

Article

Mapping Local Climate Zones (LCZ) Change in the 5 Largest Cities of Switzerland

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Abstract: In the face of climate change and population growth, Local Climate Zone (LCZ) maps have emerged as crucial tools for urban planners and policymakers to address Urban Heat Island (UHI) effects, thereby playing a significant role in mitigating climate change. This study presents a methodology for classifying major Swiss cities into LCZs, offering an efficient, cost-effective, and uniform tool for supporting climate action plans across municipalities and cantons. Initial results show that Sentinel-2, Landsat 8, and Landsat 5 imagery perform well in LCZ classification with an overall accuracy usually exceeding 80%, and Sentinel-2 displays marginally superior performance. Temporal analysis reveals that the built-up classes of Open low-rise and Open mid-rise have increased by ~3%, while Large low-rise and Bare rock or paved have decreased, and Compact mid-rise remains stable. For the natural classes, Water and Dense trees remain stable, but Low plants have declined (~4%). A general decline in overall accuracy over time is noted, attributed to landscape changes. This preliminary effort emphasizes the need to enhance and automate the methodology, integrate it into the Swiss Data Cube, and potentially extend analyses with climate data to better study UHI effects. Future work will include developing visualization and tracking services for urban planners and authorities.

Keywords: climate; urban areas; cities; Sentinel-2; Landsat



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1. Introduction

The growth of urban populations implies rapid urban development, industrialization, densification, and overall population growth. According to the United Nations Department of Economic and Social Affairs, nearly 70% of the world's population is projected to reside in urban areas by 2050 [1]. Consequently, artificial surfaces, such as buildings and roads, have replaced natural landscapes, resulting in significant changes to urban spaces and urban climates [2].

Urban climate is the study of atmospheric conditions within urban areas, which are significantly influenced by human activities and the built environment [3]. Cities tend to have higher temperatures compared to their surrounding rural areas due to the urban heat island effect, caused by factors such as increased heat absorption by buildings and roads, reduced vegetation, and waste heat from various sources [4]. Urban climates also experience altered wind patterns, changes in precipitation patterns, and increased air pollution levels, all of which have significant impacts on the local environment and public health [5].

The Urban Heat Island (UHI) effect is intensifying due to rapid urbanization and land cover changes [6] and is further exacerbated by climate change [7]. The UHI effect can be described as the difference in Land Surface Temperature (LST) observed between urban and rural areas [4]. There are many factors influencing UHI effects, such as land cover, urban morphology, and socioeconomic differences between urban and rural areas [8,9]. Cities consist of dry, impervious surfaces with construction materials covering natural

soils and vegetation. Additionally, heat and moisture are released from people and their activities [10]. In general, the impact of population growth on the UHI effect varies depending on the type of urban environment; however, as populations increase, the UHI effect intensifies due to more heat-retaining surfaces, greater energy use, and reduced green space. Specific characteristics of the urban environment, such as density, climate, and infrastructure, play critical roles in determining the extent of this impact. Moreover, the UHI effect can exacerbate existing socioeconomic disparities within cities by disproportionately impacting low-income and marginalized communities through increased health risks, economic burden, housing inequality, and reduced access to public resources. Addressing these disparities requires targeted policies and interventions that prioritize vulnerable populations in urban planning and environmental justice initiatives. Thus, due to population growth and the resulting socioeconomic impacts in the context of climate change, cities are at the forefront of adaptation efforts.

The intensification of the UHI has gained the attention of the scientific community, which has developed physical models to quantify its intensity and identify the factors influencing it [11]. The ability to obtain homogeneous, high-resolution, and global-coverage data has allowed satellite Earth Observation (EO) technologies to become a fundamental tool in the study of UHI [12]. Even though satellite EO technologies are becoming useful for studying UHIs, they are subject to limitations related to spatial and temporal resolution, atmospheric interference, data accuracy, and accessibility. These limitations can affect the precision and utility of UHI studies, particularly when detailed localized information is required. Combining EO data with ground-based measurements and advanced modeling techniques can help mitigate some of these challenges and provide a more comprehensive understanding of UHI dynamics.

Due to urbanization and expansion, the boundaries between urban and rural areas have become vague, making it difficult to accurately describe the UHI. For this reason, Ref. [10] introduced the concept of Local Climate Zone (LCZ) to classify urban and rural land cover more objectively. Local Climate Zones (LCZs) offer a more detailed and systematic approach to understanding the climate within urban areas. Developed by the World Meteorological Organization (WMO), LCZs categorize urban areas into distinct zones based on their surface cover and land use characteristics, such as compact high-rise, open low-rise, industrial, and natural. This classification enables researchers and urban planners to better analyze and model the local climate, including temperature, humidity, wind patterns, and air quality, within different parts of a city. By considering the unique characteristics of each zone, stakeholders can develop targeted strategies to mitigate urban heat islands, improve air quality, and enhance overall urban livability. However, implementing UHI mitigation strategies based on LCZ data is challenging. One major challenge is the spatial heterogeneity of cities, where diverse LCZs can be densely packed, making it difficult to effectively apply broad mitigation strategies across different zones. Additionally, existing urban infrastructure, such as dense built environments and limited green spaces, can restrict the feasibility of interventions like increasing vegetation or modifying building materials. Planners must also balance UHI mitigation with other urban priorities, such as housing demand and economic development, which can sometimes conflict with cooling strategies. Furthermore, stakeholders may resist implementing these strategies due to the costs or disruptions associated with them. Finally, the accuracy and resolution of LCZ maps can pose challenges because any misclassification or oversimplification can lead to ineffective or misplaced interventions.

LCZ maps can offer a rapid assessment of urban structures and heat-affected areas. This information can serve as a foundation for assisting urban planners and designers in identifying priority areas for UHI mitigation and implementing strategies to cool urban environments [13], with the aim of improving the wellbeing of residents [6]. Understanding the interaction between various urban forms, such as building density, street width, or the fraction of vegetated areas, and the atmosphere is essential for the redesign of cities and, more importantly, for planning future urban development [14]. Moreover, the LCZ classification in

cities with unique geographical and climatic conditions (e.g., mountainous regions, coastal areas, arid zones) can differ significantly from that in more generalized urban areas. In such unique settings, local topography, proximity to water bodies, or extreme weather patterns can create microclimates that affect how LCZs are defined and distributed. The interaction between urban morphology and these geographical features may require customized LCZ classification criteria, including adjustments in temperature thresholds, vegetation types, or building materials, to accurately capture local urban climate dynamics.

Projections indicate that the European continent will experience more frequent and severe heatwaves [15]. Switzerland, positioned at mid-latitudes and characterized by continental climatic conditions and diverse landscapes, is notably vulnerable to climate change, experiencing significant impacts from rising temperatures [16] affecting vegetation (e.g., droughts, composition) [17,18], snow (e.g., extent, duration) [19,20], and agriculture [21], as well as making cities less livable [22] caused by urbanization, which is a major land cover change driver across the country [23].

Based on these considerations, the objective of this study is to perform the first LCZ classification for the five largest cities in Switzerland: Zürich, Geneva, Basel, Lausanne, and Bern. Such a comparative study has never been undertaken to our knowledge, despite several studies specifically examining individual cities (e.g., Lausanne, Geneva, Bern) [12,24,25]. It can enable a comprehensive understanding of urban climate dynamics, facilitating informed decision-making in urban planning, climate adaptation, public health, and sustainability efforts. In addition, different satellite sensors (e.g., Sentinel-2, Landsat 8, and Landsat 5) will be compared to identify their strength and limitations for LCZ classification of Swiss cities. Ultimately, such work can pave the way for implementing a countrywide monitoring service for the impact of climate change in urban areas.

2. Materials and Methods

LCZ is a classification system based on the physical and thermal properties of urban surfaces for climate-related studies [10]. LCZ is defined as “*regions of uniform surface cover, structure, material, and human activity that span hundreds of meters to several kilometres in horizontal scale*” [10]. This system is effective for measuring the UHI effect, considering parameters such as building height, spacing, impervious surfaces, tree density, and soil moisture [26]. The classification encompasses 17 classes, divided into 10 “built types” and 7 “land cover types”, allowing for a detailed exploration of the spatial differentiation patterns within various urban thermal environments [27].

Over the past decade, there has been a significant increase in scientific interest in the Local Climate Zone (LCZ) concept, as evidenced by the increasing number of publications on the subject [2,21]. The literature review conducted by [21] reveals that LCZs have become a central part of urban climate research, particularly in studies examining the Urban Heat Island (UHI) effect. Most of these studies have been conducted in Chinese cities, with German and American cities also frequently studied. Initially developed for classifying field sites in UHI research [19], the LCZ classification system is now used in a variety of contexts, including health assessments, evaluations of urban ventilation performance, and analyses of energy consumption [2].

