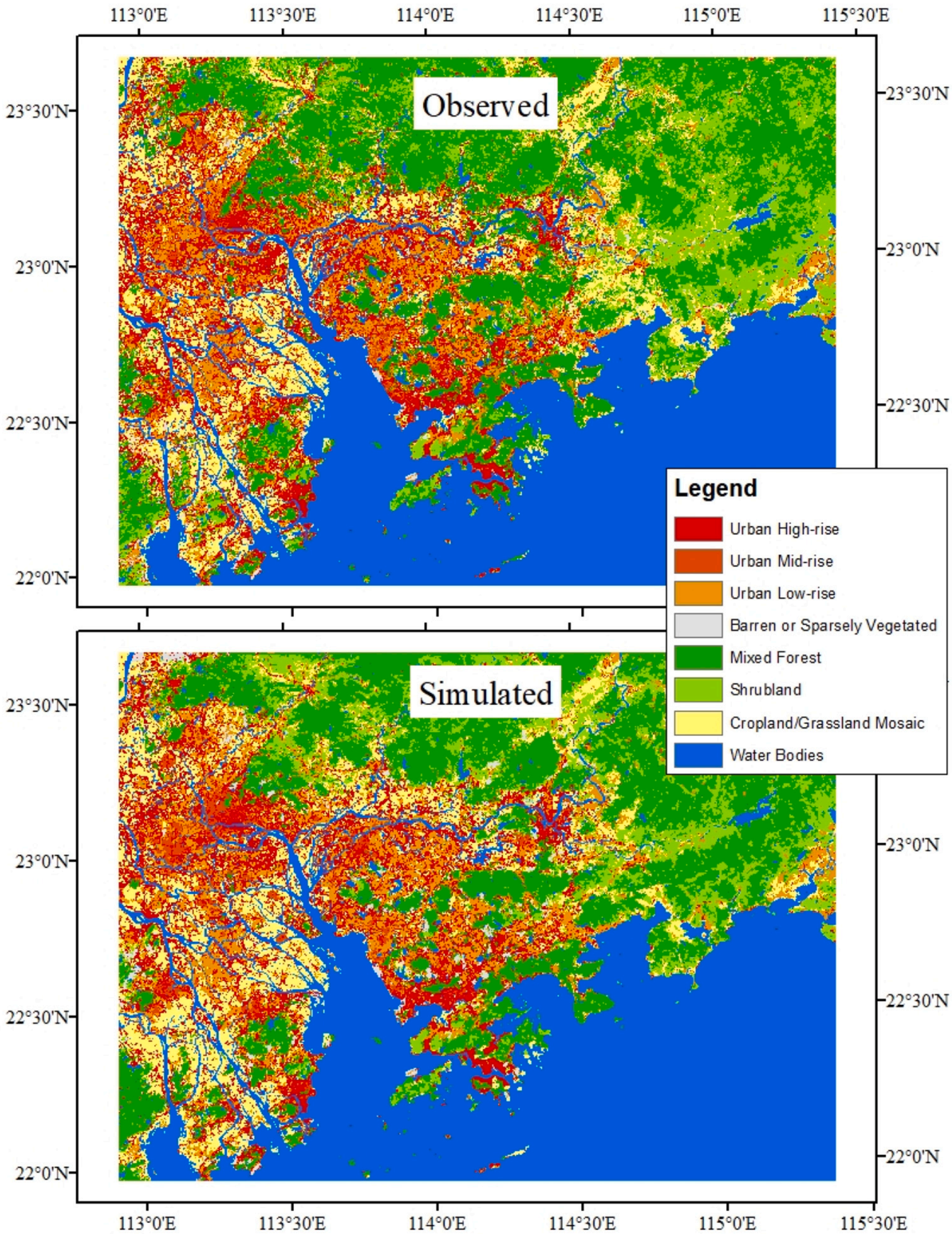

Fig. 4. The observed and simulated simplified local climate zone map in 2014.

Table 2
Confusion matrix of three types of urban lands in the Simplified Local Climate Zone (SLCZ) categories. The percentage is the portion of the total observed pixels in the corresponding land-use type.

Observed	Simulated					
	High-rise		Mid-rise		Low-rise	
	Pixels	Percentage	Pixels	Percentage	Pixels	Percentage
High-rise	427,015	84%	7795	2%	33,922	7%
Mid-rise	16,306	27%	24,303	40%	19,975	33%
Low-rise	27,102	6%	15,498	4%	344,592	82%
Other	39,731	8%	13,700	22%	20,076	5%

with three urban lands, yields considerably higher accuracies compared to that on the LCZ map, with ten urban lands. The three urban lands in SLCZ, e.g., high-, mid- and low-rise, only reflect the variation of densities, whereas the ten urban lands in LCZ incorporates more nuances like pervious/impervious covers ratios, construction materials, and functions. Our analyses also show that the spatial pattern of decreasing densities from city centers to peripheries, as reflected in the SLCZ map (observed map in Fig. 4) and predicted by the rent-bid theory (Alonso, 1964; Fujita, 1991), can be well captured by the machine learning technique in the LCLUC model (occurrence probabilities in Fig. 3). The ability of the LCLUC model to capture the center-periphery pattern explains why simulation on SLCZ outperforms that on LCZ. Since the ten urban lands in LCZ include more deliberate planning choices beyond densities, predicting the complex conversions among them may require more information than that provided by the geographic factors considered here. Nevertheless, the proposed methodology's ability to predict conversions of multiple types of urban lands allows further advances in urban climate studies.

