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Artificial intelligence for predicting urban heat island effect and optimising land use/land cover for mitigation: Prospects and recent advancements

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ABSTRACT

Rocketing global urbanisation has caused an increase in the Urban Heat Island (UHI) effect, resulting in various negative implications for the urban environment. Quantifying the Surface UHI (SUHI) effect using Land Surface Temperature (LST), Local Climate Zones (LCZ), and deep learning algorithms such as Convolutional Neural Networks (CNN) and pix2pix have prospects in aiding sustainable city planning and modification. Most research on mitigating SUHI promotes greenery as a solution, allowing LCZ optimisation to be explored. Using Heat Vulnerability Index (HVI) and evolutionary algorithms like Genetic Algorithms (GA) and Particle Swarm Optimisation (PSO) show promise in achieving high-quality optimisation solutions. This short communication explores the potential of these artificial intelligence technologies to combat the UHI effect and enhance urban sustainability.

1. Introduction

As the rate of urbanisation soared during the last few decades, most of the world's population now lives in urban environments. The world's population is urbanising at a rapid rate; it is projected that more than 68% of the world will live in urban centres by 2050, an increase from 56% in 2020 (Gu et al., 2021; WUP, 2018). This rapid increase in urbanisation has led to increased temperatures in urban centres compared to their rural surroundings, a phenomenon known today as the Urban Heat Island (UHI) effect. In China, for example, the percentage of cities experiencing extreme heat increased from 77.8% to 94.2% over 20 years (Wang et al., 2024) with a noticeable increase in psychological physical temperatures and uncomfortable days in 68% and 59% of cities, respectively during the summer (Ren et al., 2022). This phenomenon is one of the main contributors to global warming (Feinberg, 2020; Huang et al., 2019), in addition to causing many negative implications on urban energy consumption, air quality and public health (Sabrin et al., 2020).

Over the years, much research has been done on studying the UHI effect and understanding its driving factors. Remote sensing technologies have been valuable for studying the UHI effect using satellites and unmanned aerial vehicles. Most remote sensing-based studies on the UHI effect focus on the surface urban heat island (SUHI) phenomenon (Zhou et al., 2019). This phenomenon happens when land surface temperatures (LST) in urban areas are higher than their surrounding non-urban areas (Voogt and Oke, 2003). LST is relatively easy to measure and quantify from space using thermal sensors mounted onboard orbiting satellites. The SUHI intensity is significantly and positively log-linearly correlated with the urban area size (Guo et al., 2022).

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Many papers have concluded that one of the most influential drivers of SUHI is land use and land cover (LULC) (Fu and Weng, 2016; Jiang and Tian, 2010), with built-up areas having a positive correlation and vegetated areas having a negative correlation with LST (Nega and Balew, 2022; Singh et al., 2022). Based on the current research, these findings have led to many studies suggesting urban greenery as an effective way to mitigate the SUHI effect (Aflaki et al., 2017; Piroozfar et al., 2015; Shishegar, 2014). The Local Climate Zones (LCZ) classification approach, proposed by several studies (Stewart and Oke, 2012; Stewart et al., 2014), categorises LULC into classes based on their similar climate state due to the similar land use, activities and metabolic similarities. The LCZ classification comprises 10 built-up types and 7 natural land cover types. This classification has been widely utilised in various regions to study the relationship between urban surface characteristics and temperature, with many studies finding a significant correlation between LCZ types and LST (Cai et al., 2018; Geletič et al., 2016; Unal Cilek and Cilek, 2021; Yang et al., 2021), proving it a valuable approach for studying the SUHI effect.

The amount of changes required in specific LCZ areas and composition to cause a decrease in LST and mitigate the SUHI effect has not been studied thoroughly (Zhang et al., 2023), and there is an urgent need for responding to heat risks in densely populated medium to high-rise buildings (Chen et al., 2022). Thus, with the rapid advancements in artificial intelligence technologies, there is an increasing opportunity to use deep learning to quantify the relationship between LST and LCZ. In addition, computational intelligence paves the way for various LCZ optimisation methods to be tested, using non-linear models to optimise LCZ classes and increase urban greenery leading to improved urban liveability (Janga et al., 2023).