Two primary methods for classifying Local Climate Zones (LCZs) exist: Geographic Information Systems (GIS) [28–30] and Remote Sensing (RS) satellite imagery such as Landsat and Sentinel-2 [22,23]. Both methods effectively assess the relationship between urban morphology and Urban Heat Island (UHI) intensity and are widely recognized within the scientific community [8]. Additionally, a third method involves field measurements. Among these methods, RS-based classification is the most used for comparative LCZ mapping research [24]. However, the GIS-LCZ method requires extensive environmental datasets, such as digital elevation models and surface models, which are often unavailable for many European cities. This lack of data is the primary obstacle to the practical implementation of the GIS-LCZ approach [25,26]. A review by Feng and Liu [6] indicates that a universal method for LCZ mapping has not yet been established, which limits the

accuracy of such mapping. They suggest that further research is necessary to improve the methodology.

2.1. Study Areas

The study area covers the five largest cities (i.e., Zürich, Geneva, Basel, Lausanne, and Bern) in Switzerland (Figure 1), located in the lowland, between the latitudes of 45.82° and 47.81° North and the longitudes of 5.96° and 10.49° East (Table 1). The total land area is $41,285 \text{ km}^2$. These cities have been selected because they represent almost 40% of the total population of Switzerland and are the major poles of socioeconomic activities in the country. For each city, the study area was delineated by a rectangle encompassing the city and its surrounding regions. The selected years include recent summer drought periods (2022, 2018, 2003) and years within the climatic norm used as references (2017, 2003, 1992, 1985). The three most recent years (2022, 2018, and 2017) are used to compare classifications made with Landsat 8 and Sentinel-2, while the three earliest years (2003, 1992, and 1985) facilitate temporal analysis using Landsat 5.

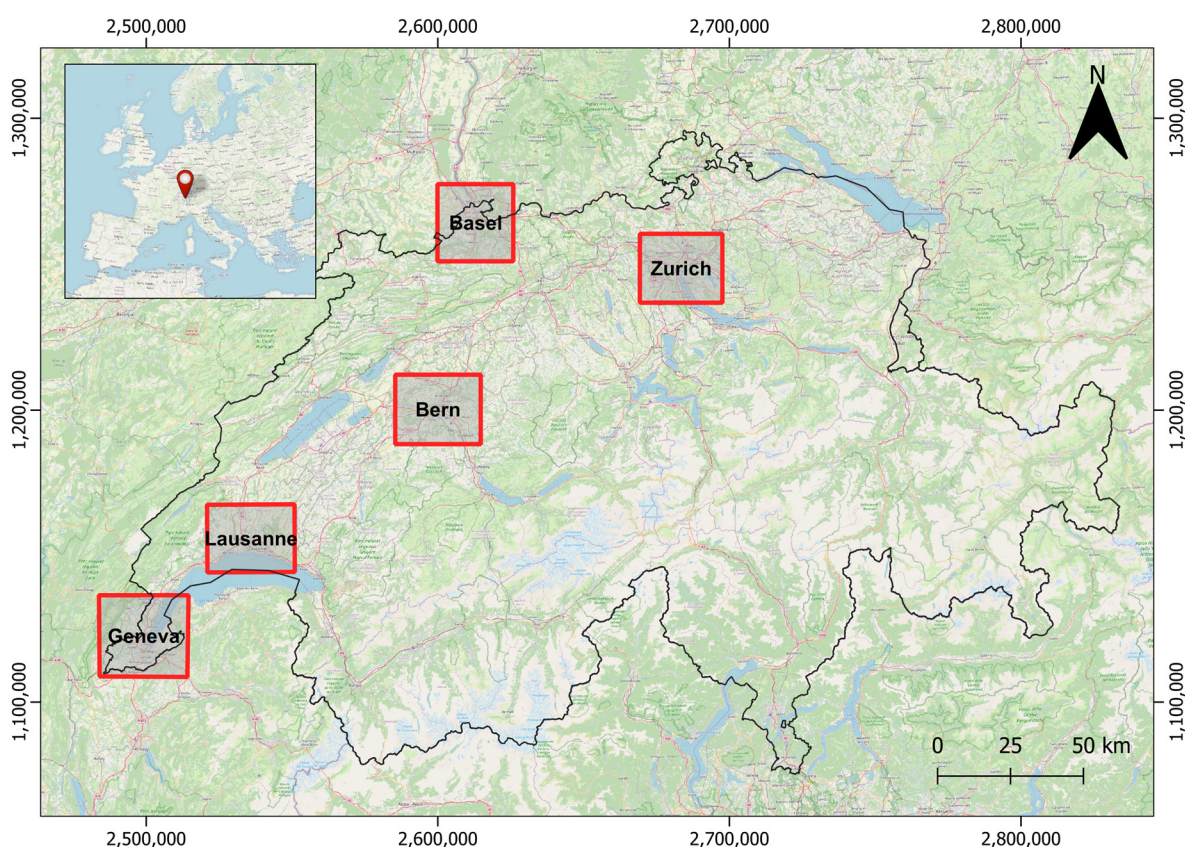


Figure 1. Locations of the study areas and their footprints (in red). Coordinate Reference System (CRS): EPSG:2056—CH1903+/LV95. Map data: OpenStreetMap.

Zürich is the most populous city, with over 400,000 inhabitants, situated in the north-east on the Swiss plateau by Lake Zürich. The Limmat River flows through the city. It has an oceanic climate (Cfb) with an annual mean temperature of 9.8°C and a warmest monthly average of 19.2°C in July (1991–2020). The urban landscape features a mix of dense historic buildings in the core and modern residential structures toward the outskirts, surrounded by hills of up to 900 m.

Geneva, the second largest city with around 200,000 inhabitants, is in the southwest along Lake Geneva. The Rhône and Arve rivers run through the city. Geneva has an oceanic climate (Cfb) with an annual mean temperature of 11.0°C and a warmest monthly average

of 20.6 °C in July (1991–2020). Its urban structure includes a dense historic center and modern residential areas in the surrounding neighborhoods.

Table 1. Characteristics of the selected cities.

City	Population (City/Agglomeration)	Area [km ²]	Density [Pop/km ²]	Latitude [°]	Longitude [°]
Zürich	4,218,787/1,334,269	87.88	20,277	47.37 N	8.54 E
Geneva	203,856/579,227	15.93	29,096	46.20 N	6.15 E
Basel	178,120/541,011	23.91	20,170	47.55 N	7.59 E
Lausanne	140,202/409,295	41.37	16,278	46.51 N	6.63 E
Bern	134,794/410,894	51.6	13,798	46.95 N	7.45 E

Basel, the third most populous city with about 173,000 inhabitants, is in the north, bordering Germany and France. It surrounds the Rhine River and has an oceanic climate (Cfb) with an annual mean temperature of 10.9 °C and a warmest monthly average of 20.2 °C in July (1991–2020). Basel’s core is historic, transitioning to modern residential structures on its outskirts.

Lausanne, the fourth largest city with about 140,000 residents, is on the northern shores of Lake Geneva. It has a temperate climate (Cfb) with an annual mean temperature of 11.3 °C and a warmest monthly average of 20.5 °C in July (1991–2020). The city is built on hills and features a historic center surrounded by modern neighborhoods.

Bern, the capital of Switzerland, has around 133,000 inhabitants and is west of the country’s center on the Swiss plateau. The Aare River crosses the city. Bern has an oceanic climate (Cfb), bordering a humid continental climate, with an annual mean temperature of 9.3 °C and a warmest monthly average of 18.8 °C in July (1991–2020). The city has a historic core with dense buildings, transitioning to modern residential areas on the outskirts, and is surrounded by hills of up to 858 m.

2.2. Data

2.2.1. Satellite Imagery: Sentinel-2

Sentinel-2 (S2) is a high-resolution, multispectral imaging mission part of the European Space Agency’s “Copernicus Land Monitoring Studies” [27]. Its primary objective is to monitor land surfaces (e.g., vegetation, soil, and built-up areas). Launched in 2015 and 2017, respectively, Sentinel-2A and 2B have 13 spectral bands, including four bands at 10 m, six at 20 m, and three at 60 m spatial resolution, all of which were used in this analysis. The revisit time over Switzerland is approximately 5 days.

