Evaluating the Accuracy of Different Local Climate Zone Maps

Ahmed Samed Akbulut [1], Elif Sertel [1]

[1] ITU, Civil Eng. Fac, Geomatics Eng. Dept., Maslak Istanbul, Turkey - (akbuluta18, sertele)@itu.edu.tr

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Abstract

Local Climate Zones (LCZs) are essential for understanding urban climates, providing crucial information for urban planning, environmental monitoring, and addressing challenges like the urban heat island effect. This study evaluates the accuracy of various LCZ maps, including those from the World Urban Database and Access Portal Tools (WUDAPT), and two independent studies by Demuzere et al. (2022) and Oliveira et al. (2020). Our analysis focuses on five major cities: Istanbul, Athens, Barcelona, Lisbon, and Paris, and explores how geographic, historical, and urban planning factors influence both LCZ classifications and their accuracy. We identify and analyze misclassifications within these maps, investigating the root causes of errors, such as misaligned or insufficient sample data, low spatial resolution of input images and inadequate vector data. Our results reveals that while LCZ maps generally perform well in certain urban settings, their accuracy diminishes in more complex or heterogeneous environments. The findings underscore the importance of refining data quality, classification methods, and spatial resolution to improve the reliability of LCZ maps, offering valuable insights for urban and regional planning, environmental management, and future research on urban climate dynamics.

1. Introduction

According to the United Nations Department of Economic and Social Affairs, nearly 70% of the global population is expected to reside in urban areas by 2050. The landscape characteristics of urban and surrounding regions have been undergoing significant changes due to population growth driven by industrialization, migration, and socio-economic factors. These transformations primarily include urban expansion, the loss of agricultural and green spaces, and deforestation, all of which have adverse effects on both the environment and the climate (Varol et al., 2023; Kabadayı et al, 2022).

Remote sensing data and methods provide crucial information for addressing the negative effects of climate change such as Urban Heat Island (UHI) and global warming. In this context, the Local Climate Zone (LCZ) framework, which classifies areas based on factors such as building types, meteorological conditions, and surface characteristics has become a critical approach. To better understand Urban Heat Islands and standardize urban temperature observations on a global scale, Stewart and Oke highlighted the need for a new LCZ classification system considering the factors such as vegetation cover, building density and construction materials (Stewart & Oke, 2012) . Figure 1 depicts the LCZ categories.

The concept of Local Climate Zones (LCZs), as introduced by Stewart and Oke in 2012, provides a standardized classification system for urban and rural areas based on their climate characteristics. LCZ categorize areas considering both physical properties (e.g., surface cover, building types) and their local climate conditions (e.g., temperature, humidity). In addition to enhancing climate modeling and urban planning, LCZs help to better understand urban climates.

The classification system divides the areas into 17 main classes, divided into 3 broad categories: ‘Urban Areas’ (e.g., dense residential, commercial, or industrial zones with specific surface types like concrete, asphalt, and buildings), ‘Rural and SemiRural Areas’ (e.g., agricultural zones, forests, grasslands) and ‘Water Bodies’ (e.g., lakes, rivers).

Each LCZ is determined by a combination of elements such as: ‘Surface Cover’ (e.g., vegetation, impervious surfaces), ‘Building Morphology’ (e.g., height, density) and ‘Human Activity’ (e.g., heat emissions from buildings, traffic).

The LCZ system makes it easier to compare the impact of different environments on local climates and supports urban climate research and heat island effect studies.