2. Can land surface temperature (LST) be estimated solely based on local climate zones (LCZ)?

Looking at the latest advancements in artificial neural networks, the ability of artificial intelligence to analyse the correlations between LCZ classes and LST and predict the impact of different LCZ classes on LST is promising. This potential would allow city planners to make informed decisions, modify city plans to mitigate the SUHI effect (Rahman et al., 2023), and forecast future LST using predicted LCZ spatial layouts generated using simulation models. In addition, estimating LST from LCZ would aid in the evaluation of different LCZ optimisation models to determine the model with the most reduction in LST. A well-trained neural network could distinguish the patterns between LST values and LCZ types. Previous studies on the UHI effect include a convolutional neural network (CNN) to predict the impact of LCZ on the thermal environment using thermal risk levels (Lau et al., 2023). This study trained a CNN model using LCZ and a three-level thermal risk level map from air temperature measurements and achieved an overall accuracy of 81.97%.

Similarly, LST maps could be predicted as an output instead of the thermal risk level. Fig. 1 illustrates the proposed methodology incorporating a CNN to estimate LST from LCZ maps showing the convolution, pooling, flattening and fully connected layers. Further research can experiment using different combinations of model variables such as input size, padding size, kernel size, activation function, batch size and the number of training epochs.

Furthermore, the introduction of pix2pix, an algorithm based on conditional generative adversarial networks (GANs), adds to the prospects of estimating LST from LCZ. Pix2pix is an image-to-image translation framework introduced by Isola et al. (2017) that can detect and learn the spatial correlation between LST and LCZ and predict LST accordingly. GANs use a generator module and a discriminator module. The generator is trained by the adversarially-trained discriminator to produce output images that cannot be distinguished from the actual images, trained to detect the fake images generated by the generator (Goodfellow et al., 2014). In a UHI study, pix2pix was used to predict the effects of different urban configurations on outdoor thermal comfort, yielding a high structural similarity index (SSIM) of 96% on the validation dataset (Shahrestani et al., 2023). Fig. 2 illustrates how a GAN model can be utilised to perform image-to-image translation to estimate LST from LCZ maps.

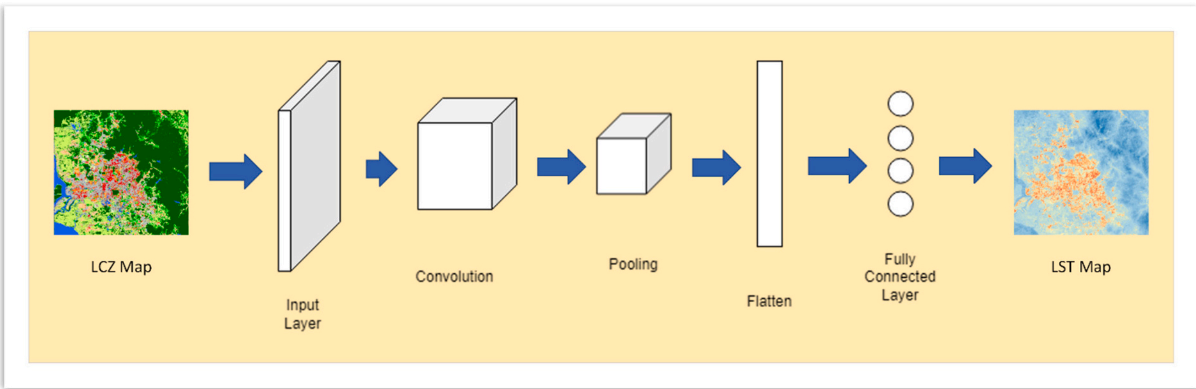

Fig. 1. Proposed convolutional neural network methodology to estimate LST from LCZ map.

