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Novel Use of Local Climate Zones: Urban Form-based Method for Carbon Sink Assessment using Convolutional Neural Network

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Abstract.

Due to the Sustainable Development Goals (SDGs) proposed by the United Nations, it is necessary to estimate the carbon sink within cities. Since carbon sink calculation can be complicated, this study aimed to propose a novel method for carbon sink estimation using Local Climate Zone (LCZ) and Convolutional Neural Network (CNN). LCZ maps of downtown Taipei City and Chiayi City were collected and applied to quantify the environment within research areas. Then, LCZ maps were split into a grid size of 50m and inputted into a CNN model for training and testing, which was structured with 4 convolutional and pooling layers. The results presented that the built environments with classes of LCZ 5, 6, and 9 have a higher potential of contributing to a carbon sink. The lower intensity of urbanization provided more spaces for vegetation growth, which is beneficial for the carbon sink. Additionally, the results demonstrated the effectiveness of the proposed CNN model in carbon sink estimation, which reached a high R² score and low Mean Absolute Error (MAE) of over 0.75 and approximately 29 (1000kgCO₂e.yr) with 50% sampling, respectively. The proposed method can be seriously affected by the accuracy of the LCZ map, resulting in poorer and less reliable estimation due to incorrect environmental quantification. However, the proposed method can help with carbon sink estimation within cities. Overall, this study proposed a novel use of LCZ apart from previous, presented the relationship between urbanization intensity and carbon sink, and also a simple method for carbon sink estimation.

Keywords: Local Climate Zone; Remote Sensing; Carbon sink; Convolutional Neural Network

1. Introduction

Global warming is one of the most critical issues worldwide, which is causing several problems, such as Urban Heat Islands (UHI), exacerbation of outdoor thermal comfort, and various kinds of health problems (Assaf and Assaad 2023; Lin et al. 2010; Mohajerani et al. 2017). Therefore, mitigation and adaptation are necessary. Greenhouse gas emissions are one of the most important causes of global warming, such as carbon dioxide (CO₂) and nitrous oxide, leading to more problems with global warming (Zhao et al. 2023; Lashof and Ahuja 1990; Mohajan 2011). Since United Nations aimed to halve global greenhouse gas emissions by 2030 and achieve zero emissions by 2050 (Alkurt et al. 2023), different countries determined several policies for the target of net-zero emissions, including Taiwan.

Within the target of net-zero emissions, reducing carbon emissions is a well-known topic worldwide. Carbon sink is one of the most important strategies for carbon emission reduction. Oceans and forests play an important role in carbon emission reduction, which helps to absorb the artificial carbon emissions due to human activities (Gruber et al. 2023; Peng et al. 2023). Marginal seas can help absorb carbon emissions due to the rich biological activities and physical mixing processes, which have become an essential field of study worldwide (Zhang et al. 2023). On the other hand, carbon emissions can be also reduced by photosynthesis from vegetation in forests, which absorb the atmospheric CO₂ through sequestration (Moon et al. 2024; Li et al. 2024). Due to the importance of oceans and forests in carbon emissions reduction, it is necessary to protect the natural landscape during different kinds of development. However, the destruction and reduction of natural landscapes, especially forestry and green spaces, in the process of urbanization is a common phenomenon. Therefore, it is necessary to understand the relationship between carbon sink from vegetation (CSv) and urban patterns, for the reference of further urban planning. Moreover, an easy-to-use method is required to assess the CSv within cities, to determine the level of carbon sink.

To understand the spatial distribution within cities, remote sensing was regarded as an efficient and cost-effective approach, which can help to observe various kinds of land surface characteristics on a large scale (Bagan and Yamagata 2012). According to the advantages of remote sensing, it is widely applied in urban studies, such as investigating the distribution of natural landscapes, Land Uses Land Cover (LULC), and land surface temperature (Kaplan et al. 2017; Gxumisa and Breytenbach 2017; Avdan and Jovanovska 2016). Furthermore, the Local Climate Zone (LCZ) is another well-known approach in urban studies, which contains various features in urban areas, such as building height, sky visibility, roughness length, and material albedo (Molnár et al. 2019). Based on the fine performance of LCZ, it was widely applied in urban studies, especially studies related to UHI, urban climate, and weather modeling (Stewart and Oke 2012; Stewart 2011). Therefore, LCZ is an excellent approach to quantifying the urban environment, which comprehensively and intuitively presents the urban environment with 17 classes, including 10 classes (Class 1 to 10) of the built environment and 7 classes (Class 11 to 17) of the natural landscape, respectively (Lau et al. 2019). According to the great success and achievements of LCZ in numerous urban studies, LCZ was applied in this study for environmental quantification.

With the advancement of computers, Machine learning (ML) and Deep learning (DL) are the most critical issues worldwide nowadays. ML and DL helped in numerous tasks in different fields, such as marine environmental monitoring, understanding the relationship between environmental variables, and commercial applications (Lau and Huang 2024; Lau and Lin 2024a; Jordan and Mitchell. 2015). Within various models of ML and DL, Convolutional Neural Networks (CNN) were well-known in image-related studies, including image classification, object recognition, and object segmentation (Redmon et al. 2016; Kayalibay et al. 2017). According to the special characteristic and great applicability of CNN, it is finely achieved in different urban studies, such as understanding urban form from 2D images for prediction, identifying the thermal risk based on the pattern of LCZ, and predicting the expansion of

urban area (Yang and Kwon 2023; Lau et al. 2023; Boulila et al. 2021). The feasibility and applicability of understanding the pattern of urban areas using CNN were determined according to the great achievements in previous studies. Therefore, CNN was regarded as a good approach for urban pattern recognition, and it is helpful for further prediction and analysis. Unlike previous studies, this study applied the combination of CNN and LCZ to investigate the relationship between LCZ patterns and carbon sequestration, rather than climate issues that were investigated in the past. This is a novel method that doesn't require complex calculation and detailed vegetation information.

In this study, LCZ maps of Taipei City and Chiayi City in Taiwan were obtained from open sources and applied to quantify the urban environment of the 2 research areas, presenting the spatial distribution of built areas and natural landscapes within cities. Then, a general CNN model was further applied to help understand the relationship between CSv and urban patterns grouped by LCZs, which also built a simple method for urban CSv estimation. After that, the results of urban CSv estimation and statistical analyses will be shown, presenting the effectiveness and limitations of the proposed method. Finally, several discussions will be given, including the relationship between CSv and LCZ patterns, the prediction performance of the proposed CNN model, and a comparison with recent studies.

2. Materials and methods

2.1. Research areas and Local Climate Zone (LCZ) maps

The greater the population, the higher the intensity of urbanization (Polinesi et al. 2020). Therefore, two cities in Taiwan with relatively high population densities were selected for the subsequent analysis in this study, which are Taipei City and Chiayi City. Taipei City is located in northern Taiwan and has a great population density of 9231.47 people/km². As the capital city of Taiwan, Taipei City has developed rapidly in recent decades and the high intensity of urbanization has led to a significant reduction in natural landscapes (Liu and Shen 2014). Therefore, the CSv in Taipei City may be decreased due to the urbanization in recent decades. On the other hand, Chiayi City is the second most densely populated city in Taiwan, with a population density of 4384.80 people/km². Chiayi is located in southern Taiwan and is a less urbanized city compared to Taipei City. Chiayi City is densely packed with low- and mid-rise buildings, ranging from 3 to 9 floors. As the population migrates to other cities for work, Chiayi City's population density growth has stopped, which may lead to a slowdown in urbanization development. Due to the factor of population density, Taipei City and Chiayi City were selected in this study, and their locations are shown in Fig 1.