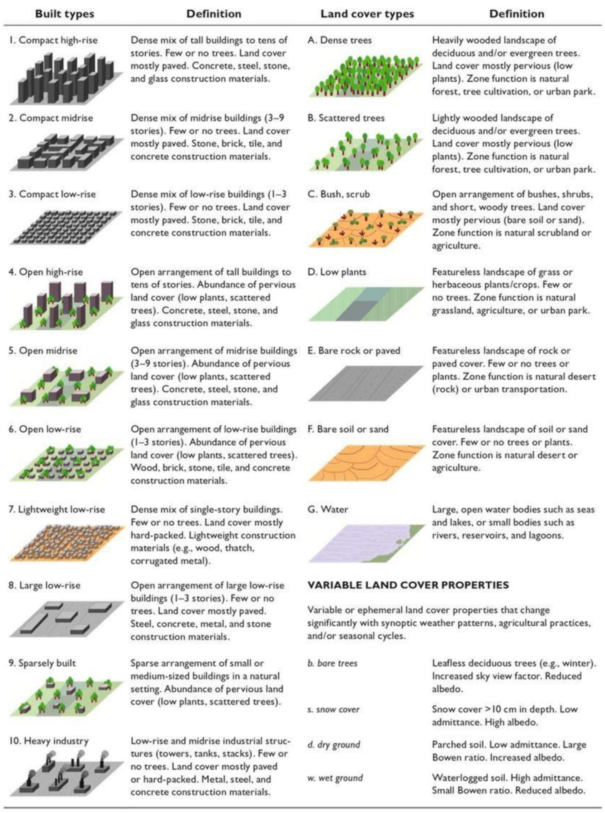

Figure 1. Local Climate Zones (Stewart and Oke, 2012).

In this study, we aim to assess the accuracy of various Local Climate Zone (LCZ) maps, including the World Urban Database and Access Portal Tools (WUDAPT), So2Sat LCZ42, data from the study by Demuzere et al. (2022), and data from the study by Oliveira et al. (2020). Our analysis focused on five selected cities:

Istanbul, Athens, Barcelona, Lisbon, and Paris. Additionally, we compared the landscape characteristics of these cities and examined the resulting accuracy values. Our analysis provided valuable insights into how geographical, historical, and urban planning factors influence both local climate zones and the reliability of LCZ classifications in different urban settings.

2. Study Area

This study focuses on comparing the classification accuracy values of Local Climate Zone (LCZ) maps for Istanbul, Athens, Barcelona, Lisbon, and Paris, aiming to assess how accurately different urban forms and geographical settings are represented by LCZ maps from various sources.

Figure 2. Selected cities for the research (a) Istanbul, (b) Athens, (c) Barcelona, (d) Lisbon, (e) Paris.

These cities were selected based on their distinct urban characteristics and potential similarities or contrasts with Istanbul to provide a comprehensive comparative analysis. We aim to highlight the potential microclimatic differences between Istanbul and major European urban centers and to evaluate the classification accuracy of LCZ mapping across diverse urban contexts. LCZ approach method has also been used for different cities around the world such as LCZ database produced by Bechtel et al. (2015) and global map of LCZs produced by Demuzere et al. (2022).

Istanbul is a city which connects Asia to Europe. The city has a unique characteristic with the combination of numerous water sources, complex urban environment with different microclimatic conditions and Bosporus Strait.

Athens, the capital city of Greece, is a city with rich historical background and shows the effect of Mediterranean climate. In a study conducted in 1999, it was mentioned that the effects of the Mediterranean climate were seen in the city. (Philandras et al, 1998) The urban structure of the city consists of a dense mixture of ancient monuments, modern buildings and natural green areas. The warm climate of Athens combined with its densely populated urban core presents significantly interesting microclimatic situations. The combination of historical and modern elements provides a wonderful example for LCZ classification.

Lisbon is a coastal city with a unique urban landscape, which is also the capital city of Portugal. The architectural diversity and regular city structure make it a good example to investigate. Its proximity to the Atlantic Ocean moderates the Mediterranean climate, making Lisbon an ideal location for exploring how coastal environments and complex urban forms interact in LCZ classifications. In the study conducted by Silva et al., it was emphasized that temperatures in the city exceeded 35 degrees and the UHI effect is predicted to increase until 2100. (Silva et al, 2022) For these reasons, Lisbon is one of the most suitable cities for examining LCZ maps.

Paris exhibits similar characteristic as Istanbul with the dense and historical structures and beng the city located around a massive water body (Seine River). Sarkar and De Ridder's study focused on Urban Heat Island and observed a 6 degree difference compared to rural areas. (Sarkar and Ridder, 2010) Since the UHI effect is observed very clearly in Paris, Paris is an ideal study area in this study where LCZ datasets are examined.