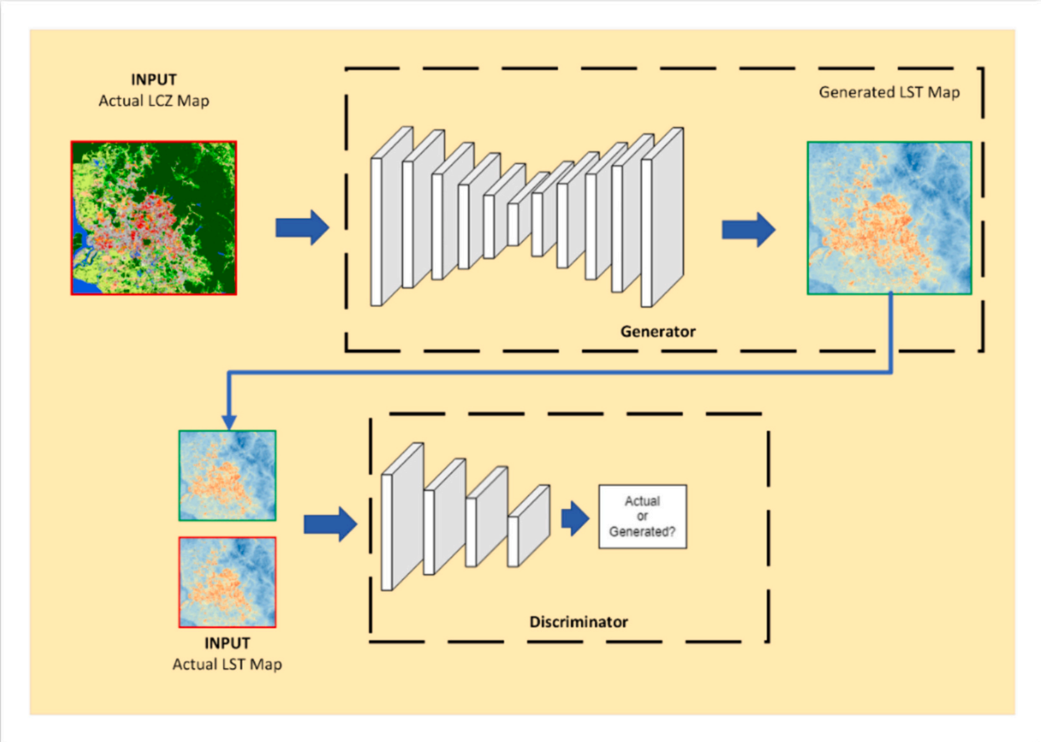

Fig. 2. Proposed generative adversarial network (pix2pix) methodology to estimate LST from LCZ map.

3. How can computational intelligence optimise local climate zone (LCZ) areas for SUHI mitigation?

The need to optimise urban morphology for SUHI mitigation is crucial to achieving the United Nations Sustainable Development Goals (SDG) for sustainable cities and communities (11) and climate change (13). By optimising LCZ classes in an urban environment, a reduction in temperature can be achieved. For example, Yi et al. (2022) concluded that transforming compact midrise and low-rise built LCZ to open midrise and low-rise would decrease temperatures by 1–3 °C. Several studies have used LCZ optimisation techniques to reduce temperature using mathematical model solvers (Yang et al., 2020; Zhang et al., 2023). In Zhang et al. (2023), several indices were used to develop a heat vulnerability index (HVI) model, such as normalised difference in vegetation index (NDVI), normalised difference building index (NDBI), population density (PD), modified normalised difference water index (MNDWI) and road density (RD). A mathematical function is used to obtain the minimum HVI, using population and LCZ area as constraints. Solving such an optimisation problem using computational intelligence and evolutionary algorithms has a significant prospect of getting optimal solutions.

Two of the most used emerging evolutionary algorithms in LULC optimisation are the genetic algorithm (GA) (Ding et al., 2021; Rahman and Szabó, 2021) and Particle Swarm Optimisation (PSO) (Memmah et al., 2015). GA is an algorithm commonly used to generate high-quality solutions to optimisation problems by simulating biological evolutionary processes. Objective functions and constraints would be input to the algorithm to achieve global optimisation. In a thermal comfort study, Xu et al. (2019) used GA to optimise the urban layout for microclimate performance in a cold region of China using universal thermal comfort index (UTCI) range as the objective; the optimisation process achieved high accuracy of acceptable UTCI ranges. In a recent UHI research, Chen et al. (2023) used a GA to reorganise LCZ to reduce LST and map the optimised spatial layout using the Future Land Use Simulation (FLUS) model, resulting in a 5.2 °C reduction in average LST.