This study utilized an ortho-rectified Level-2A product that provides atmospherically corrected surface reflectance scenes, making them directly suitable for analysis. The atmospheric correction addresses various phenomena, including Rayleigh scattering by air molecules, absorption and scattering by atmospheric gases (notably ozone, oxygen, and water vapor), and the effects of aerosol particles. Due to the high spatial and temporal resolutions and open access availability of Sentinel-2 data, these satellites are extensively used in land cover classification studies [28].

2.2.2. Satellite Imagery: Landsat 5 and 8

Landsat 5 (L5) and Landsat 8 (L8) are components of the “Landsat Program”, managed by the National Aeronautics and Space Administration (NASA) and the U.S. Geological Survey (USGS), with the primary objective of acquiring multispectral imagery of Earth [29]. Landsat 5 holds the record as the longest-running EO mission, operating from March 1984 until June 2013. This study utilized the Level 2, Collection 2, Tier 1 dataset from Landsat 5, which provides atmospherically corrected surface reflectance to mitigate effects such as aerosol scattering and thin clouds. The dataset includes seven bands: three for the visible spectrum, two for near-infrared, and one for mid-infrared, all at a resolution of 30 m, with

the thermal band excluded. Landsat 5 provided imagery of Switzerland approximately every 16 days.

Landsat 8, launched in February 2013, replaced Landsat 5 and complemented Landsat 7. The Level 2, Collection 2, Tier 1 dataset from Landsat 8 was similarly used for surface reflectance analysis. It includes seven bands (1 to 7) capturing visible, near-infrared, and shortwave infrared surface reflectance, all retained for this study, also at a 30-m resolution, with a 16-day revisit cycle.

Landsat satellite imagery (5, 7, and 8) is frequently utilized for Local Climate Zone (LCZ) mapping in urban areas due to its cost-effectiveness and accessibility. Researchers have also leveraged Sentinel missions (1 and 2), particularly for larger spatial scales [30]. Notably, Sentinel-2 includes additional bands, such as bands 5, 6, and 7 (the red-edge bands), which are not covered by Landsat 8.

2.2.3. Ancillary Data

Within our analytical framework, we incorporated additional data, primarily to visually identify LCZ classes and create training and testing areas. We also used building height data for Geneva, Lausanne, Bern, and Basel-Stadt as a predictor in our Machine Learning Classification module. For Zürich, only building footprints were available because the height data were not accessible. Conversely, no data were obtained for Basel-Land. Additionally, very high-resolution Google satellite imagery was integrated into QGIS through the QuickMapServices Plugin. In some instances, Google Earth and Google Maps were used to visualize the landscape in 3D, particularly when height data were unavailable.

2.3. Methodology

The methodology implemented in this study is based on remote sensing. This section provides a detailed overview of the adopted approach. The LCZ classification was conducted in three steps, as summarized in Figure 2 and detailed in the following subsections. First, we downloaded and pre-processed satellite data for the selected cities and time-period. Second, we produced training and validation samples for each city and the relevant LCZ classes. Third, images were classified using a Random Forest algorithm, and statistical accuracy measurements were produced to evaluate the reliability of the maps.

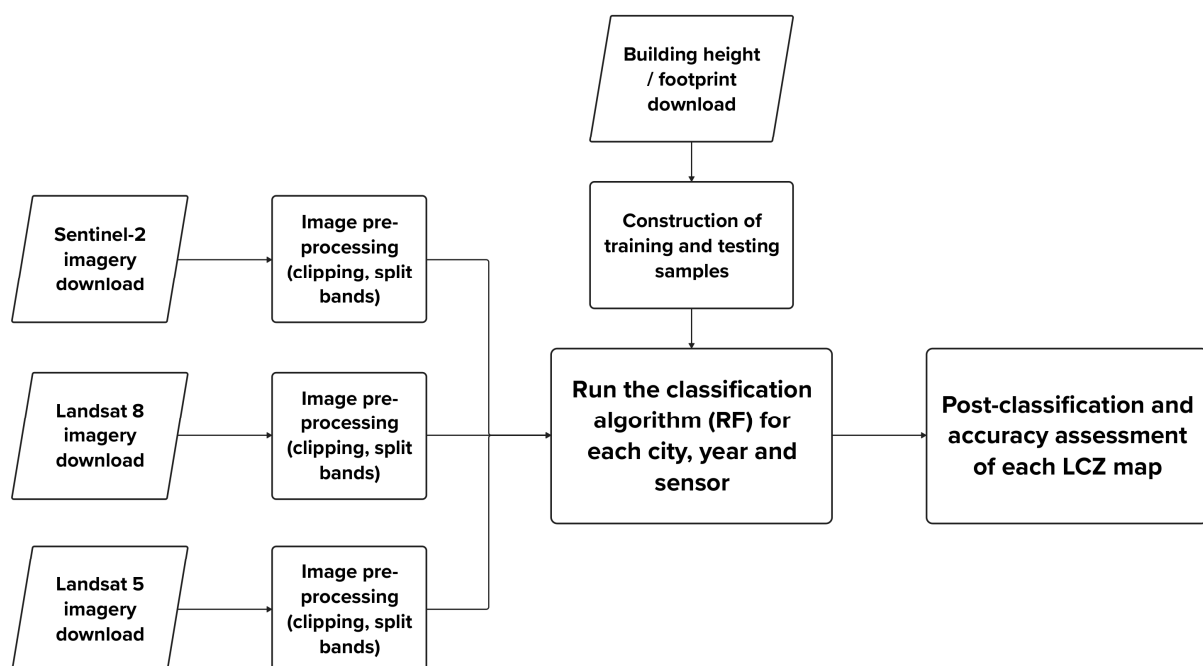


Figure 2. Flowcharts of the summarized methodology adopted in this study to create and analyze the LCZ maps of the main Swiss cities.

2.3.1. Satellite Imagery Preprocessing

Remote sensing data acquisition was conducted using the Google Earth Engine, processing data from the Sentinel-2, Landsat 5, and Landsat 8 archives. All gathered satellite data are at the Analysis Ready Data (ARD) level, ensuring that all scenes are consistently calibrated (i.e., accounting for atmospheric and radiometric corrections), allowing immediate analysis [31]. The data were cropped to the boundaries of the region of interest (ROI) and resampled to a common grid size. Six different years (2022, 2018, 2017, 2003, 1992, and 1985) were selected for analysis across five cities in Switzerland (Table 2). The selection included years with notable summer drought events (2022, 2018, and 2003) and control years (1985, 1992, and 2017) representing standard climatic conditions.

Table 2. Satellites and years associated with all cities.

Cities	Satellite	Years
All	Sentinel-2	2017, 2018, and 2022
All	Landsat 8	2017, 2018, and 2022
All	Landsat 5	1985, 1992, and 2003

For each city, year, and sensor, raster data were downloaded to represent the median values for each pixel from May to September, with limited cloud cover (<20%) during this period. Each multiband raster was then split into individual bands using the semi-automatic classification plugin in QGIS [31].

2.3.2. LCZ Mapping and Samples Production

We selected eight classes from the 17 Local Climate Zone (LCZ) classes proposed by [5], chosen based on their relevance to the study areas, as outlined in Table 3. The semi-automatic classification plugin [31] in QGIS was utilized to delineate the training and testing areas (TA) on the satellite imagery for the purpose of supervised LCZ classification, facilitating LCZ mapping. The selection of both training and testing samples was guided by building height information, local knowledge, and the use of Google Maps and Google Earth. A total of 65 Regions of Interest (ROIs) per class were gathered over stable areas (i.e., no change), and subsequently, a random selection in a balanced manner (by LCZ class) was applied, adhering to a commonly used ratio of 70%/30% for training/testing, as recommended by [9]. The training samples were utilized to train the classifier, while the testing samples were used to evaluate the classification accuracy during the post-processing stage.

Table 3. Local Climate Zone classes kept for the classification of Swiss cities. Names, descriptions, and images are taken from [10].

Classe Name	Description
Compact mid-rise	Dense mix of mid-rise buildings (3–9 stories). Few or no trees.
	Land cover is mostly paved. Stone, brick, tile, and concrete construction materials.
Open mid-rise	Open arrangement of mid-rise buildings (3–9 stories). Abundance of pervious land cover (low plants, scattered trees). Concrete, steel, stone, and glass construction materials.
Open low-rise	Open arrangement of low-rise buildings (1–3 stories). Abundance of pervious land cover (low plants, scattered trees). Wood, brick, stone, tile, and concrete construction materials.