Barcelona is a coastal city in the northeastern Spain where rich architectural history, a diverse urban layout and Mediterranean climate stands out.

3. Dataset

This study utilized several LCZ datasets, including WUDAPT (Demuzere et al, 2019), So2Sat LCZ42 (Zhu et al, 2020), data from the 2022 study by Demuzere et al. (also available on Zenodo) (Demuzere et al, 2022), and data from the 2020 study by Oliveira et al. (Oliveira et al, 2020)

The WUDAPT data, generated by Demuzere et al. (2019), was obtained from the World Urban Database portal. In their study, Demuzere et al. (2022) used Landsat and Sentinel imagery to create 100-meter resolution LCZ data for 150 functional urban areas worldwide, including Istanbul, Athens, Barcelona, Lisbon, and Paris. Additionally, they developed an LCZ generator linked to the WUDAPT database (Demuzere et al., 2021). This generator allows users to create LCZ maps by uploading sample data, addressing the growing need for such tools in urban climate studies.

The So2Sat LCZ42 dataset, prepared by Zhu et al. (2020), was generated using SAR and multispectral satellite images along with artificial intelligence methods. It includes LCZ maps for 42 cities, including Istanbul and Paris. However, the output of this project was published in separate patches and lacked any geographic information, making the So2Sat dataset unsuitable for comparative analysis in this study, since it was not possible to generate complete city LCZ maps of the selected areas.

Oliveira et al., (2020) produced the LCZ maps of 5 major cities in Europe, including Athens, Barcelona and Lisbon using Copernicus and Landsat data. In our study, we also utilized Landsat and Sentinel-2 data, primarily for visual interpretation, to identify potential sources of error in LCZ map generation using very high-resolution Google Earth data as reference. Although the spatial resolution of Landsat and Sentinel-2 data did not meet the project’s requirements, they were useful for detecting large areas, such as croplands (classified as class 14 in LCZ). However, these images were not suitable for height determination of the buildings.

4. Methodology

The methodology of this study includes a review of existing LCZ studies for the selected study areas. The WUDAPT methodology by Mitraka et al. (2015) was considered while examining the LCZ classification methods. Next, suitable cities, available in the datasets and comparable to one another, were selected. The LCZ maps for these cities were then obtained from various data sources. Using QGIS software, Google Satellite imagery, and Sentinel-2 images from the Google Earth Engine (GEE) platform, we analyzed the spatial alignment of these datasets visually. We then generated 50x50 meter polygon grids for different LCZ classes for a quantitative analysis. Since the spatial resolution of Sentinel-2 images was insufficient for clear identification of several LCZ classes, we were predominantly used Google Satellite images for creating reference data. At least 20 samples were drawn for each class to be used for the validation. Then, we applied the Zonal Statistics tool, and the majority class for each zone was assigned to the classified column in the attribute table. To conduct accuracy assessment, a confusion matrix was created, and overall accuracy, producer accuracy, user accuracy, and the kappa coefficient were calculated based on this matrix (Varol et al., 2022). Similarly, in Sertel and Akay's study, kappa and accuracy values were calculated and a kappa coefficient of 0.932 was obtained with an overall accuracy of 95.46%. (Sertel and Akay, 2015)

The accuracy of the different LCZ maps was evaluated, and misclassified areas were identified. The errors were analyzed, and possible causes behind these errors were examined.

5. Results

The Kappa values from our accuracy assessment for the different cities and datasets are presented in Table 1.

	Wudapt	**Demuzere**	**Oliveira**	**Average**
Istanbul	0,76	0,80	-	0,78
Barcelona	0,79	0,82	0,66	0,76
Lisbon	0,82	0,79	0,72	0,77
Athens	0,80	0,74	0,53	0,69
Paris	0,71	0,62	-	0,66
Average	0,77	0,75	0,64	

Table 1. Kappa values.

The Kappa values for the Oliveira LCZ maps are the lowest compared to those of WUDAPT and Demuzere LCZ data. WUDAPT shows significantly higher Kappa values than Demuzere for Athens and Paris. While WUDAPT slightly outperformed Demuzere in Lisbon, the reverse was true for Istanbul and Barcelona.