PSO can optimise variables by using an information-sharing mechanism between particles (Kennedy and Eberhart, 1995); it was used in many land use studies to perform multi-objective optimisation (Masoomi et al., 2013; Sahebgharani, 2016) and make spatial decisions in land use management (Ma et al., 2011). Several studies utilised PSO to mitigate UHI by optimising building designs to reduce energy consumption (Wu et al., 2023) and optimising land use to reduce LST (Zhang et al., 2021). To the best of our knowledge, no research has been done on the optimisation of LCZ for UHI mitigation using PSO to date.

The fusion of the HVI model, evolutionary algorithms, and FLUS to optimise and map LCZ spatially provides the potential for high-quality optimisation solutions to be explored. Fig. 3 illustrates the proposed LCZ optimisation methodology using the HVI model, optimisation function, evolutionary algorithms, and spatial mapping. HVI will be calculated using a mathematical function from Exposure, Sensitivity, and adaptability. LCZ and HVI will then be input in the objective function, with population and certain LCZ areas, such as green spaces and water bodies, as constraints. The evolutionary algorithms will then find the minimum objective

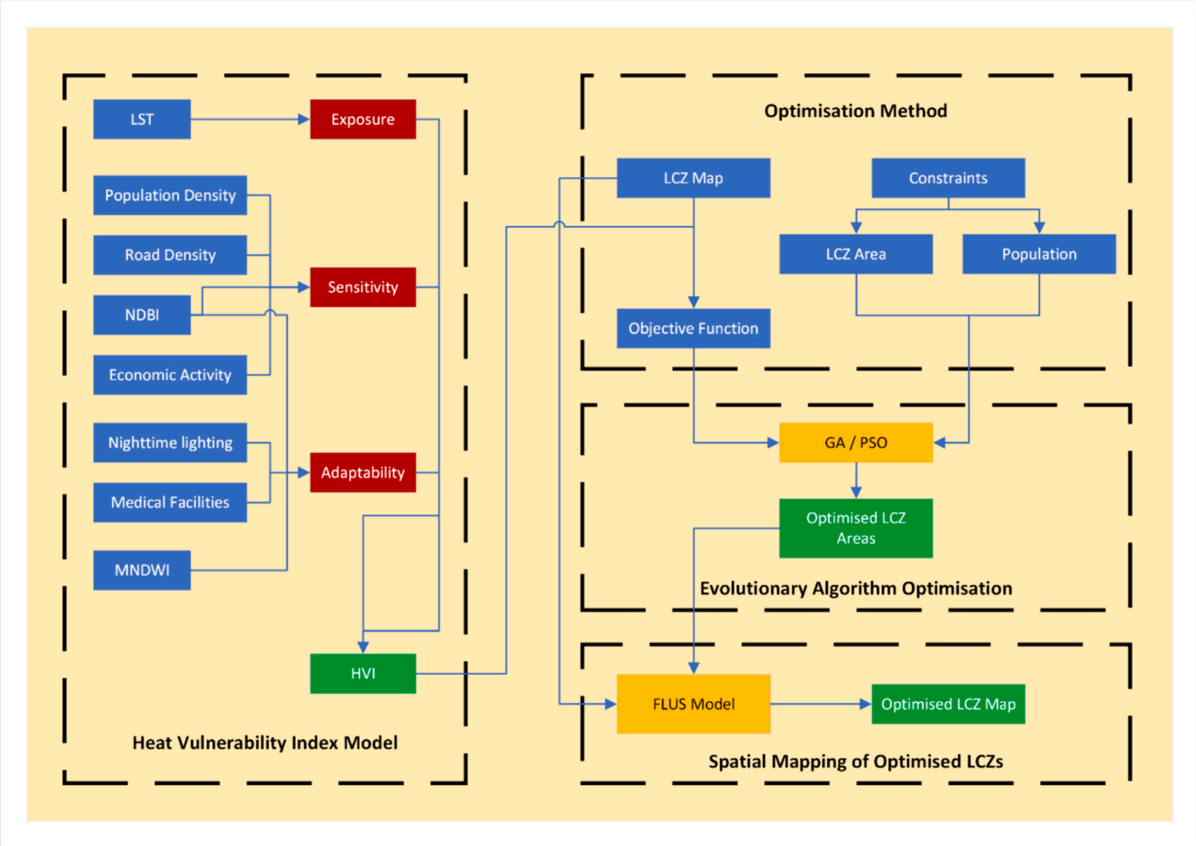

Fig. 3. Proposed LCZ optimisation scheme using the HVI model, evolutionary algorithms and FLUS model.

function to achieve the optimised result, followed by the spatial mapping of the optimised LCZ layout using the FLUS model.

The GA and PSO optimisation results could be evaluated by utilising the best performing LCZ to LST estimation neural network model. The resulting LST spatial layout would be mapped to graph box plots of LCZ against LST. These plots will be of significant value to compare the average reduction in temperature in the GA and PSO models. Thus, the best performing optimisation model could be determined.

CRediT authorship contribution statement

Omar Y.A. Mohamed: Writing – original draft. **Izni Zahidi:** Writing – review & editing.

Declaration of competing interest

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.

Data availability

No data was used for the research described in the article.

References