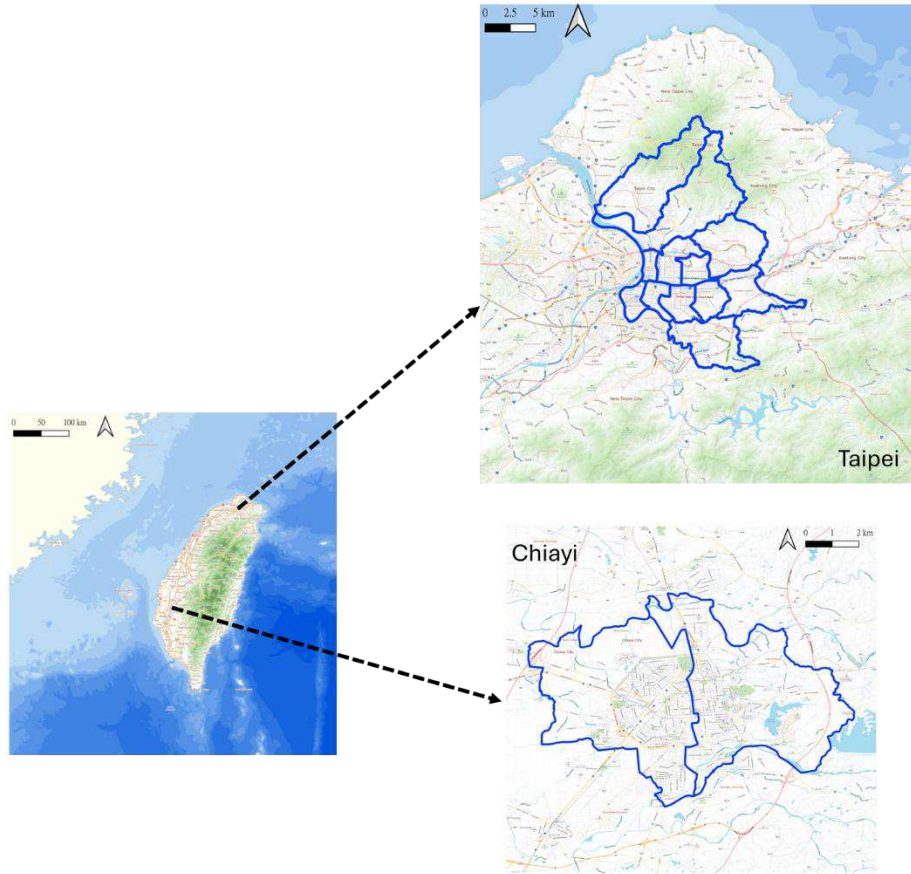


Fig 1. Research areas including Taipei and Chiayi cities. Basemap: E-Map of Taiwan provided by National Land Surveying and Mapping Center in Taiwan

To qualify the environments within downtown Taipei City and Chiayi City, the LCZ maps were obtained and used for the subsequent analysis, as shown in Fig 2. The LCZ map with a spatial resolution of 100 m was obtained from <https://zenodo.org/records/7324909>, which is a global LCZ map that is free and available to download and use (Demuzere et al. 2023). The details of LCZ are shown in Table 1. Since the above global LCZ map achieved an overall accuracy rate of over 70%, it is regarded as acceptable and reliable. Therefore, the LCZ maps of downtown Taipei City and Chiayi City were further applied to the subsequent analysis. For the LCZ map of downtown Taipei City, grids with LCZ 1, 2, 6, and 9 are densely packed in the built areas, and grids with natural landscapes like LCZ 11, 12, and 14 are mostly distributed in the outside regions. On the other hand, the LCZ map of Chiayi City presented the lower intensity of urbanization, which was mostly packed with the grids with LCZ 2, 3, 5, and 8 in the built area. Although Chiayi City has a lower intensity of urbanization, lower levels of greening can be investigated through the LCZ map. Most of the outside areas are generated with grids with LCZ 6, 14, and a few LCZ 11, and 12. However, the above LCZ maps comprehensively presented the built-up and natural environment within downtown Taipei City and Chiayi City, which are helpful to the subsequent analysis.

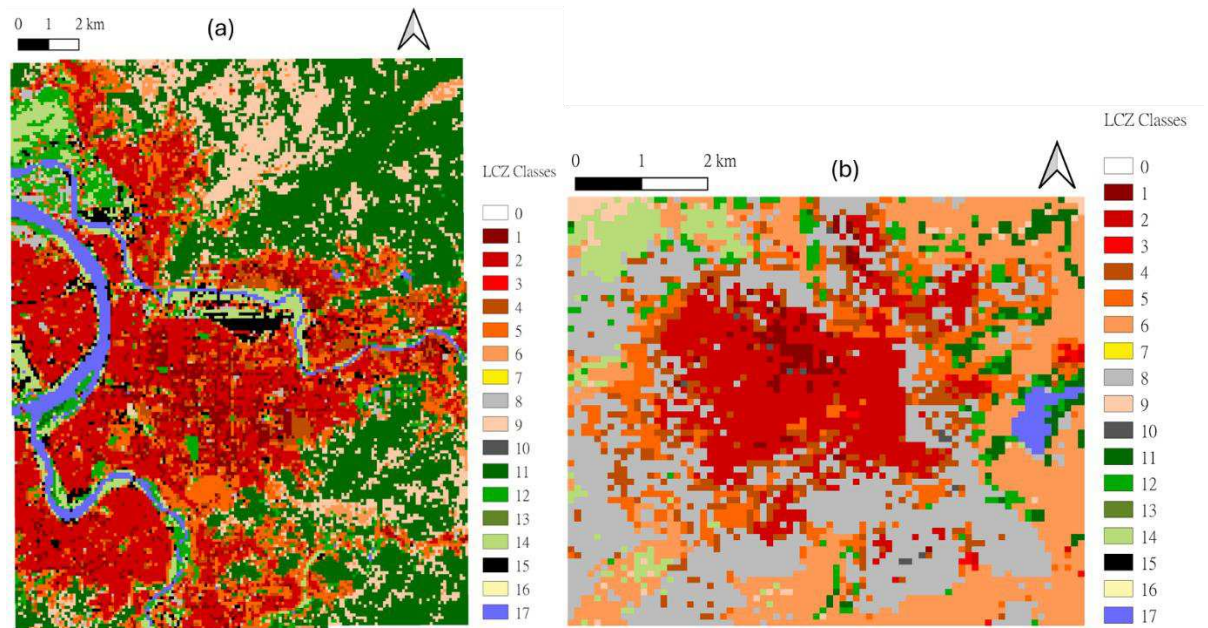


Fig 2. LCZ maps of (a) Downtown Taipei City and (b) Chiayi City.