In Oliveira's study, classes 1-2-3 and classes 4-5-6 were treated as two distinct categories, rather than as six separate classes. Classes 1-2-3 represent dense mixes of buildings constructed from stone, brick, tile, and concrete, with the primary distinction between these classes being the height of the buildings. Similarly, the only difference between classes 4-5-6 is the number of floors in the buildings. However, identifying the height (number of floors) of buildings from remotely sensed data is a challenging task. As a result, combining these classes into a single category, while overlooking the height differences, simplifies the classification process. As a result, it is expected that the Kappa value in Oliveira’s study should be higher. However, contrary to expectations, it was not higher than those of either WUDAPT or Demuzere in any of the cities.

To better understand the differences in dataset accuracy and identify the main reasons behind these variations, a class-based analysis was conducted (Figure 3). This approach allows for a more detailed evaluation of class misclassifications and provides valuable insights into the deficiencies and misclassifications within the datasets.

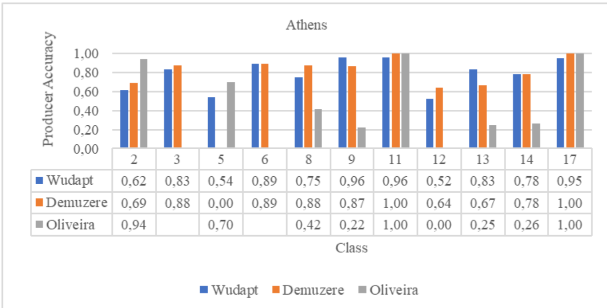

Figure 3. Producer Accuracy Values of Datasets in Athens.

Producer accuracy shows the proportion of reference data represents to a class that are correctly classified and measures the ability of the classification model by comparing the real examples. When producer accuracy values for Athens examined, it was found that Oliveira's study shows lower accuracy across most classes, particularly in classes 8, 9, 12, and 14. Following these findings, a detailed analysis was conducted using images from Google Satellite and Google Earth Engine to further investigate the relevant classes.

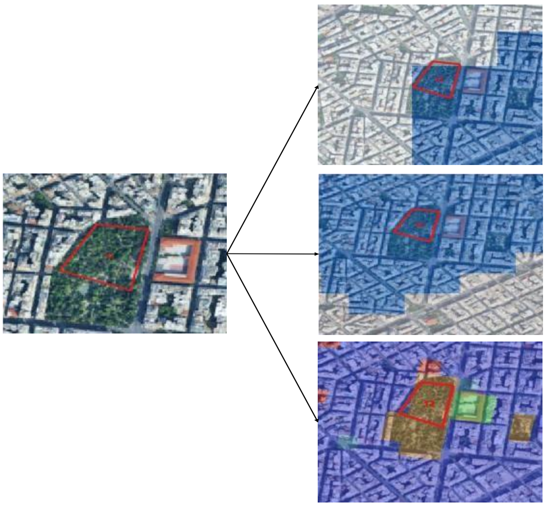

Figure 4. Classification examples for Athens from different datasets (a) Wudapt, (b) Demuzere, (c) Oliveira.

As shown in Figure 4, the area outlined with a red border should be classified as class 12, as it is entirely covered with scattered trees. However, when the examples were reviewed, this area was classified as class 2 in both WUDAPT and Demuzere datasets. In contrast, Oliveira's dataset classified this area as class 11.

Initially, the cause of the misclassification in WUDAPT and Demuzere was investigated. This area is located at the center of the city, surrounded by compact mid-rise buildings (class 2). To further analyze the issue, the size of the area was measured, and it was found to be greater than 100x100 meters. Since the minimum mapping unit (MMU) in these studies is defined as 100x100 meters, this area should have been classified as class 12.

The misclassification in Oliveira’s dataset was also investigated. Classes 11 and 12 are the most likely to be confused with each other, so this confusion might be expected initially. However, the producer accuracy for class 12 in Athens was calculated as 0. Given this, this issue may be stemmed from the sample data used in the study being either unrepresentative or insufficient in number.