Combining the LCZ scheme with LCLUC modeling can facilitate climate forecasts in urban areas. Used in the World Urban Database and Access Portal Tools (WUDAPT) project, the LCZ scheme allows gathering information on climate-relevant surface properties of cities globally and thus enables forecasts of how urban areas will react to future climate change. By providing additional information on future changes of multiple urban lands, our methodology further facilitates forecasts of urban climate as the combined results of climate change and urbanization. For instance, a meteorological modeling study of urban climate in Singapore found that the daily peak urban heat island intensities can range from 2.2 to 3.6 °C among different LCZ types (Mughal et al., 2019). Without predicting multiple urban lands with the proposed method, the meteorological models may neglect a 1.4 °C temperature variation within a tropical urban area. Given the spatially varying socioeconomic vulnerabilities within cities (Harlan et al., 2006), forecasts of the spatial variation of future warming, enabled by our method, are critical in identifying and prioritizing supports for the most vulnerable urban residents.

The proposed methodology can also facilitate studies of climate change adaptation and mitigation in urban areas. Climate adaptation measures can be investigated by examining the planning choices upon urban lands with various densities. Although our method cannot accurately simulate the land changes in the full 17-category LCZ map, reflecting pervious/impervious covers ratios, construction materials, and functions, it can simulate changes in the 8-category SLCZ map, reflecting various urban land densities. Planning choices of perviousness, materials, and functions can be added in the SLCZ-based LCLUC forecasts to construct different climate adaptation scenarios. For instance, a previous study found a ~ 1 °C annual nighttime temperature difference between compact high-rise (LCZ 1) and open high-rise (LCZ 4) in Vancouver, Canada (Stewart et al., 2014). In the SLCZ-based LCLUC forecasts, LCZ 1 and 4 are grouped as high-rise (SLCZ 1). Based on the SLCZ forecasts, we can set up two scenarios: 1) all new high-rise (SLCZ 1) urban lands are built as compact high-rise (LCZ 1) or 2) all new SLCZ 1 lands are built as open high-rise (LCZ 2). The temperature difference between these two scenarios may differ from that found in Vancouver, depending on background climates and scales of future urban land expansion (Huang et al., 2019; Zhao et al., 2014; Zhou et al., 2017). Using the two scenarios (compact versus open high-rise) as inputs into meteorological modeling, we can assess whether and how much these urban planning options may increase or reduce warming from climate change and urbanization. These LCZ-based planning options, involving urban forms and functions, provide more complexity and flexibility, compared to the common options examined in the existing urban climatology literature, such as green and white roofs (Georgescu et al., 2014; Zhao et al., 2017).

Climate change mitigation studies can also benefit from forecasting conversions of SLCZs because of the linkages between climate conditions, urban density, and energy consumption. In urban areas, two major greenhouse gases (GHG) emission sources are the transportation and building sectors. In terms of transportation energy use, it is well known that higher urban density encourages low-emission travel modes like public transit, cycling, and walking (Kennedy et al., 2009). However, recent studies (Seto et al., 2014; Stokes and Seto, 2016) suggest that the spatial configuration of various types of urban lands also matters, because it determines the accessibility to opportunities/services and thus travel patterns. Combining this knowledge with the density-specific forecasts of urban lands, we can potentially estimate the future transportation-related energy demands and thus GHG emission. Regarding the building sector, more than half of the total global building final energy is used for space heating and cooling (Urge-Vorsatz et al., 2013), which will be affected by local urban climates. The forecasts of future urban climates, improved by the prosed methods, can potentially provide more reliable building energy demands and, thus, emission estimates. Moreover, the possibility to evaluate cooling potentials of more urban adaptation options, as discussed above, can further advance studies on co-benefits of climate mitigation and adaptation in urban areas.

6. Conclusion

Despite the potentials in studying climate change in urban areas, the information provided by local climate zones (LCZ) mapping scheme is insufficient for forecasts of future urban climates, especially in the rapidly urbanizing regions. That is because rapid urbanization can drastically alter the future spatial pattern of multi-type urban lands, making the current LCZ maps inappropriate in climate forecasts. To facilitate urban climate forecasts with future LCZ maps, we propose a new methodological framework to simulate transitions among multi-type urban lands using land-cover/land-use change (LCLUC) modeling. To test the proposed method, we apply it to the LCZ maps of the Pearl River Delta (PRD) metropolitan area, simulating the changes from 2009 to 2014.

Comparison between the observed and simulated maps suggests that the LCLUC model can reliably predict conversions among simplified local climate zones (SLCZ), with three urban lands, but can poorly predict those among full LCZ categories, with ten urban lands. Conversions among SLCZ only reflect changes in densities determined by the bid rent curve, which can be captured by machine learning and geographical factors. On the other hand, the conversions among ten built-up types of urban lands in LCZ include deliberate planning choices on perviousness, materials, and functions, whose predictions are beyond the capabilities of conventional

LCLUC models. Nevertheless, the proposed method's ability to simulate spatial changes in urban densities can facilitate forecasts of future climate change in urban areas. Furthermore, the density-based SLCZ maps forecasts can be extended into LCZ maps by adding deliberate planning choices. Since these planning choices affect spatial variations of climate impacts and energy consumption in cities, they can constitute multiple climate mitigation and adaptation scenarios. Overall, the proposed methodological framework can potentially provide critical information on future urban lands that are useful in forecasting, mitigating, and adapting to changes in urban climates, especially for those cities and regions under fast urbanization but lack of land-use data.

Declaration of Competing Interest

None.

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Appendix

The complete list of geographical drivers used in GeoSOS-FLUS:

- Elevation
- Slope
- Aspect
- Distance to city centers
- Distance to town centers
- Distance to roads
- Distance to highways
- Distance to railway stations

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