Table 3. *Cont.*

Classe Name	Description
Large low-rise	Open arrangement of large low-rise buildings (1–3 stories). Few or no trees. Land cover is mostly paved. Steel, concrete, metal, and stone construction materials.
Dense trees	Heavily wooded landscape of deciduous and/or evergreen trees. Land cover is mostly pervious (low plants). Zone function is natural forest, tree cultivation, or urban park.
Low plants	Featureless landscape of grass or herbaceous plants/crops. Few or no trees. Zone function is natural grassland, agriculture, or urban park.
Bare rock or paved	Featureless landscape of rock or paved cover. Few or no trees or plants. Zone function is natural desert (rock) or urban transportation.
Water	Large, open water bodies such as seas and lakes, or small bodies such as rivers, reservoirs, and lagoons.

As suggested by [21], TAs correspond to polygons of similar and homogeneous LCZs over patches of appropriate dimensions, which they consider optimal at one square kilometer. One set of training and testing areas was created and utilized per city. Sentinel-2 imagery from 2022 was chosen as a reference due to its superior spatial and spectral resolution compared to Landsat imagery. An illustration of the training and testing areas collected for Bern is depicted in Figure 3.

2.3.3. Image Classification and Accuracy Assessment

The LCZ classification was performed using the Random Forest (RF) classifier algorithm of the semi-automatic classification plugin in QGIS, employing 100 trees. RF classifiers are widely used in image classification [32], leveraging multiple decision trees trained on variations in the training data. The final output is determined by the majority consensus of the individual decision trees, providing high-accuracy results while minimizing the risk of overfitting [32,33].

An accuracy assessment was conducted using Overall Accuracy (OA), Producer's Accuracy (PA), and User's Accuracy (UA) for each class. The overall accuracy indicates the percentage of correctly classified samples. PA represents the probability that a certain land cover (class) on the ground is correctly classified as such, while UA denotes the probability that the class on the map corresponds to the actual land cover on the ground, serving as an indicator of reliability. These accuracies are computed from an error matrix, presented in Table 4, which compares the reference and classified data. An error matrix (also known as a confusion matrix) is a tool used to assess the accuracy of a classification process, particularly in remote sensing, in which images are classified into different categories. It allows to derive metrics such as the Overall, Producer, and User accuracies. Rows represent the actual (or reference) classes, often determined by ground truth data, whereas columns represent the predicted classes assigned by the classification model. Diagonal elements indicate the number of correctly classified instances for each class (where the actual and predicted classes match), and Off-diagonal elements indicate misclassified instances (where the actual class differs from the predicted class). The error matrix and corresponding accuracy measures were computed in QGIS using specialized tools within the plugin.

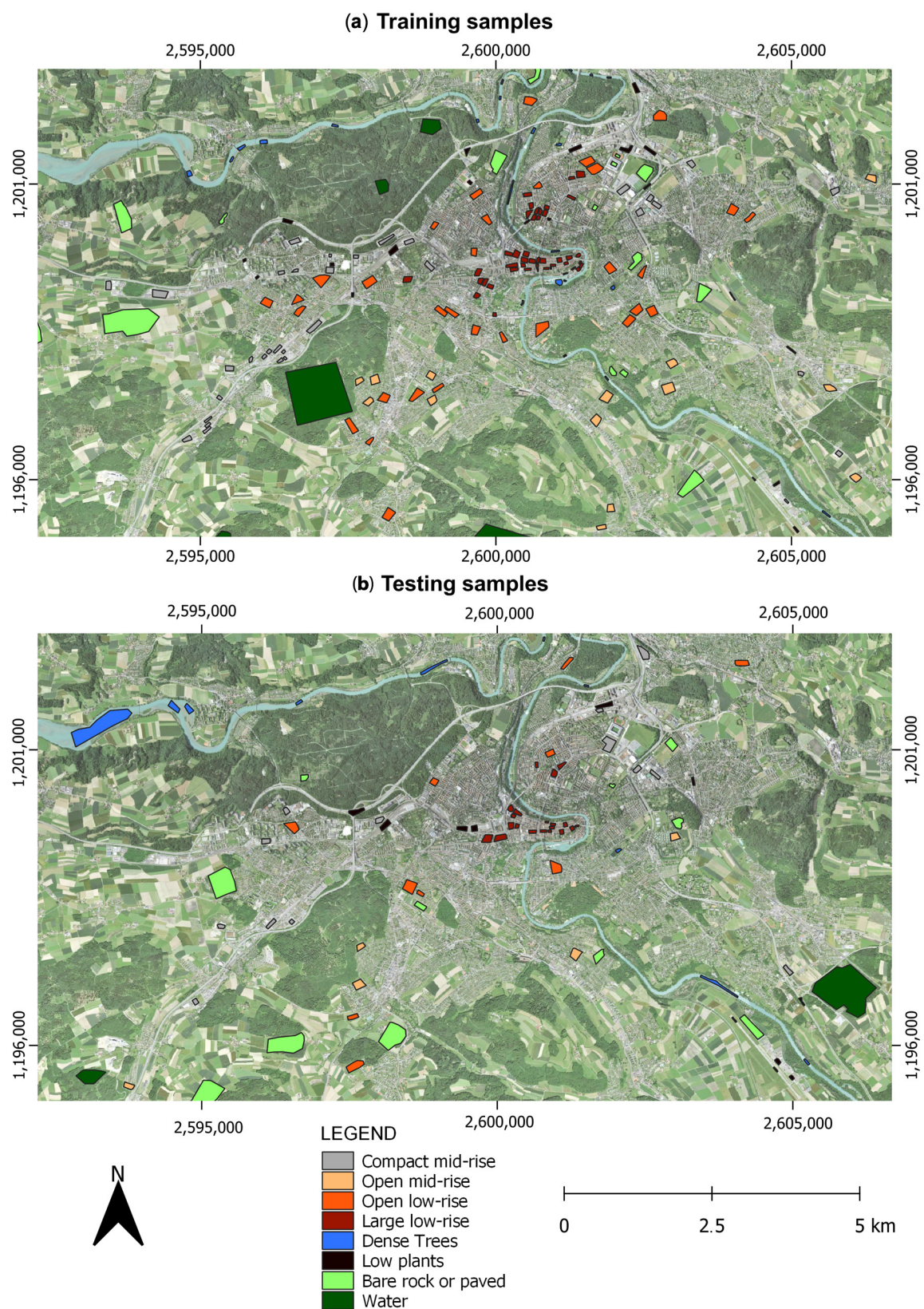


Figure 3. Distribution of training (a) and testing (b) samples for the LCZ classification of Bern. It provides a zoomed-in view of the city center in comparison to the entire extent used for classification, ensuring enhanced clarity. Coordinate Reference System (CRS): EPSG:2056—CH1903+/LV95.

Table 4. Scheme of the error matrix, where k is the number of classes used, and n is the number of collected sample units. The items in the major diagonal (a_{ii}) are the number of samples correctly identified, while the other items are classification errors.

		Ground Truth				Total
		1	2	...	k	
Class	1	α_{11}	α_{12}	...	α_{1k}	α_{1+}
	2	α_{21}	α_{22}	...	α_{2k}	α_{2+}
	...	...	...	...	...	...
	k	α_{k1}	α_{k2}	...	α_{kk}	α_{k+}
Total		α_{+1}	α_{+2}	...	α_{+k}	n

Statistical values for each LCZ map and its respective classes were meticulously examined through the presentation of graphs and tables, facilitating comparisons across satellites and exploration of temporal variations. These accuracy measures are essential for interpreting the reliability of LCZ maps and understanding potential variations across satellites and over time.

The overall accuracy (OA), expressed in percentage, is defined as:

$$OA [\%] = \sum_{i=1}^k \frac{a_{ii}}{n} \quad (1)$$

where k represents the number of classes used, n is the number of collected sample units, and a_{ii} corresponds to the major diagonal, which are the samples correctly identified.

The producer's accuracy (PA), expressed as a percentage for each class, is defined as the ratio between the correct samples (a_{ii}) and the column total (α_{+i}):

$$PA [\%] = \frac{a_{ii}}{\alpha_{+i}} \quad (2)$$

User's accuracy (UA), expressed as a percentage for each class, is defined as the ratio between correct samples (a_{ii}) and the row total (α_{i+}):

$$UA [\%] = \frac{a_{ii}}{\alpha_{i+}} \quad (3)$$

Furthermore, achieving high overall accuracies does not inherently ensure the accuracy of the resulting Local Climate Zone map. For instance, inadequate discrimination of LCZ types in the training samples may result in an artificially elevated OA [14].

During classification, the process also produces an algorithm raster for each LCZ map. This raster represents the "distance" of an image pixel from a specific spectral signature. This raster can be useful for identifying pixels that require the collection of more similar spectral signatures if the distance is too low. The calculation of each pixel's value involves associating its spectral signature with the class in which it has been classified.