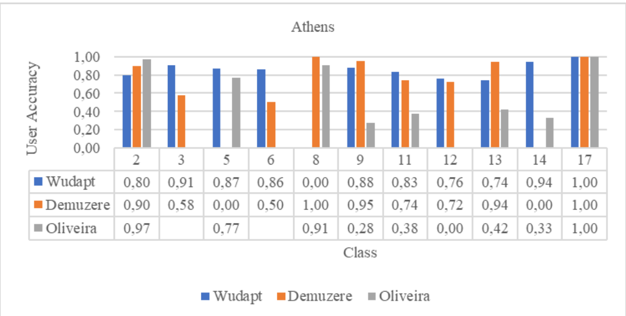

Figure 5. User Accuracy Values of Datasets in Athens.

User accuracy value indicates the proportion of the correctly classified instances out of all examples and reflects the reliability of the classification for the end user.

Another example of misclassified areas is shown in Figure 6. As can be seen, the area is covered with buildings that have 3 to 9 floors. Therefore, it should be classified as compact mid-rise (class 2).

While both Demuzere and Oliveira correctly classified the area, WUDAPT classified it as class 3. The confusion between class 2 and class 3 likely stems from incorrect sample data or the insufficient vector data regarding building heights, which was used in the classification.

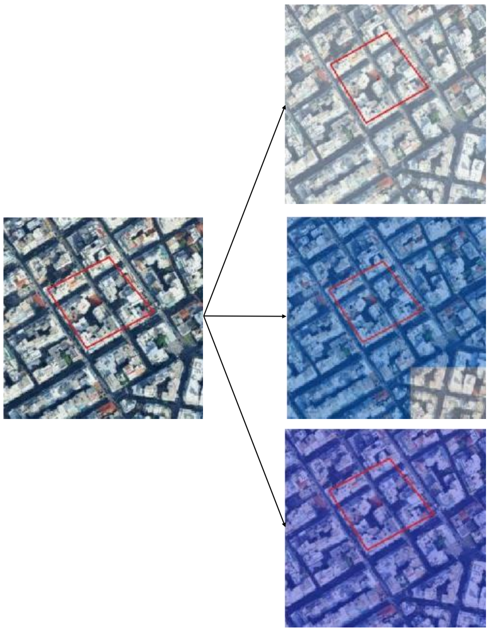

Figure 6. Classification examples for Athens from different datasets (a) Wudapt, (b) Demuzere, (c) Oliveira.

The low accuracy observed for Athens can be attributed to several factors. First, the city’s complex urban structure may have negatively impacted the classification. Athens is characterized by a mix of buildings with varying heights, as well as historical areas. The presence of such diverse classes within a relatively small area likely reduced accuracy. Additionally, the Mediterranean climate, which supports a wide range of plant species, may have further complicated the classification. Finally, the reference data used may not have fully captured the unique urban characteristics of Athens. Together, these factors likely contributed to the reduced accuracy in Athens

Lisbon stands out as the city with the highest Kappa value among all cities with LCZ maps from all three datasets. Therefore, its success was analyzed on a class-based level. The accuracy of each class was evaluated, and the possible reasons behind the high accuracy were investigated (Figure 7).

Figure 7. Producer Accuracy Values of Datasets in Lisbon.

In Lisbon, Wudapt dataset shows very good results for most of the classes including 2, 6, 8, 11, 15, 17, 17. However, the producer accuracy for class 3 is notably low, at just 0.43. Similarly, Demuzere’s producer accuracy values are good or very good for most of the classes except the class 3 and class 6. On the contrary of these 2 datasets, Oliveira's dataset doesn't provide good results in general. We further investigated the reason of obtaining low accuracy for class 3.