Table 1. Descriptions of LCZ classes.

#	Colors	Description	#	Colors	Description
1		Compact high-rise	10		Heavy industry
2		Compact mid-rise	11		Dense trees
3		Compact low-rise	12		Scatter trees
4		Open high-rise	13		Bush, scrubs
5		Open mid-rise	14		Low plants
6		Open low-rise	15		Bare rock or paved
7		Lightweight low-rise	16		Bare soil or sand
8		Large low-rise	17		Water

9		Sparsely built	0		No Data
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2.2. Carbon sink calculation

Before the calculation of CS_v, the vegetation models within research areas were required. Therefore, this study generated the 3D vegetation models using SPOT 6 images and K-means clustering (Lau and Lin 2024b). First, SPOT 6 images were obtained, and pansharpened to generate an image with higher spatial and spectral resolution (Yuan et al. 2018). The process of pan-sharpening combines panchromatic and multispectral images to generate a new image with higher spatial and spectral resolution, enabling land surface observation and classification in detail (Yuan et al., 2018). After the above pan-sharpening, an image with a spatial resolution of 1.5 m was generated. Then, the maps of the Normalized Difference Vegetation Index (NDVI) were calculated based on the above pan-sharpened images. After that, pixels from pan-sharpened images with an NDVI threshold of 0.3 were kept (El-Gammal et al. 2014), and further clustered using K-means Clustering. 5 clusters were obtained, and clusters of tree canopy were manually selected. Finally, the tree canopy segmentation results were overlapped with the ETH Global Sentinel-2 10-m Canopy Height map (Lang et al. 2023), to complete the 3D vegetation models within the research areas. The above method was proposed in the previous studies, and regarded as effective and accurate for 3D vegetation modeling. Therefore, it was applied in this study to model the vegetation distribution within research areas.

According to the above 3D vegetation model, the CS_v was calculated based on the references from the green building guideline in Taiwan. From the above guideline, there are different carbon sequestration abilities for different vegetations, and the details are shown in Table 2 (Lin 2015). Based on the above references, the CS_v of each grid within research areas can be calculated as follows:

$$CS_v = A_{BT} * 1.75 + A_{ST} * 0.83 + A_s * 0.5 + A_{GF} * 0.35$$

Where ABT = area of big tree canopy, AST= area of small tree canopy, A_s = area of shrubs, and AGF= area of green fields. The area of vegetation types will be categorized from the 3D vegetation model based on the thresholds in Table 2. Therefore, the CS_v distribution of downtown Taipei City and Chiayi City was calculated based on the above processes. The above processes were conducted using QGIS, including the 3D vegetation modeling and CS_v calculation.

Table 2. Carbon sequestration abilities for vegetations provided by the Taiwan green building guideline.

Vegetation types	Threshold	Carbon sequestration (kgCO ₂ e/m ² /yr)
Big trees (Neem, Eggplant, etc...)	Height > 10 m	1.75
Small trees (Abel, Soapberry, etc...)	10 m > Height > 1 m	0.83
Shrubs	1 m > Height > 0 m	0.5
Green fields	Height < 1 m	0.35

2.3. Convolutional Neural Network (CNN)

CNN was not only applied in this study to understand the patterns of LCZ, and their impacts on CSv but also to build a simple forecasting method for urban CSv estimation. CNN was widely applied to pattern recognition in different fields, such as environmental studies and robotic systems (Zhao et al. 2018; Nagi et al. 2012). CNN was also applied in urban studies, including land cover change monitoring and LCZ pattern analysis (Zhang et al. 2019). Therefore, CNN was used in this study to help understand the relationship between CSv and LCZ and to further build a simple model for CSv forecasting based on the LCZ map. A general CNN model was structured and used in this study, which contained 4 convolutional layers, 4 pooling layers, and 1 flattened layer, as shown in Fig 3 (LeCun et al. 1998). Before the training process of the CNN, the spatial resolution of the LCZ maps was first resampled from 100 m to 10 m. Then, the LCZ maps were divided into images with a size of $(50 \times 50 \times 1)$ and inputted into the CNN model for training after removing the scattered data. Therefore, the CNN model was trained to estimate the CSv within a grid with size of 2,500 m². Furthermore, the CNN models for downtown Taipei City and Chiayi City were trained with sampling percentages ranging from 50% to 80%, respectively. The above models were trained with 100 epochs, and with a loss function of Mean Absolute Error (MAE) and the Adam optimizer with a learning rate of 0.001. After the training processes, the R² score and MAE during the testing processes will be calculated, to assess the performance of the above models. In general, R² scores of 0.25, 0.50, and 0.75 indicate that the model explains the dataset weakly, moderately, or strongly (Henseler 2017). And the MAE presents the difference between the model's prediction and ground truth. Moreover, the datasets of downtown Taipei City and Chiayi City were further tested using the CNN models trained with the dataset of Chiayi City and downtown Taipei City, respectively, to assess the applicability of the above models.

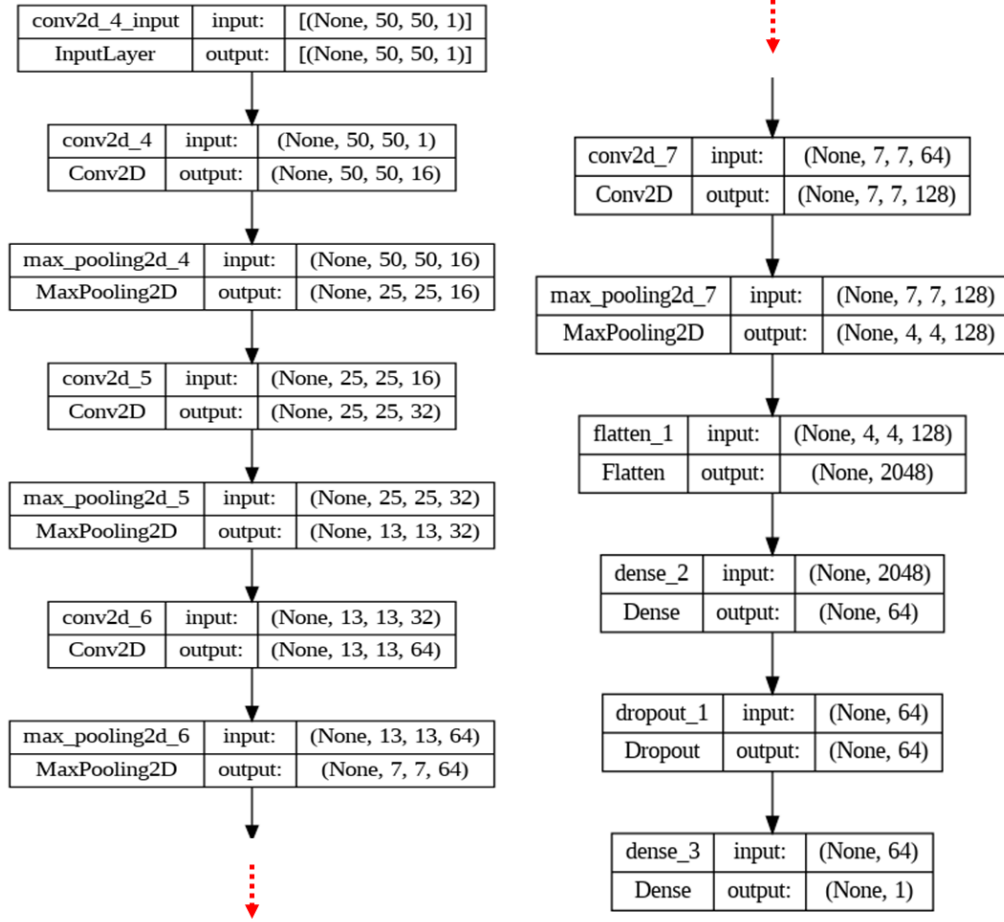


Fig 3. The CNN model structured and used in this study.