Aflaki, A., Mirnezhad, M., Ghaffarianhoseini, A., Ghaffarianhoseini, A., Omrany, H., Wang, Z.-H., Akbari, H., 2017. Urban heat island mitigation strategies: a state-of-the-art review on Kuala Lumpur, Singapore and Hong Kong. Cities 62, 131–145. https://doi.org/10.1016/j.cities.2016.09.003.

Cai, M., Ren, C., Xu, Y., Lau, K.K.-L., Wang, R., 2018. Investigating the relationship between local climate zone and land surface temperature using an improved WUDAPT methodology – a case study of Yangtze River Delta, China. Urban Clim. 24, 485–502. https://doi.org/10.1016/j.uclim.2017.05.010.

Chen, B., Xie, M., Feng, Q., Wu, R., Jiang, L., 2022. Diurnal heat exposure risk mapping and related governance zoning: a case study of Beijing, China. Sustain. Cities Soc. 81, 103831 https://doi.org/10.1016/j.scs.2022.103831.

Chen, J., Shi, R., Sun, G., Guo, Y., Deng, M., Zhang, X., 2023. Simulation-based optimization of the urban thermal environment through local climate zones reorganization in Changsha City, China with the FLUS model. Sustainability 15 (16).

Ding, X., Zheng, M., Zheng, X., 2021. The application of genetic algorithm in land use optimization research: a review. Land 10 (5).

Feinberg, A., 2020. Urban heat island amplification estimates on global warming using an albedo model. SN Appl. Sci. 2 (12), 2178. https://doi.org/10.1007/s42452-020-03889-3.

Fu, P., Weng, Q., 2016. A time series analysis of urbanization induced land use and land cover change and its impact on land surface temperature with Landsat imagery. Remote Sens. Environ. 175, 205–214. https://doi.org/10.1016/j.rse.2015.12.040.

Geletič, J., Lehnert, M., Dobrovolný, P., 2016. Land surface temperature differences within local climate zones, based on two central European cities. Remote Sens. 8 (10).

Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., Bengio, Y., 2014. Generative adversarial nets. Adv. Neural Inf. Proces. Syst. 27.

Gu, D., Andreev, K., Dupre, M.E., 2021. Major trends in population growth around the world. China CDC Wkly 3 (28), 604–613. https://doi.org/10.46234/ccdcw2021.160.

Guo, Y., Ren, Z., Dong, Y., Hu, N., Wang, C., Zhang, P., Jia, G., He, X., 2022. Strengthening of surface urban heat island effect driven primarily by urban size under rapid urbanization: national evidence from China. GIScі. Remote Sens. 59 (1), 2127–2143. https://doi.org/10.1080/15481603.2022.2147301.