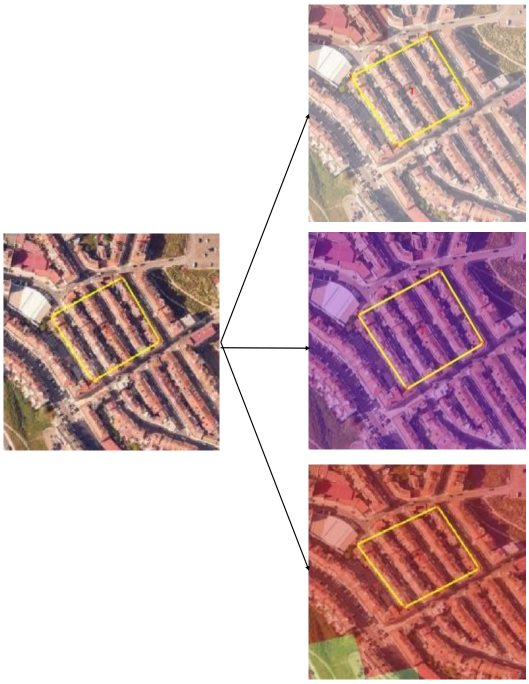

Figure 8. Classification examples for Lisbon from different datasets (a) Wudapt, (b) Demuzere, (c) Oliveira.

An example from the reference data is shown in Figure 8. The area is entirely covered with buildings that have 1-3 floors, and there are no green spaces, making it a clear example of class 3. However, this area was misclassified as class 6 in WUDAPT, a class typically associated with areas containing significant green spaces. Similarly, Demuzere misclassified the area as class 8, which is usually assigned to areas with buildings made from steel or metal. In contrast, these buildings are made of brick. The misclassifications in WUDAPT and Demuzere are most likely due to issues with the sample data. Oliveira, on the other hand, correctly classified the area. Grouping classes 1-2-3 as a single category might have improved the accuracy of Oliveira's study.

The high accuracy of LCZ maps in Lisbon can be attributed to several factors that set it apart from the other cities in the study. First and foremost, Lisbon's uniform urban structure and perfectly designed city plan and specific boundaries likely facilitated better classification results. The spatial distribution of agricultural areas in specific locations within the city may also have contributed to the higher accuracy. Another important factor might be the quality of the reference data used for classification in Lisbon. The reference and validation datasets likely provided a strong representation of the city's local characteristics. In contrast, the other cities in the study—such as Istanbul, Athens, Barcelona, and Paris—have more complex urban structures.

We conducted an extensive analysis of the two datasets for Istanbul, which stands out with high Kappa values, significantly outperforming Paris. For most classes, both WUDAPT and Demuzere datasets show good or very good results. For class 2, the producer accuracy of WUDAPT (0.83) is higher than that of Demuzere (0.59). However, for classes 9 and 12, Demuzere's accuracy metrics are better than those of WUDAPT.

Figure 9. Producer Accuracy Values of Datasets in Istanbul.

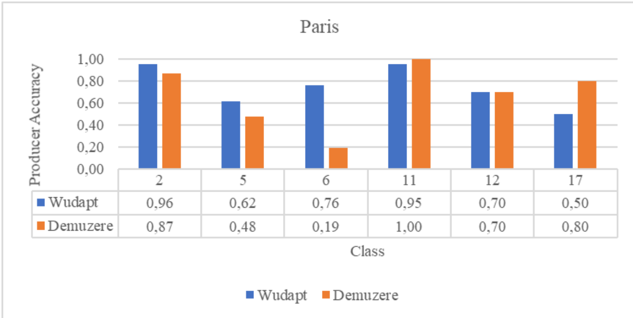

Figure 10. Producer Accuracy Values of Datasets in Paris.