2.4. Correlation analysis

Although the indices of R^2 score and MAE finely assessed the coefficient of determination and the errors made by the CNN models, further analysis was conducted to examine the correlation between observed datasets and the CNN predictions. This is necessary to determine whether high prediction accuracy, as indicated by R^2 and MAE, also reflected a consistent structural similarity or linear relationship between the data. Models may make errors while failing to capture the true pattern or trend of the target data, especially when facing biases or systematic deviations. Therefore, cosine similarity and Pearson correlation were applied to assess the level of alignment between the observed and predicted values, as well as the mutual resemblance across different regions (e.g., Taipei vs. Chiayi). In summary, 4 groups of data were assessed using the above-mentioned methods, including “Taipei_observed vs Chiayi_observed”,

“Taipei_observed vs Taipei_CNN”, “Chiayi_observed vs Chiayi_CNN”, and “Taipei_CNN vs Chiayi_CNN”. The groups were selected to present the correlation between observed datasets and predictions. Cosine similarity is a metric that is widely used for similarity assessment, which is generally based on Bhattacharya’s distance, and focuses on orientation (Bhattacharya, 1946; Ye, 2011). It is also a widely applied metric in vector similarity assessment. Cosine similarity ranged from -1 to 1, mostly between 0 to 1. When cosine similarity is near 1, it presents a highly similar orientation. By contrast, when cosine similarity is near 0, it presents less similarity, presenting the data are nearly perpendicular to each other. The cosine similarity can be calculated as

$$\text{below: cosine similarity} = \frac{\sum_{i=1}^n A_i * B_i}{\sqrt{\sum_{i=1}^n A_i^2} * \sqrt{\sum_{i=1}^n B_i^2}}$$

Where A_i and B_i are the i elements in vectors A and B , n is the dimension of vector.

On the other hand, Pearson correlation is another well-known metrics that present the strength and direction of a linear relationship between two vectors, which is widely applied in numerous statistical tasks, such as data analysis, classification, and clustering (Zhou et al., 2016). In general, Pearson correlation ranged from -1 to 1. A Pearson correlation coefficient greater than or less than 0 indicates a positive or negative correlation, respectively, and a coefficient equal to 0 indicates that there is no linear correlation between the two vectors. The above coefficient can be calculated as below:

$$\text{Pearson correlation coefficient} = \frac{\sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^n (X_i - \bar{X})^2} * \sqrt{\sum_{i=1}^n (Y_i - \bar{Y})^2}}$$

Where X_i and Y_i are the i sample in vector X and Y , $\bar{X}$ and $\bar{Y}$ are the mean values in vector X and Y , and n is the amount of data in vectors.

3. Results

3.1. Vegetation-based carbon sink in Taipei and Chiayi cities

With the preprocessed 3D vegetation models, the CSv distribution in downtown Taipei City and Chiayi City was calculated and shown in Fig 4. For better understanding, the same legend for the CSv range was applied. For downtown Taipei City, the CSv ranged from 0 to 12,202 kgCO₂e/yr. Most of the grids with higher CSv are distributed outside Taipei City, consistent with the distribution of natural landscape LCZ classes, such as LCZ 11, 12, and 14. Within the built area, green spaces with larger areas provided more CSv, like Da’an Park and 228 Park. For Chiayi City, the CSv ranged from 0 to 40,776

kgCO₂e/yr. Grids with higher CSv are distributed outside Chiayi City, surrounding the built area. Combined with the LCZ map, most of the grids with higher CSv have an LCZ class of LCZ 2, 5, 6, and 8, which were different from downtown Taipei City's results. However, after the above calculation, the CSv maps were resampled to a spatial resolution of 500 m, for the subsequent analysis using CNN. As shown in Fig 4, the resampled maps of C_sv have a relatively rough presentation but are still able to observe the distribution of CSv within the research areas. For better understanding, the unit of the maps was changed to 1000 kgCO₂e/yr. After that, the CSv maps of downtown Taipei City and Chiayi City ranged from 19,300 to 303,000 kgCO₂e/yr and 3,570 to 507,350 kgCO₂e/yr, respectively. The distribution of CSv was similar to the maps with a spatial resolution of 100 m, which did not affect the observation of CSv. Therefore, the resampled maps were further applied to the subsequent analysis.