Huang, K., Li, X., Liu, X., Seto, K.C., 2019. Projecting global urban land expansion and heat island intensification through 2050. Environ. Res. Lett. 14 (11), 114037 https://doi.org/10.1088/1748-9326/ab4b71.

Isola, P., Zhu, J.-Y., Zhou, T., Efros, A.A., 2017. Image-to-image translation with conditional adversarial networks. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition.

Janga, B., Asamani, G.P., Sun, Z., Cristea, N., 2023. A review of practical AI for remote sensing in earth sciences. Remote Sens. 15 (16).

Jiang, J., Tian, G., 2010. Analysis of the impact of land use/land cover change on land surface temperature with remote sensing. Procedia Environ. Sci. 2, 571–575. https://doi.org/10.1016/j.proenv.2010.10.062.

Kennedy, J., Eberhart, R., 1995. Particle swarm optimization. In: Proceedings of ICNN'95 - International Conference on Neural Networks, 27 Nov.-1 Dec. 1995.

Lau, T.-K., Chen, Y.-C., Lin, T.-P., 2023. Application of local climate zones combined with machine learning to predict the impact of urban structure patterns on thermal environment. Urban Clim. 52, 101731 https://doi.org/10.1016/j.uclim.2023.101731.

Ma, S., He, J., Liu, F., Yu, Y., 2011. Land-use spatial optimization based on PSO algorithm. Geo-spat. Inf. Sci. 14 (1), 54–61. https://doi.org/10.1007/s11806-011-0437-8.

Masoomi, Z., Mesgari, M.S., Hamrah, M., 2013. Allocation of urban land uses by multi-objective particle swarm optimization algorithm. Int. J. Geogr. Inf. Sci. 27 (3), 542–566. https://doi.org/10.1080/13658816.2012.698016.

Memmah, M.-M., Lescourret, F., Yao, X., Lavigne, C., 2015. Metaheuristics for agricultural land use optimization. A review. Agron. Sustain. Dev. 35 (3), 975–998. https://doi.org/10.1007/s13593-015-0303-4.

Nega, W., Balew, A., 2022. The relationship between land use land cover and land surface temperature using remote sensing: systematic reviews of studies globally over the past 5 years. Environ. Sci. Pollut. Res. 29 (28), 42493–42508. https://doi.org/10.1007/s11356-022-19997-z.

Piroozfar, P., Farr, E.R., Pomponi, F., 2015. Urban Heat Island (UHI) mitigating strategies: a case-based comparative analysis. Sustain. Cities Soc. 19.

Rahman, M.M., Szabó, G., 2021. Multi-objective urban land use optimization using spatial data: a systematic review. Sustain. Cities Soc. 74, 103214 https://doi.org/10.1016/j.scs.2021.103214.

Rahman, A., Roy, S.S., Talukdar, S., 2023. Advancements in Urban Environmental Studies: Application of Geospatial Technology and Artificial Intelligence in Urban Studies. Springer Nature.

Ren, Z., Fu, Y., Dong, Y., Zhang, P., He, X., 2022. Rapid urbanization and climate change significantly contribute to worsening urban human thermal comfort: a national 183-city, 26-year study in China. Urban Clim. 43, 101154 https://doi.org/10.1016/j.uclim.2022.101154.

Sabrin, S., Karimi, M., Fahad, M.G.R., Nazari, R., 2020. Quantifying environmental and social vulnerability: role of urban Heat Island and air quality, a case study of Camden, NJ. Urban Clim. 34, 100699 https://doi.org/10.1016/j.uclim.2020.100699.

Sahebgharani, A., 2016. Multi-objective land use optimization through parallel particle swarm algorithm case study Baboldasht district of Isfahan, Iran. J. Urban Environ. Eng. 10 (1), 42–49. http://www.jstor.org/stable/26240810.

Shahrestani, S.S., Zomorodian, Z.S., Karami, M., Mostafavi, F., 2023. A novel machine learning-based framework for mapping outdoor thermal comfort. Adv. Build. Energy Res. 17 (1), 53–72. https://doi.org/10.1080/17512549.2022.2152865.