3. Results

3.1. Final Maps and Cumulative Histograms

Forty-five final Local Climate Zone (LCZ) maps were generated. Each map distinctly delineates various urban areas, with discernible geographical features such as water bodies, vegetation, infrastructure, and building distributions. For instance, an illustration is provided for the city of Zürich in Figure 4, showing a comparison between Landsat 8 (L8) and Sentinel-2 (S2) imagery for the year 2017.

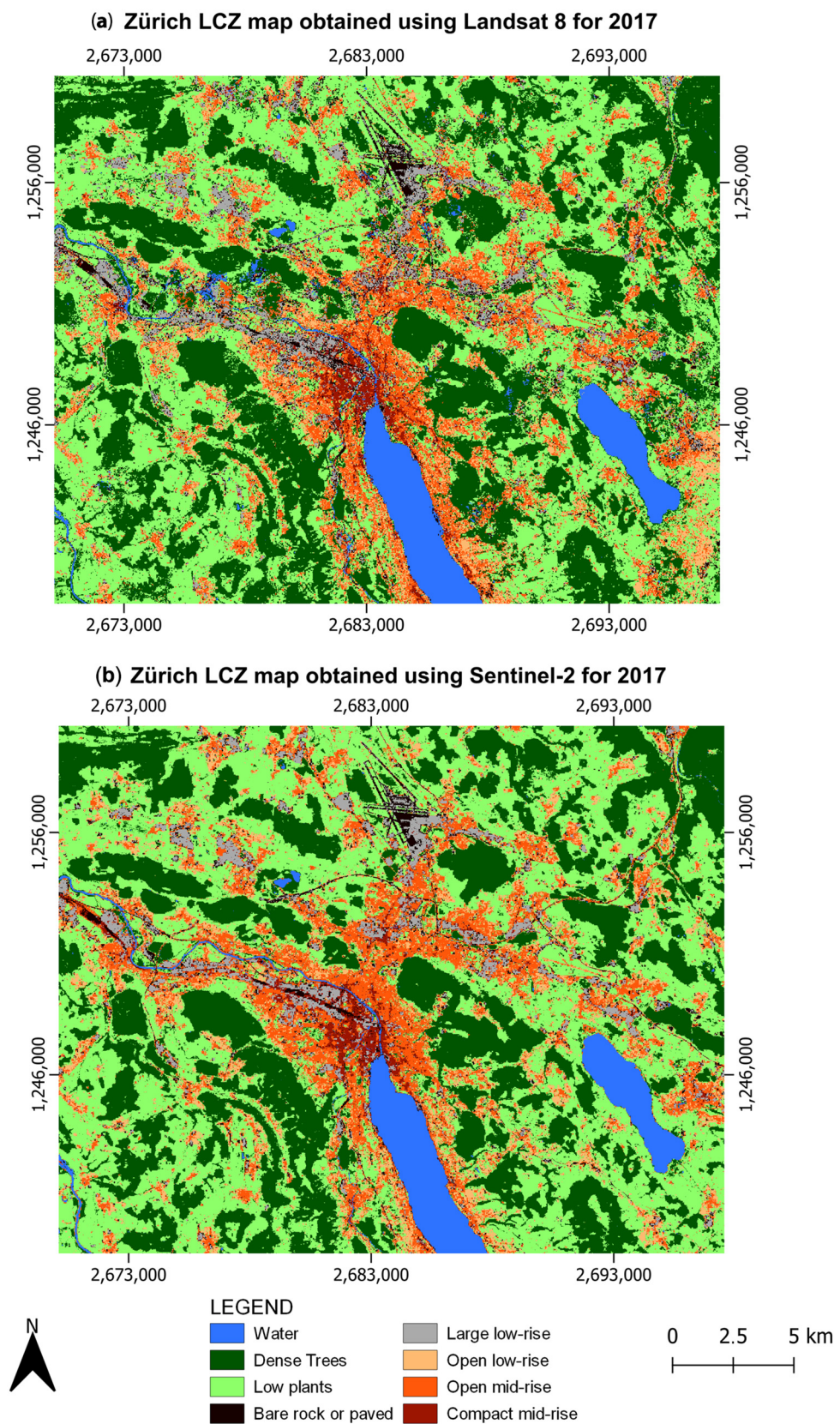


Figure 4. Comparison of LCZ maps for Zürich using Landsat 8 (a) and Sentinel-2 (b) sensors for 2017.

The LCZ maps for Zürich show recognizable characteristics, visually indicating satisfactory classification in both cases. Specifically, the S2-derived map demonstrates smoother transitions and more uniform zones, particularly evident in the prevalence of *open mid-rise*

rise zones. Conversely, the L8-derived map presents fewer distinct boundaries between classes, attributable to a higher pixel count per class and coarser spatial resolution. Notably, the *Open low-rise* category is more pronounced in the L8-derived map compared to the S2-derived counterpart.

An important observation is the misclassification of lakes in the central-western region of the L8-derived map, which is not realistic for the actual landscape. Additionally, notable disparities exist between the two maps, particularly on the right side, where numerous pixels classified as *Low plants* in the S2-derived map are categorized as either *Open low-rise* or *Dense trees* in the L8-derived map.

The Local Climate Zone (LCZ) map computed from Landsat 5 (L5) imagery over Geneva for the year 1985 exhibits the lowest Overall Accuracy (OA) among all datasets. A comparative analysis between this L5 1985 map and its L8 2022 counterpart is presented in Figure 5. While both classifications visually capture recognizable features, differences are evident in the classification of LCZ classes within the northwestern region of the 1985 map. Overall, an extension of the built environment can be observed in the whole area, although some built areas seem to disappear over time, principally in this confused region in the northwest. The general structure of the city remains the same in the two situations.

Subsequently, the temporal evolution of the total area classified for each class in the LCZ maps for Zürich was compiled and represented in cumulative histograms in Figure 6. First, most of the area lies in the categories of *Low plants* and *Dense trees*, followed by *Open mid-rise* and *Open low-rise*. Then, the comparison between S2 and L8 shows that the sensor classified the pixels differently, with differences in percentage for almost every class. Some are smaller than others; *Water* is similar, while *Low plants* can reveal a gap between the two sensors. Finally, the temporal evolution of the city includes a decrease in area for *Low plants* and *Large low-rise*, while it increases for *Open mid-rise* and *Open low-rise* (S2 and L5). The categories *Compact mid-rise* and *Bare rock or paved* stay stable over time.

The LCZ maps of Lausanne (Figure S1—Supplementary Materials) illustrate a landscape primarily characterized by *Low plants*, *Water*, and *Dense trees*, with *Open low-rise* constituting a notable built-up class. Overall, the natural classes exhibit relatively stable trends over time, albeit with minor fluctuations observed in the *Low plants* category. Conversely, certain built-up classes demonstrate temporal increases, such as *Open low-rise* or *Open mid-rise*, while others, like *Large low-rise* and *Bare rock or paved*, experience declines, with *Compact mid-rise* exhibiting temporal constancy. Notably, the disparity in surface area between the S2 and L8 datasets is negligible for Lausanne.

The cumulative histograms for Bern (Figure S2—Supplementary Materials) showcase an area predominantly covered by *Low plants* (approximately 50%) and *Dense trees* (approximately 33%). The foremost built-up class is *Open low-rise*, constituting approximately 7% of the surface area, followed by *Open mid-rise*, accounting for about 4.5%. While the distribution of classes exhibits minimal variance between 1985 and 2022, discernible fluctuations occur over intermediate periods. For instance, *Dense trees*, *Low plants*, and *Open low-rise* classes appear to increase between 1985 and 2017 before experiencing subsequent declines until 2022. Conversely, *Large low-rise*, *Compact mid-rise*, and *Water* categories maintain temporal stability. Moreover, *Bare rock or paved* decreases over time, while *Open mid-rise* shows a global increase. Notably, S2 and L8 show similar results, with S2 exhibiting higher surface coverage in *Low plants* and L8 displaying increased coverage in *Dense trees* and *Open low-rise* classes.