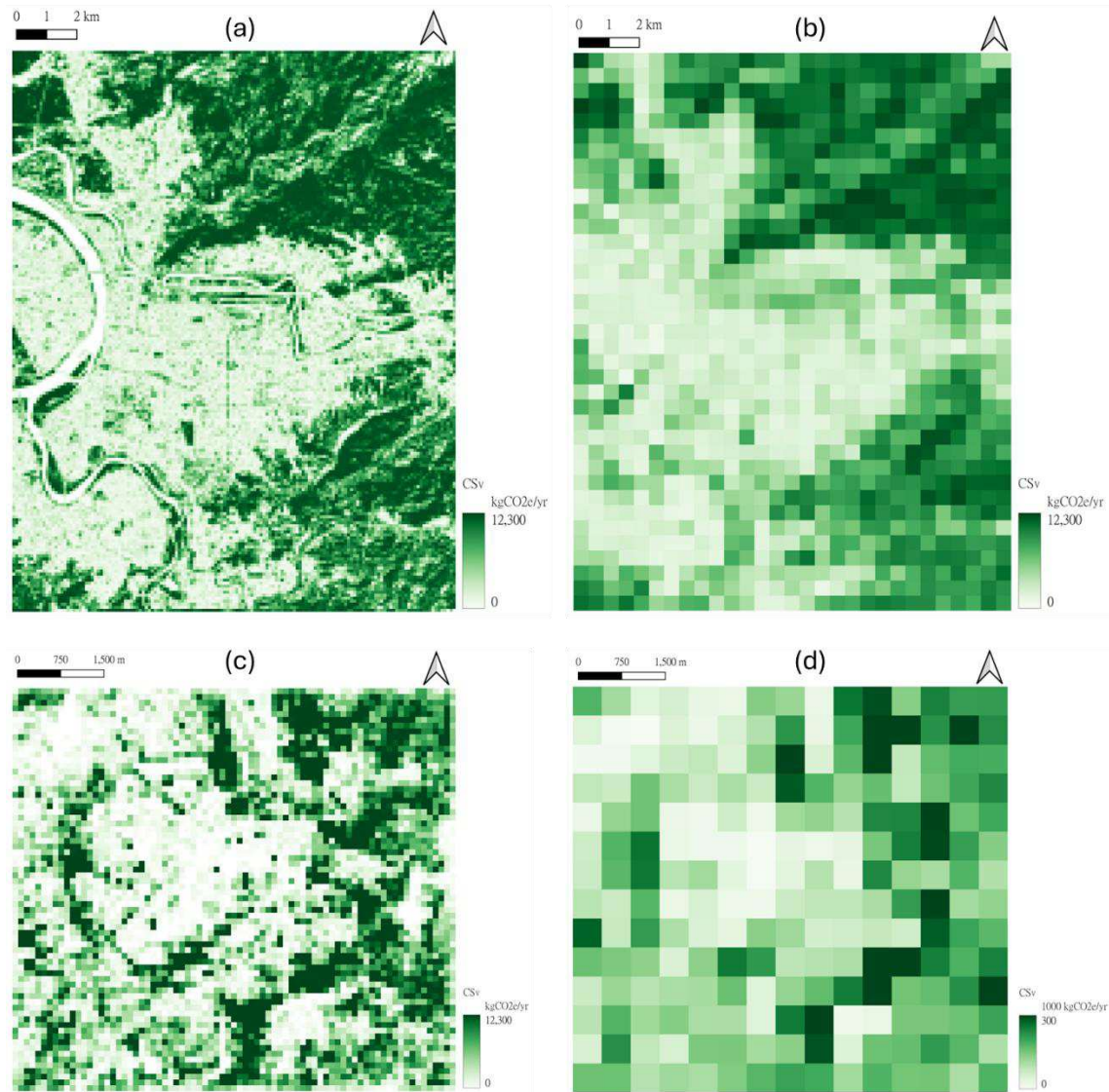


Fig 4. CSv maps in downtown Taipei City with grid size of (a) 100 m and (b) 500 m, and in Chiayi City with grid size of (c) 100 m, and (d) 500 m.

3.2. CNN performance of Carbon sink estimation

To develop a simple method for CSv estimation within cities, CNN was applied in this study, which was well-trained with two datasets. The results are shown in Table 3. From Table 3, the CNN models finely performed with a dataset of downtown Taipei City, which explained the testing and whole datasets strongly with an R2 score over 0.75. The CNN models also achieved a low MAE with datasets of downtown Taipei City, which was lower than 30 units. However, the R2 score of the above CNN models decreased with the decreasing sampling percentage, but still acceptably and flexibly performed. On the other hand, the CNN models performed badly with a dataset of Chiayi City, which has a low R2 score with testing datasets. Although the above CNN models have a positive R2 score with the whole dataset of Chiayi City, the R2 scores were similar to the sampling percentage, which presented that the models were not able to face any strange dataset. Moreover, the CNN models trained with Chiayi City datasets also have a relatively high MAE in different datasets compared to the CNN models trained with downtown Taipei City datasets, which presents lower applicability and feasibility. Furthermore, all of the above models have a low R2 score and high MAE when facing strange datasets, especially the Chiayi City models. Although the R2 scores of the downtown Taipei City model were low when facing the strange datasets, the R2 score increased with the decreasing sampling percentage, which presenting the fewer samples provided higher flexibility for the models. However, there are different performances made by the downtown Taipei City and Chiayi City models, which makes it hard to determine the feasibility and applicability of the proposed method. Therefore, further analysis will be subsequently discussed.

Table 3. CNN models performance in datasets of downtown Taipei City and Chiayi City

Sampling		R2 score			MAE (1000 kgCO2e/yr)		
Taipei	Testing dataset	Whole dataset	Strange dataset	Testing dataset	Whole dataset	Strange dataset	
80%	0.803	0.908	0.083	26.23	18.56	60.81	
70%	0.792	0.909	0.117	27.63	18.01	59.74	
60%	0.802	0.904	0.198	26.83	18.16	56.60	
50%	0.755	0.868	0.105	29.72	23.27	60.99	
Chiayi							
80%	-0.170	0.838	-0.468	51.89	23.62	78.60	
70%	-0.587	0.592	-0.936	63.86	40.27	87.66	
60%	-1.483	0.418	0.218	69.56	50.61	60.60	
50%	-0.429	0.505	0.049	63.26	45.22	65.16	

3.3. Correlation analysis

In addition to the prediction performance, the correlation analyses were conducted to further investigate the relationships between the datasets and the CNN model predictions. Cosine similarity and Pearson correlation coefficient were calculated based on the 4 groups of comparison, including “Taipei_observed vs Chiayi_observed”, “Taipei_observed vs Taipei_CNN”, “Chiayi_observed vs Chiayi_CNN”, and “Taipei_CNN vs Chiayi_CNN”, and the results are shown in Table 4. From Table 4, the relatively high correlation in groups “Taipei_observed vs Taipei_CNN” and “Chiayi_observed vs Chiayi_CNN” can be observed, which indicates that the CNN models learnt the relationship between LCZ patterns and CSv very well, especially in Taipei City. Although the CNN models demonstrated the capability to capture the spatial distribution trends of CSv associated with LCZ patterns, the relatively high MAE and low R2 score present that the predictions may have deviated from the actual magnitudes. This phenomenon could result from systematic bias in the model outputs, where predictions consistently over- or under-estimated the observed values, or from a scale mismatch between the predicted and observed datasets. In particular, the dataset of Chiayi City might have featured more heterogeneous or less representative samples, making it more challenging for the model to generalize accurately across all LCZ classes. Overall, the CNN models comprehensively learnt the relationship between CSv and LCZ patterns, which are highly correlated. However, bias and noise may seriously affect the performance of CSv prediction, especially in Chiayi City, which has fewer representative features. On the other hand, city-based comparisons were conducted to investigate the relationship between CSv and LCZ patterns observed and predicted in the two different cities. From Table 4, the low values of correlation from groups “Taipei_observed vs Chiayi_observed” and “Taipei_CNN vs Chiayi_CNN” were presented. The results showed that the observations in Taipei City and Chiayi City have low correlation, which explains the bad performance of the CNN models when they are dealing with strange datasets. The results presented that Taipei City and Chiayi City have different spatial patterns of CSv values, which may be caused by the different kinds of urban structures, land use patterns, and other socioeconomic conditions. The results also indicated that the CNN models were able to learn the distinct relationships between CSv and LCZ patterns specific to each city, rather than overfitting to a generalized pattern. This demonstrates the models’ high sensitivity to spatial heterogeneity and pattern variations across different urban environments.