Shishegar, N., 2014. The impacts of green areas on mitigating urban heat island effect: a review. Int. J. Environ. Sustain. 9 (1), 119–130. https://doi.org/10.18848/2325-1077/CGP/v09i01/55081.

Singh, V.D., Rehan Ali, S., Kant Piyoosh, A., 2022. A Review on the Relationship between LULC and LST using Geospatial Technologies. Proceedings of the 2022 11th International Conference on System Modeling and Advancement in Research Trends, SMART 2022.

Stewart, I.D., Oke, T.R., 2012. Local climate zones for urban temperature studies. Bull. Am. Meteorol. Soc. 93 (12), 1879–1900.

Stewart, I.D., Oke, T.R., Krayenhoff, E.S., 2014. Evaluation of the 'local climate zone' scheme using temperature observations and model simulations [article]. Int. J. Climatol. 34 (4), 1062–1080. https://doi.org/10.1002/joc.3746.

Unal Cilek, M., Cilek, A., 2021. Analyses of land surface temperature (LST) variability among local climate zones (LCZs) comparing Landsat-8 and ENVI-met model data. Sustain. Cities Soc. 69, 102877 https://doi.org/10.1016/j.scs.2021.102877.

Voogt, J.A., Oke, T.R., 2003. Thermal remote sensing of urban climates. Remote Sens. Environ. 86 (3), 370–384. https://doi.org/10.1016/S0034-4257(03)00079-8.

Wang, C., Ren, Z., Guo, Y., Zhang, P., Hong, S., Ma, Z., Hong, W., Wang, X., 2024. Assessing urban population exposure risk to extreme heat: patterns, trends, and implications for climate resilience in China (2000−2020). Sustain. Cities Soc. 103, 105260 https://doi.org/10.1016/j.scs.2024.105260.

Wu, X., Li, X., Qin, Y., Xu, W., Liu, Y., 2023. Intelligent multiobjective optimization design for NZEBs in China: four climatic regions. Appl. Energy 339, 120934. https://doi.org/10.1016/j.apenergy.2023.120934.

WUP, 2018. World Urbanization Prospects: The 2018 Revision. United Nations Department of Economic and Social Affairs/Population Division. https://population.un.org/wup/Publications/Files/WUP2018-Report.pdf.

Xu, X., Liu, Y., Wang, W., Xu, N., Liu, K., Yu, G., 2019. Urban layout optimization based on genetic algorithm for microclimate performance in the cold region of China. Appl. Sci. 9 (22).

Yang, J., Wang, Y., Xiu, C., Xiao, X., Xia, J., Jin, C., 2020. Optimizing local climate zones to mitigate urban heat island effect in human settlements. J. Clean. Prod. 275, 123767 https://doi.org/10.1016/j.jclepro.2020.123767.

Yang, J., Ren, J., Sun, D., Xiao, X., Xia, J., Jin, C., Li, X., 2021. Understanding land surface temperature impact factors based on local climate zones. Sustain. Cities Soc. 69, 102818 https://doi.org/10.1016/j.scs.2021.102818.

Yi, C., Kwon, H.-G., Yang, H., 2022. Spatial temperature differences in local climate zones of Seoul metropolitan area during a heatwave. Urban Clim. 41, 101012 https://doi.org/10.1016/j.uclim.2021.101012.

Zhang, Y., Chen, X., Lv, D., Zhang, Y., 2021. Optimization of urban heat effect mitigation based on multi-type ant colony algorithm. Appl. Soft Comput. 112, 107758 https://doi.org/10.1016/j.asoc.2021.107758.

Zhang, R., Yang, J., Ma, X., Xiao, X., Xia, J., 2023. Optimal allocation of local climate zones based on heat vulnerability perspective. Sustain. Cities Soc. 99, 104981 https://doi.org/10.1016/j.scs.2023.104981.

Zhou, D., Xiao, J., Bonafoni, S., Berger, C., Deilami, K., Zhou, Y., Frolking, S., Yao, R., Qiao, Z., Sobrino, J.A., 2019. Satellite remote sensing of surface urban heat islands: progress, challenges, and perspectives. Remote Sens. 11 (1), 48. https://www.mdpi.com/2072-4292/11/1/48.