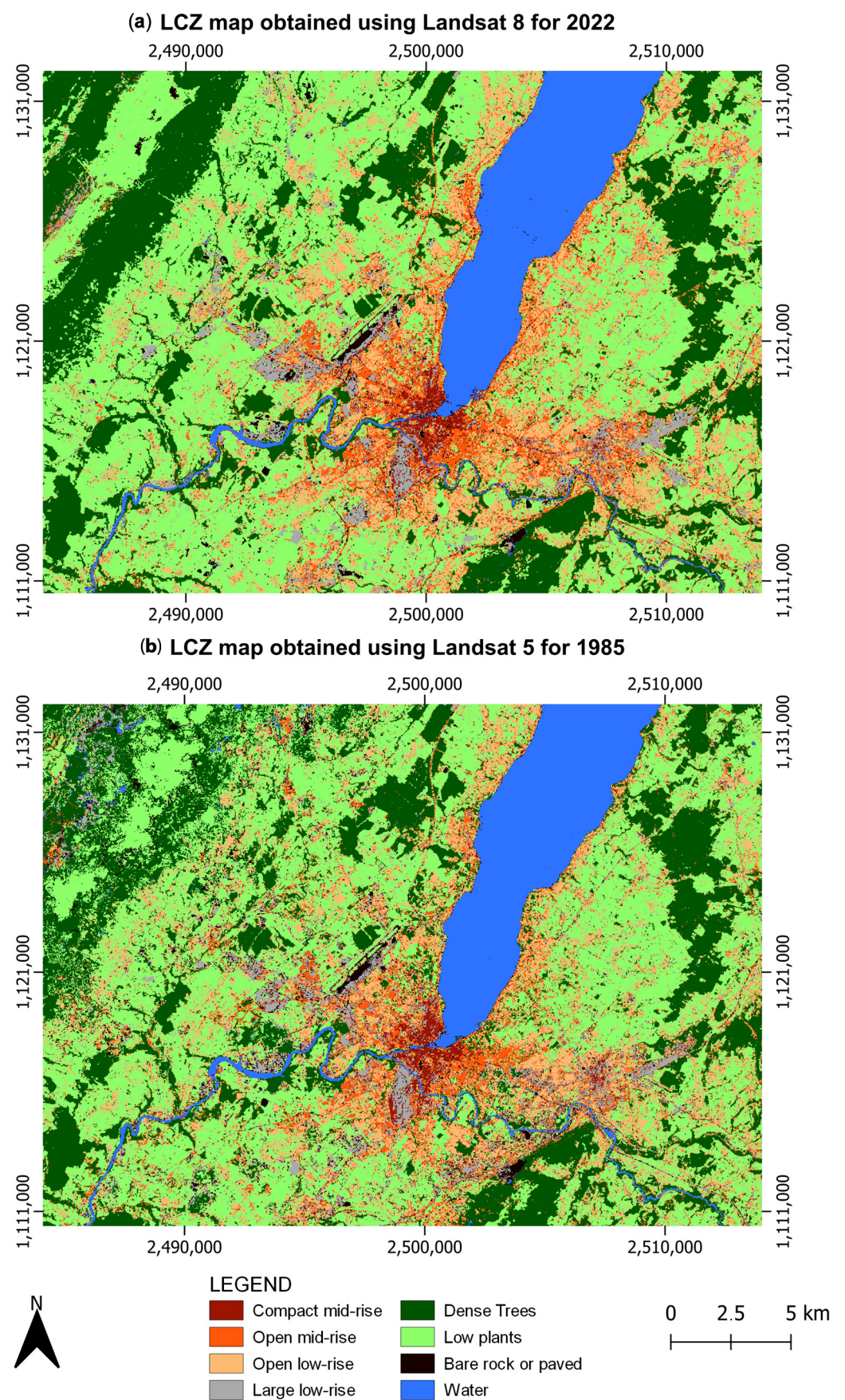


Figure 5. Temporal comparison of LCZ maps of Geneva for 2022 (a) and 1985 (b).

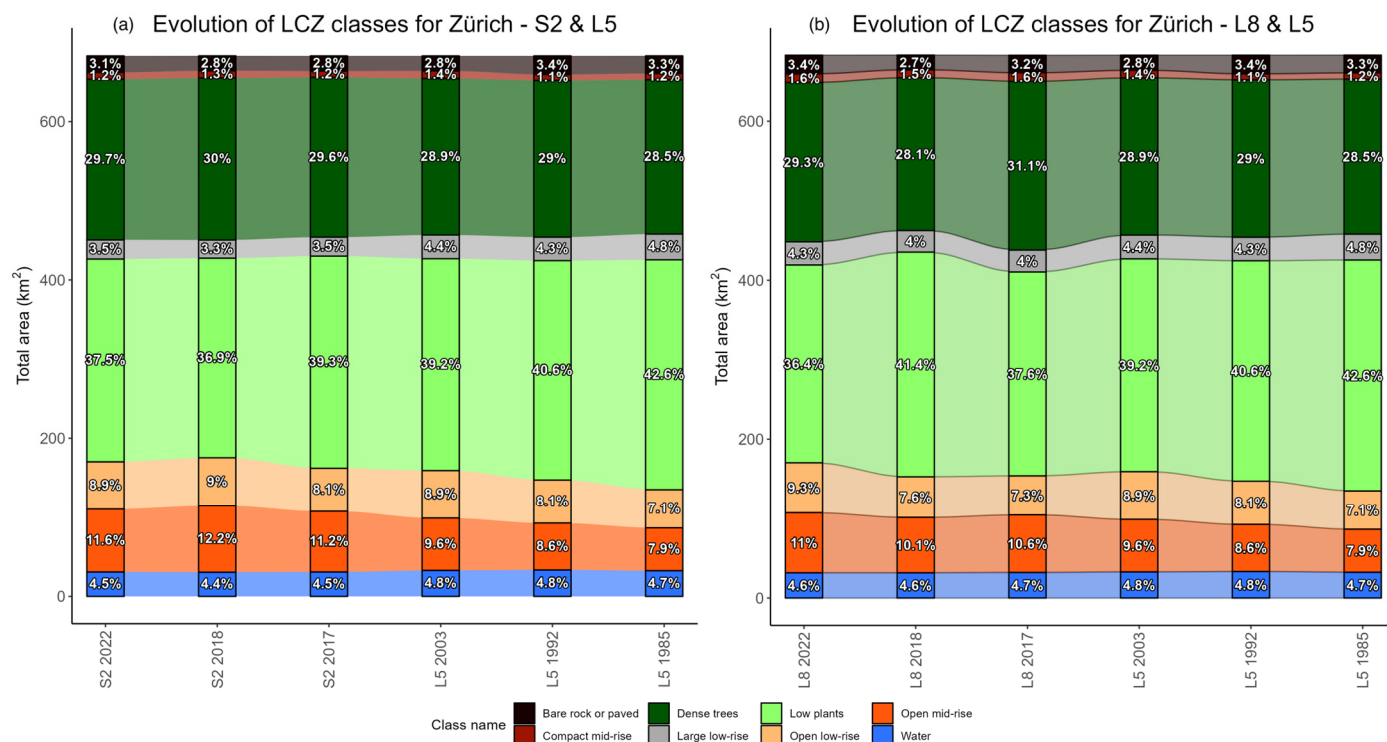


Figure 6. Evolution diagram illustrating the evolution of the total area [km²] for each LCZ class in the Zürich LCZ maps. The column bars represent the percentage proportion of each class, and the flow between bars depicts the transition of categories between dates. The data for Sentinel-2 and Landsat 5 are on the left (a), while the results for Landsat 8 and Landsat 5 are on the right (b).

The LCZ maps of Basel (Figure S3—Supplementary Materials) show a predominant surface cover composed of *Dense trees* and *Low plants*, followed by *Open low-rise*. The *Low plants* class exhibits a trend of incremental variation over time, while conversely, *Dense trees* and *Large low-rise* classes display a declining trend. *Water*, *Open low-rise*, *Open mid-rise*, and *Compact mid-rise* classes are mostly stable across time and sensor types. Notably, *Bare rock or paved* rock exhibits a decreasing trend in the S2 maps, whereas it remains relatively stable in the L8 maps. Additionally, S2 maps depict less coverage of *Water* compared to L8, while *Dense trees* have a larger surface area with S2 than with L8.

In the LCZ maps of Geneva (Figure S4—Supplementary Materials), *Low plants* and *Dense trees* are the classes most represented, followed by *Open low-rise* and *Water*. A noticeable trend toward an increase in the surface area of *Open low-rise* and *Open mid-rise* classes over time is evident. Conversely, *Large low-rise* and *Bare rock or paved* classes show a tendency to decrease. *Water* and *Compact mid-rise* classes are stable during the whole period. Moreover, while the surface covered by *Dense trees* and *Low plants* fluctuates over time, it remains relatively stable between 1985 and 2022. Both the S2 and L8 sensors provided similar results, albeit with minor disparities. For instance, the surface area of *Large low-rise* is greater in L8 classifications than in S2. Additionally, L8 classifications for 2017 and 2018 yield higher percentages for *Low plants* and *Bare rock or paved* but lower percentages for *Dense trees*, *Open low-rise*, and *Open mid-rise* classes.