Table 4. Statistical analysis using cosine similarity and Pearson Correlation

Group	Cosine Similarity	Pearson Correlation
Taipei_observed vs Chiayi_observed	0.181	0.035
Taipei_observed vs Taipei_CNN	0.999	p-value: 0.894
Chiayi_observed vs Chiayi_CNN	0.881	0.999
		p-value: 0
		0.852

		p-value: 0
Taipei_CNN vs Chiayi_CNN	0.168	-0.005
		p-value: 0.983

4. Discussions

4.1. Relationship between CSv and LCZs

To analyze the impact of LCZ on CSv, grids with relatively high CSv were further selected and analyzed. Grids with CSv greater than the upper quartile (top 25%) were selected, including CSv information and LCZ patterns. The number of each LCZs in the above grids were counted and the proportions of each LCZ were analyzed. The above processes were conducted with the datasets of downtown Taipei City and Chiayi City, and the results are shown in Fig 5. The observation results in Taipei City and Chiayi City were presented in blue and green colors, respectively. And the CNN prediction results in Taipei City and Chiayi City were presented in orange and red colors, respectively. From Fig 5, the impacts of each LCZ on CSv were presented. In downtown Taipei, LCZ 11 has the greatest impact on higher CSv, with the number of pixels exceeding 60% of the total. Followed by LCZ 9, 12, 14, 6, and 5, accounting for approximately 25.8%, 3.3%, 2.6%, 2.4% and 1.5% respectively. A similar trend was learned by the CNN models, resulting in the greatest impact of LCZ 11 on CSv, with the number of pixels about 68.8%. The following are LCZ 9, 6, 12, 14, and 5, with percentages of approximately 26.0%, 1.9%, 1.6%, 0.6%, and 0.6%, respectively. The trends by observation and CNN learning are slightly different, but both determine the greater importance of LCZ 11, 9, 6, 12, 14, and 5 on CSv. On the other hand, the trend observed from Chiayi City was different. The LCZ 6 has the biggest impact on CSv, with pixels of about 34.8%. Followed by LCZ 8, 5, 4, and 11, with pixel counts of about 23.3%, 15.2%, 6.6% and 6.6%, respectively. The above results show that low-rise built-up areas have a greater impact on CSv compared to natural landscapes, which is not reliable (Fan and Wei 2022). However, a similar trend was learned by the CNN model, which regarded the biggest impact of LCZ 6 on CSv, with a pixel count of about 53.0%. The following are LCZ 14, 8, 5, and 11, with pixels counting 10.6%, 10.3%, 7.6%, and 6.3%, respectively. However, according to the unreliable trend observed, the CNN model trained with the Chiayi City dataset was also regarded as unreliable and not applicable. Therefore, the CNN model trained with the downtown Taipei City dataset was used for the subsequent analysis and discussions.

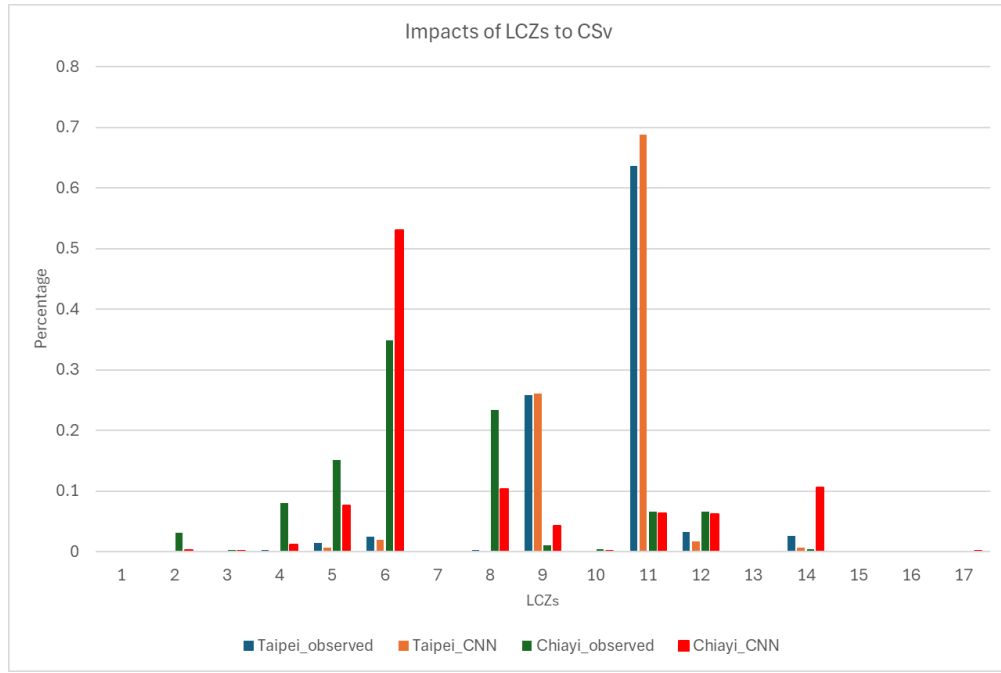


Fig 5. Impacts of LCZs on CSv.

According to the above analysis, the built environments of LCZ 5, 6, and 9 have a high potential for CSv contribution. The results showed the lower rise and density of buildings allow vegetation to grow healthy and efficiently. A similar phenomenon can be found in previous studies, which presented the impact of urbanization on the growth of vegetation (Tan and Ismail 2014). In addition, the higher potential of CSv contribution may also benefit from the lower intensity of urbanization because there are more spaces for crown development, which is important, especially for the street trees (Sæbø et al. 2005). However, the results showed that LCZ 11 and 12 also have a high potential for CSv contribution, which represents the forests within cities. Although forest is important in CSv, grassland is more flexible and reliable in different conditions, which can provide steady CSv in general (Dass et al. 2018). Therefore, the LCZ 14 is also playing a critical role in CSv within cities. Overall, the above results can be a reference to urban planning works in the future, to ensure a relatively high level of CSv while developing.

4.2. CNN predictions performance

According to the higher feasibility and applicability of the CNN model trained with the downtown Taipei City dataset with 60% sampling, it was applied to the discussions in this study. The above CNN model was applied to estimate the CSv within downtown Taipei City and Chiayi City, respectively. The misjudgments were shown in Fig 6 and further discussed. For predictions in downtown Taipei City, under- and over-estimation over 30,000 kgCO₂e/yr were labeled and shown in Fig 6. First, the CNN model performed fine in most of the built-up area, resulting in a low MAE. Moreover, misjudgments can be easily observed in the forests within mountains surrounding downtown Taipei City, which may be affected by the complicated scenarios of vegetation. However, the natural forests usually have a good potential in CSv, which is determined in previous studies (Favero et al. 2020) and can be omitted in the

CSv estimation within cities. Furthermore, under- and over-estimation can be observed in the urban park or forestry and the water bodies, respectively. For the over-estimations found in the water bodies, they could be affected by the less consideration of carbon sink from water. On the other hand, there are several issues that may cause the underestimation of CSv in urban parks and forestry. First, the misclassified LCZ classes may seriously affect the learning process of the CNN model, which may cause the misjudgment of CSv (Xia et al. 2022). Furthermore, the spatial resolution of the LCZ map may not be detailed enough to describe the vegetation distribution within cities, which quantified the urban environment to a few classes of LCZ. However, the proposed method was developed to simplify the estimation of CSv, which should balance the cost of urban modeling and estimation performance. Finally, although the grids in this study gridded objectively based on the coordinates of research areas, the gridding method may seriously affect the performance of CSv estimation, which should be further considered in the future.