Due to Istanbul's complex city structure and large number of classes, its accuracy metrics were expected to be lower. However, upon examining the producer accuracy values, it was found that classes in Paris were frequently misclassified. In general, water classes do not cause confusion in most areas, but in Paris, confusion arose because the reference data for the water class was drawn from the Seine River. While reference data of class 17 was taken from large water bodies and increased accuracy in other study areas, in Paris, the relatively narrow width of the Seine River resulted in decreased accuracy. (Figure 10)

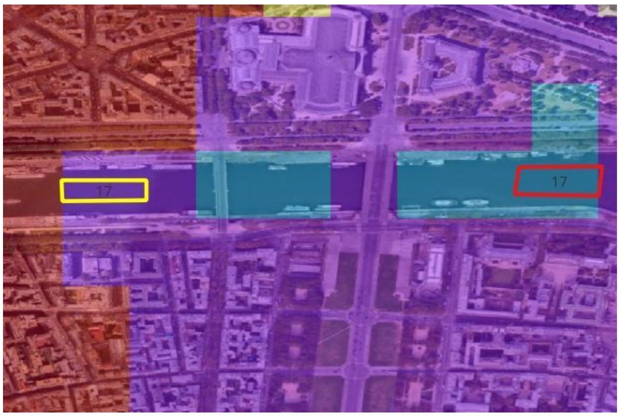

Figure 11. Reference data for class 17 in Paris.

In Figure 11, the blue places show the areas classified as class 17 in Paris, while purple represents class 8, and red shows class 2. The red polygon is correctly classified as class 17, but the yellow polygon has been misclassified, as shown in the figure. The reason of this problem might stem from the width of Seine River. In some parts, the river is narrower than 100 meters, which is the minimum mapping unit. Additionally, the presence of numerous bridges and roads along the river further complicates the classification and contributes to the reduced accuracy.

To summarize, several factors contribute to the reduced accuracy in LCZ map production, including insufficient or incorrectly drawn samples, samples that do not adequately represent the relevant classes, temporally incompatible samples, insufficient information in the vector data used, and the low spatial resolution of the satellite images. Additionally, while LCZ maps generally achieve high accuracy in certain classes, their accuracy tends to be lower in more complex or heterogeneous areas.

6. Conclusion

The Oliveira, Demuzere, and WUDAPT datasets used in this study have previously reported accuracy values around 80% for LCZ classifications. However, the results obtained in this study were found to be lower than the accuracy values reported in the original studies.

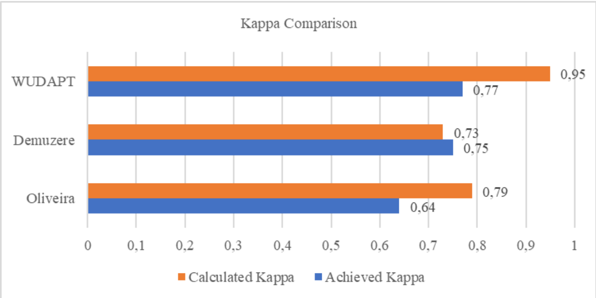

Figure 12. Comparison of reported kappa values of studies and calculated kappa values.

In the WUDAPT study, it was reported that the kappa value for most locations, except Serbia (RI), Spain (SP), United Kingdom (UK) and Vatican City (VT), was above 0.95. (Demuzere et al, 2022). However, in this study, the Kappa value was found to be 0.77. Furthermore, even for Lisbon, the city with the highest Kappa value in this study, the value reached only 0.82, while it dropped to 0.71 for Paris. In short, the 0.95 value reported in the original study appears to be overestimated.

In Demuzere's study, the Kappa value was reported to be 0.73, with the note that this value could vary between 0.65 and 0.80 depending on the region (Demuzere et al., 2019). These reported values align closely with the Kappa value of 0.75 found in this study. However, our class-wise accuracy assessment showed that some classes exhibited very low accuracy levels.

The Kappa value reported in Oliveira's study was 0.79 (Oliveira et al., 2020). Despite this higher reported Kappa, the value calculated in this study was much lower. This significant discrepancy could be attributed to several factors, including the differences in the samples used for the accuracy and input datasets.

To sum up, several factors contribute to the differences in accuracy metrics of different LCZ maps, including variations in the reference data used for validation, geographic differences, and challenges in applying a general classification method to more complex and diverse urban environments. While the accuracy values reported by Demuzere and WUDAPT were close to the declared values, Oliveira's accuracy was considerably lower.

The findings from this study provide valuable insights that can help improve accuracy in future LCZ studies. These results have the potential to contribute to urban and regional planning, inform urban strategies, and enhance our understanding of the urban heat island effect.

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