3.2. Overall, Producer, User Accuracies and Error Matrix

A total of 15 LCZ maps were generated for Sentinel-2, 15 for Landsat 8, and 15 for Landsat 5. The accuracy of these maps can be found in Figure 7 for the overall accuracy (OA) and in Figures 8 and 9 for the user's accuracy (UA) and producer's accuracy (PA), respectively (Table 5).

The overall accuracy of each LCZ map was calculated using the error matrix. Most of the results showed an overall accuracy higher than 80%, except for Basel with Landsat 5

in 1992 and 1985, with 79.9% and 78.3%, respectively, and for Geneva with Landsat 5 in 1985, with an overall accuracy of 63.7%. Generally, OA evolves with time, showing higher accuracy in more recent years. Sentinel-2 generally achieves an OA higher than 90%, except for Basel, Bern in 2017, and Lugano in 2018 and 2017. Zürich and Lausanne also obtain OA in this range for Landsat 8, while Bern and Lugano for L8 2022 reach this threshold as well. Additionally, there is no clear overall decline in accuracy when examining the Landsat 5 results, but it is still possible to observe one for Basel, Geneva, and Lausanne. There are even some instances of a very high OA for L5 imagery, such as Zürich, Lausanne, or Lugano.

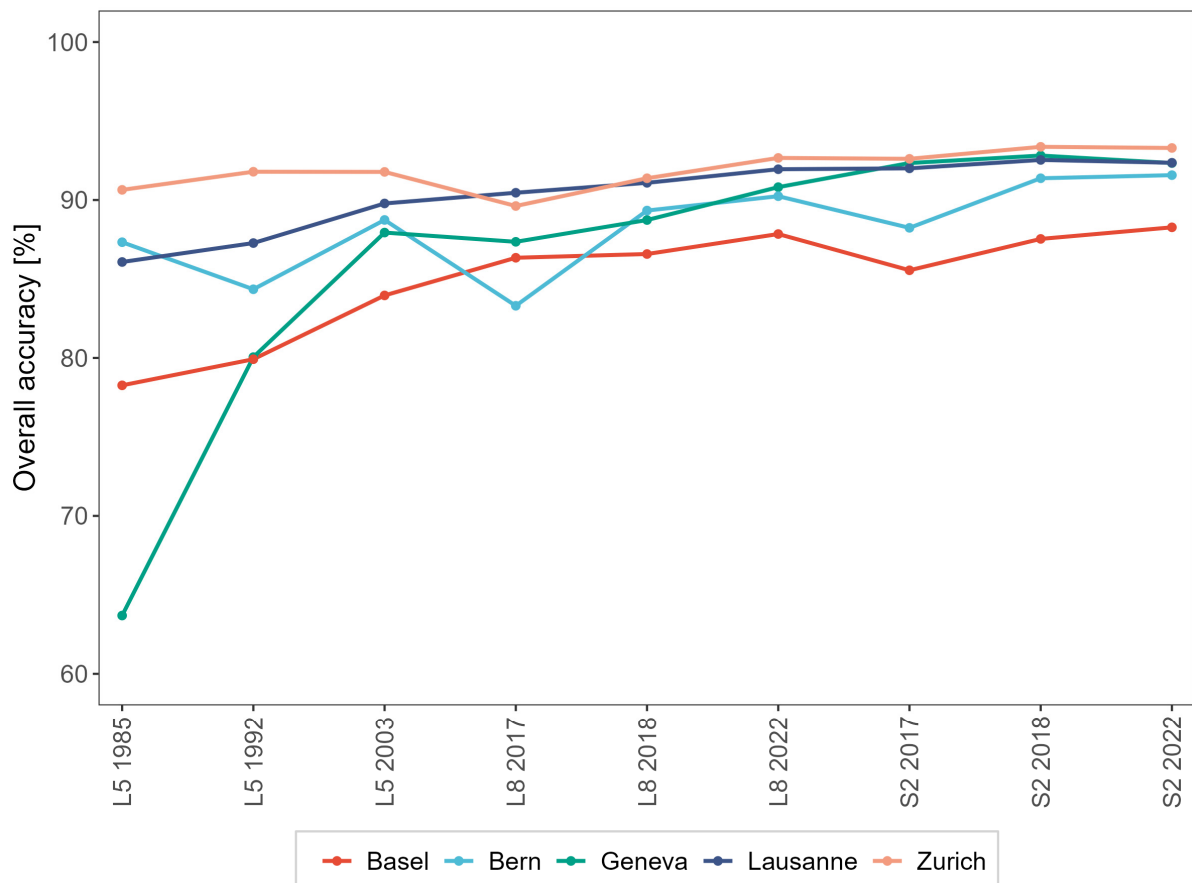


Figure 7. Overall accuracy (OA) for every LCZ map obtained in this study.

Table 5. Producer's Accuracy (PA) and User's Accuracy (UA) for some LCZ maps of the city of Geneva.

Class Name	Geneva							
	Sentinel-2: 2022		Landsat 8: 2022		Landsat 5: 1992		Landsat 5: 1985	
	PA [%]	UA [%]	PA [%]	UA [%]	PA [%]	UA [%]	PA [%]	UA [%]
Compact mid-rise	81.1	79.6	76.2	78.3	74.2	74.6	80.1	75.6
Open mid-rise	63.7	59.9	51.4	49.2	34.5	34.2	29.6	31.6
Open low-rise	72.9	73.0	68.6	71.3	55.0	59.0	49.1	58.0
Large low-rise	84.5	90.9	75.9	85.4	58.0	61.5	40.5	59.5
Dense trees	98.3	99.8	99.5	99.7	84.0	98.7	49.7	89.1
Low plants	95.0	93.0	93.9	92.9	90.3	72.0	81.6	48.4
Bare rock or paved	81.1	71.2	76.4	52.5	21.9	20.0	32.0	11.8
Water	99.8	100	99.8	100	99.7	99.6	99.8	99.6