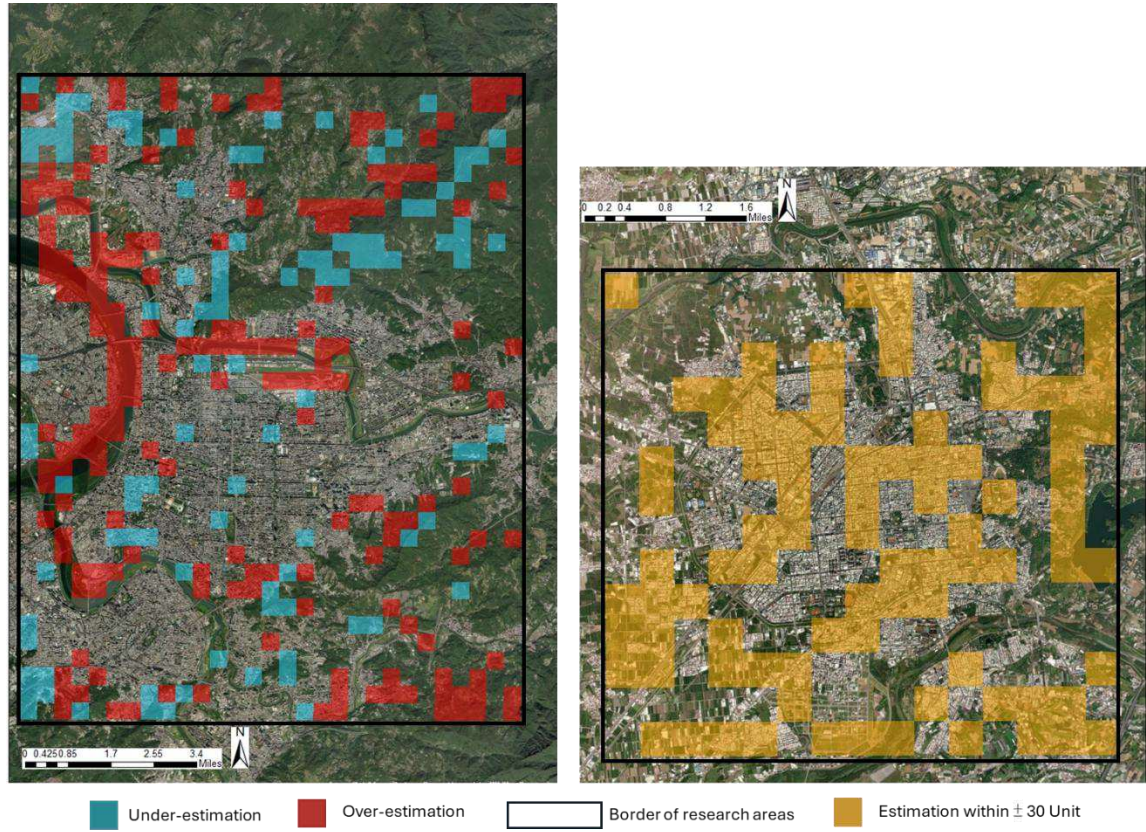


Fig 6. Misjudgments made in downtown Taipei City and predictions with low error made in Chiayi City by the CNN model (Basemap: World imagery from ArcGIS)

For the CSv estimation in Chiayi City using the CNN model, the predictions with MAE lower than 30,000 kgCO₂e/yr were labeled, as shown in Fig 6. Similar to the predictions in downtown Taipei City, most of the CSv within built-up areas were accurately predicted. Although almost 40% of areas have a fine CSv estimation, the errors in other areas were big, resulting in a low R² score and high MAE.

Therefore, the causes of misjudgments in Chiayi City were further investigated. As shown in Fig 7, there are some misclassifications in the LCZ map of Chiayi City. First, region 1 showed the areas of natural landscapes were classified to LCZ 5, 8, and 9, which caused the higher importance of LCZ 5, 6, and 8 to CSv in Fig 6. The CNN models learned the above relationship and then resulted in a bad performance in CSv estimation with a low R2 score and high MAE. Furthermore, regions 2 and 3 showed the misclassifications of urban parks and forestry from the LCZ map, which mainly classified LCZ 2, 4, and 8. The less accurate performance of classification could be affected by the spatial resolution and mixed pixels of satellite images (Foody 1996), and the misclassification may lead to the wrong direction of analysis. Although the LCZ maps that are available to download and use can conveniently help in related studies, the accuracy of classification should be further validated. However, the LCZ map was generated by a subjective artificial interpretation method, which often leads to biases of errors in the classification results. Therefore, the LCZ map should be carefully generated with experts that well-trained and have a good understanding of the local environment (Shi et al. 2018). Overall, the above CNN model was regarded as an efficient and effective approach for understanding the relationship between CSv and LCZ groups, and also a convenient tool for simple CSv estimation within cities, provided that a complete and accurate LCZ map is ensured. The proposed CNN model in this study reached a high R2 score and low MAE in the downtown dataset and finely performed in almost 40% of grids within the Chiayi dataset. Most of the errors were caused by the misclassification of the LCZ map, which should be further corrected and improved in the future. Finally, the feasibility and applicability of the proposed CNN model were determined, which can help to easily estimate the CSv within cities based on the LCZ map.

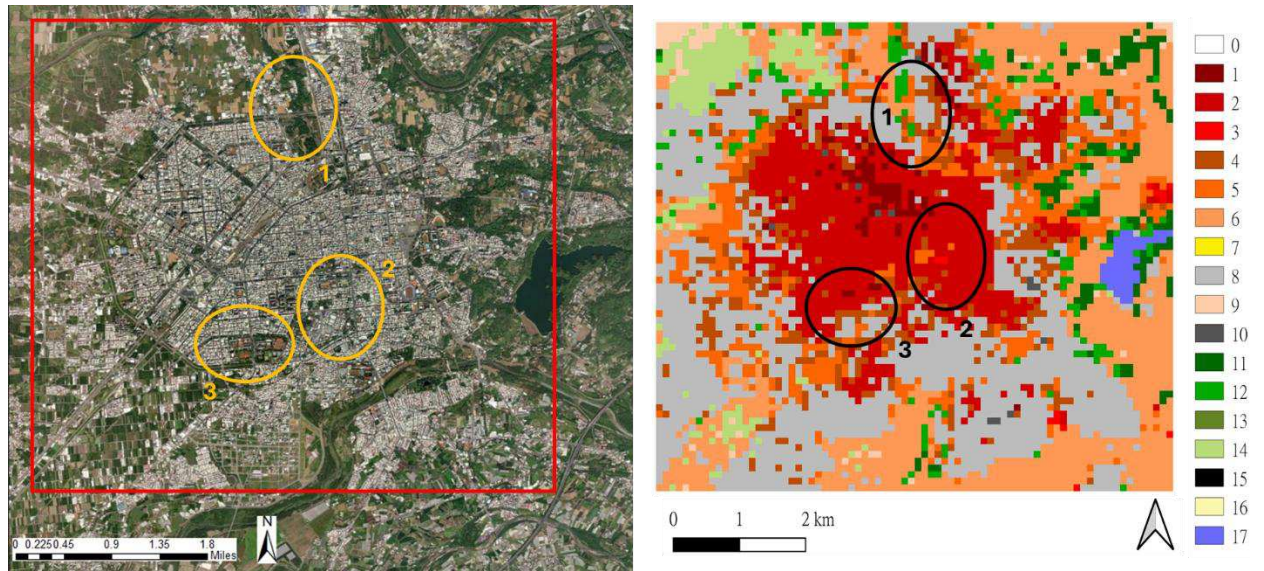


Fig 7. Comparison between satellite image (basemap from ArcGIS) and LCZ map in Chiayi City. (Red boundary: research area of Chiayi City)

4.3. Comparison with related studies

This study proposed a novel use of LCZ, which has been applied to CSv estimation in cities. To describe the novelty in this study, comparative analyses are required. Therefore, this study is going to discuss the novelty of this study in two ways: typical uses of LCZ and CSv estimation.

As mentioned before, LCZ is an approach that developed to quantify urban form in 17 classes, which has been widely applied in urban studies. In general, LCZ was commonly used in urban climate-related studies, such as modeling urban thermal environment, urban ventilation, and relationships between landscapes and climate conditions (Chen et al., 2017; Zhao et al., 2020). Although some studies discussed about the relationship between LCZ classes and carbon emissions, relevant innovations are lacking nowadays (Chen et al., 2024). This study proposed a new method to conveniently and accurately estimate CSv in a city using LCZ and CNN, which may help the sustainable development in the future. Moreover, the relationship between LCZ classes and CSv was determined, and the findings can be a good reference to the urban planning in future. Overall, this study proposed a novel use of LCZ, which presented that LCZ has a great potential in urban studies by quantifying urban conditions for different subsequent analyses.

On the other hand, this study proposed a new method for CSv estimation in a city. To compare the performance of CSv estimation in different studies, remote sensing-based carbon sink assessments were referred, since LCZ is an approach that based on satellite imageries. Although different studies have controversial views in carbon sink estimation, the findings in previous studies determined the effectiveness of remote sensing and ML, and they have been widely applied to the relevant research. Most of the previous studies assessed carbon sink based on the single pixel (grid) with values of NDVI, Enhanced Vegetation Index (EVI), and other indices (González-Alonso et al., 2006; Dai et al., 2020). After that, recent studies further considered about the geospatial pattern of landscape, to enhance the performance of carbon sink assessment, including the urban green spaces spatial structure and landscape morphology (Cui et al., 2024; Li et al., 2024). Unlike previous studies, this study proposed a method that requires lower quality of satellite imagery and urban information, which quantifies urban conditions using LCZ. After that, the grids with urban form generated with LCZs will be analyzed using CNN. The proposed method may lower the difficulties of CSv estimation due to the lower requirements of datasets, which may make CSv estimation become more convenient, efficient, and cost effective.

4.4. Limitations and suggestions

This study analyzed the relationship between CSv and LCZ by statistics and the CNN model, respectively. Furthermore, a simple method for CSv estimation within cities was proposed. Although the feasibility and applicability were determined, there are some limitations that should be discussed, and related improvement and enhancement should be suggested. First, as mentioned before, the analysis of the relationship between LCZ and CSv was limited by the accuracy of the LCZ map. The misclassification may cause the wrong analysis and further estimation of the CSv. Therefore, the LCZ

map is suggested to be generated, sampled, and classified with the local experts, who have an excellent understanding of the research areas. And different LCZ maps of research areas should be generated separately with their own sampling dataset, to ensure the LCZ map will not be affected by the subjective opinions of other experts. After that, the spatial resolution of satellite imageries limited the classification results of LCZ maps, which may omit and misclassify the land cover type, such as omitting the urban park and urban forestry. Therefore, satellite imagery with relatively high spatial resolution is recommended for use for land surface observation, and other quantification methods of land surface characteristics can be considered, such as the combination of remote sensing products and ML algorithms and remote sensing indexes-based methods (Phan et al. 2021; Woldegebriel Tessema and Girma Abebe 2023). Moreover, the gridding method was also mentioned and should be improved in the future although this study objectively gridded based on the coordinates. Sensitivity tests can be further conducted to identify the spatial resolution and grid location for LCZ classification (Zheng et al. 2018). In addition, more factors should be further considered in the future, including climate and terrain conditions, which may seriously affect the capacity of CSv (Feng et al., 2023; Zhou et al., 2022). For example, CSv may have different correlation with air temperature and relative humidity in different areas, and it could be affected by climate changes and human activities. Therefore, it is important to enhance the related estimation approach by considering more factors and aspects. Finally, more ML algorithms can be tested and applied to understand the relationship between LCZ and CSv, such as Long Short-Term Memory (LSTMs) and Transformer (Zhou et al. 2019; Qing et al. 2021).

5. Conclusions

In summary, this study proposed a new method for CSv estimation within cities using LCZ and CNN. This is a cost-effective and efficient method for CSv estimation compared with previous studies, which does not require vegetation information and digital models in detail. Unlike previous LCZ applications, this study quantified urban environments using LCZ to understand the relationship between CSv and LCZ classes. Additionally, this study determined the relationship between CSv and LCZ classes in the two research areas, Taipei City and Chiayi City. Natural landscapes of LCZ 11, 12, and 14 have a relatively high potential of contributing to CSv, which has been presented in the results. Built environments of LCZ 5, 6, and 9 also have a high potential of contributing to CSv, presenting more open areas and vegetation within cities may enhance the capacity of CSv within cities. On the other hand, the CNN models applied in this study perfectly learnt the relationship between CSv and LCZ classes within the two research areas, according to the high correlation coefficients. However, a low correlation between Taipei City and Chiayi City has been observed, which explains the bad performance of CNN models when dealing with strange datasets. Therefore, a local and specific CSv estimation model is recommended for each city in the future. Moreover, the CNN models in Taipei City made predictions with high correlation coefficient, high R² score, and low MAE compared with the observed data, which presented the feasibility and reliability of the proposed method. By contrast, although the high correlation

between the prediction from CNN models and observed data in Chiayi City was determined, a relatively low R2 score and high MAE were made by the CNN model. This may be caused by the systematic bias and scale mismatch. Therefore, hyperparameter optimization for CNN models and gridding methods were recommended to be tested in the future, to enhance the performance of prediction in CSv within cities. Overall, the results presented that the CNN models were able to comprehensively learn the relationship between CSv and the urban environment through LCZ patterns. This study provided a novel way for CSv estimation within cities, which is cost-effective and efficient, since CSv estimation is important in carbon emission reduction.

Statements and Declarations

Ethics approval and consent to participate

Not applicable

Consent for publication

Not applicable

Availability of data and material

The datasets used and/or analyzed during the current study available from the corresponding author on reasonable request.

Competing interests

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

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Authors' contributions

Tsz-Kin Lau was responsible to the works of formal analysis, data collection, data visualization, manuscript drafting and editing; Li-Tzu Yu was responsible to the works of formal analysis and data visualization; Tzu-Ping Lin was responsible to the works of supervision and manuscript editing.

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