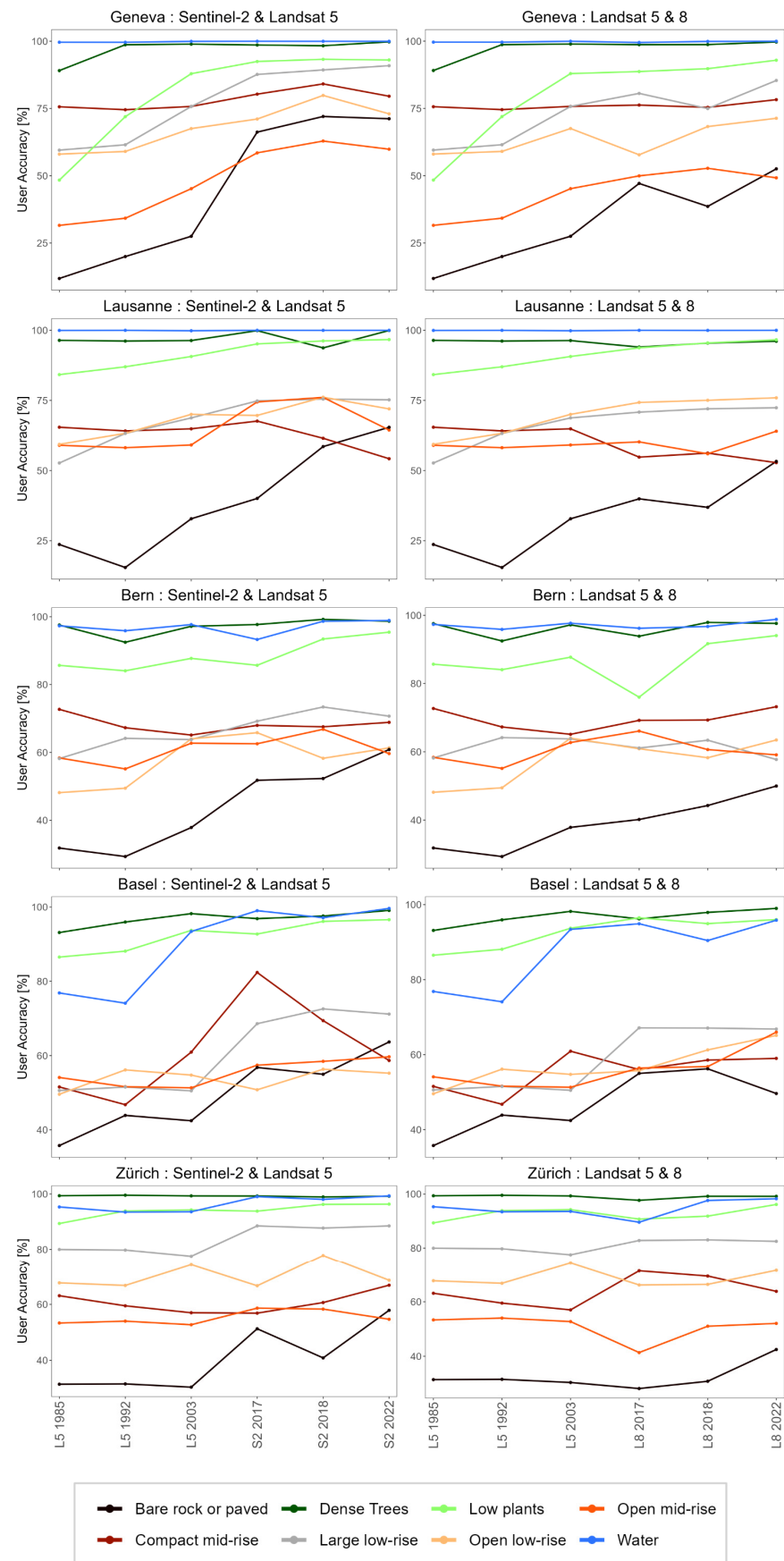


Figure 8. User's Accuracy for every city. On the left, there are the results for the LCZ maps with Landsat 5 and Sentinel-2, while on the right, you can see the results for Landsat 5 and Landsat 8.

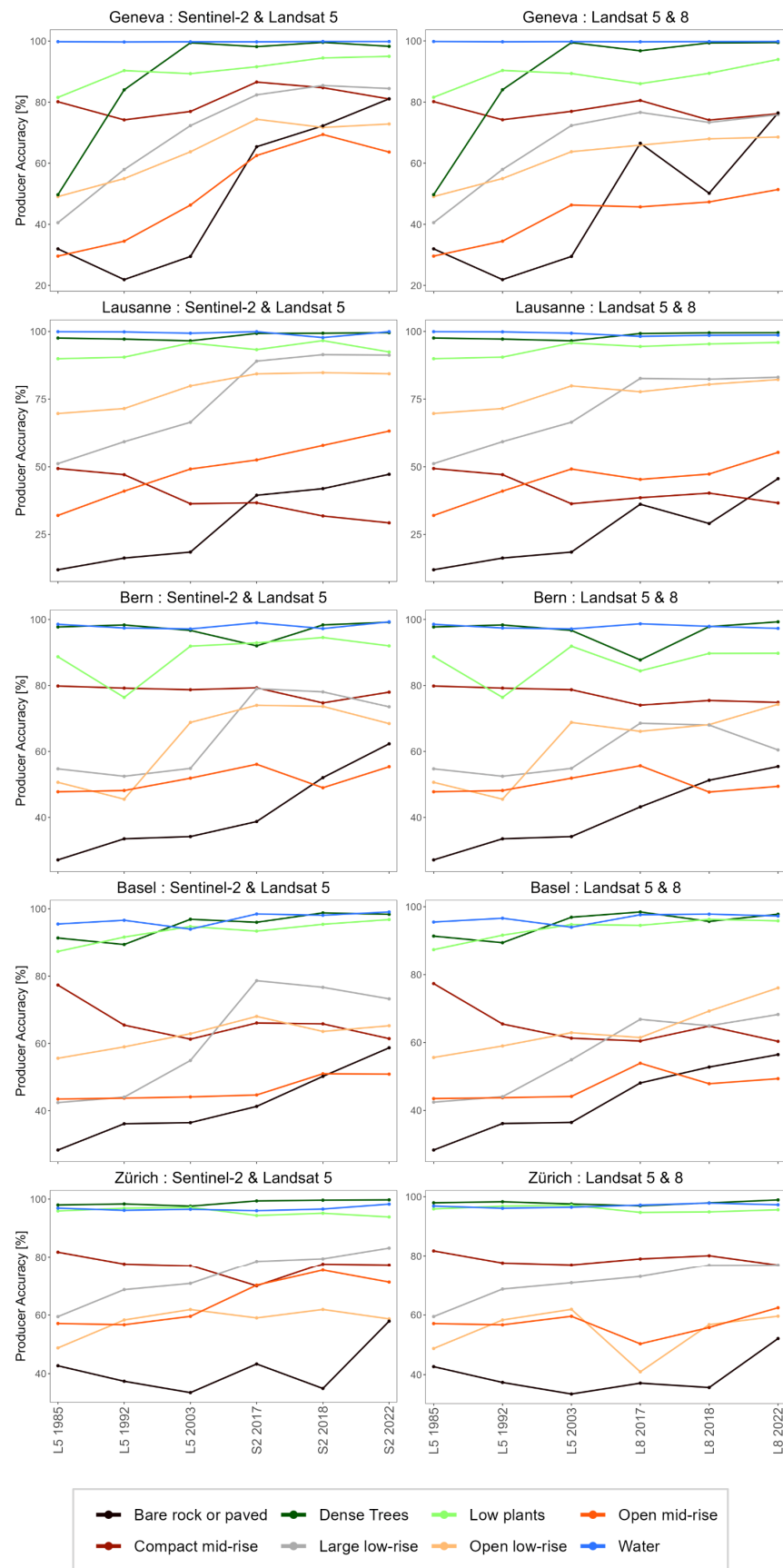


Figure 9. Producer's accuracy for every city. On the left, there are the results for the LCZ maps with Landsat 5 and Sentinel-2, while on the right, you can find the results of Landsat 5 and Landsat 8.

User's Accuracy (UA) and Producer's Accuracy (PA) illustrate the specific classification performance for each class. The highest results are obtained for natural classes, notably Water and Dense trees, followed by Low plants. The built-up types show lower accuracies, with results that can fall very low, especially Bare rock or paved and Open mid-rise. Generally, accuracies are lower for Landsat 5 and slightly better for Sentinel-2 than for Landsat 8, with some exceptions.

All LCZ maps of Geneva have an overall accuracy above 80%, except for Landsat 5 in 1985, which obtained 63.7%, marking the lowest OA for the entire study. The results show a slightly better OA for S2 than for L8 and a decline for L5. This accuracy diminishes over time for the two Landsat satellites. In detail, PA and UA follow the general trend, with higher numbers for the natural class and lower accuracies for built-up types. It is noteworthy that *Low plants* show a significant decrease in UA and *Dense trees* in PA, for L5 in 1992 and L5 in 1985, which are only found for Geneva. The most significant decrease in UA and PsA for a built-up type is observed in the class *Bare rock or paved*. Table 4 summarizes, for the sake of conciseness, PA and UA for a few maps of Geneva. All results can be found in Table S1 (Supplementary Materials).

Similarly, the LCZ maps of Lausanne demonstrate an OA above 86%, with Sentinel-2 exhibiting a marginal improvement over Landsat 8. Although a diminution in accuracy is observed with Landsat 5, satisfactory results remain. The PA and UA are high for all natural classes, while built-up classes follow the general trend. Most classes either maintain consistent accuracies or exhibit a declining trend over time. The UA graph (Figure 8) underscores a discernible discrepancy, with the lowest accuracy recorded in the *Bare rock or paved* class.

Conversely, LCZ maps of Bern attain an OA exceeding 83.3%, with Sentinel-2 outperforming Landsat 8, particularly in 2017. Landsat 5 yields good accuracies, ranging between 84% and 89%, but does not exhibit a linear decrease. Both UA and PA favor natural classes, with the best performances observed for *Water* and *Dense trees*. Conversely, *Open mid-rise* and *Bare rock or paved* classes register the lowest ranks in PA, with the latter being distinctive solely in UA. The temporal evolution is relatively small, except for *Bare rock*.

Basel has all its LCZ maps above 78.3% of OA or above 85.6% if L5 is not considered. Temporal evolution can be observed visually, with a general decrease over time (Figure 8). No overall accuracy reaches 90%. For both producer and user accuracies, there is a clear separation between the natural and built-up classes. However, the accuracies are more constant for natural classes for PA. The behavior of building-up classes is, however, similar for both accuracies, with a reduction over time globally. An exception can be noted: for the class *Compact mid-rise*, the higher PA can be found for L5 1985, which is the opposite behavior of other classes.

All LCZ maps for Zürich have an OA over 90%, except for L8 2017, with 89.6%. The accuracies are constant over time, with a 2.7% difference between S2 2022 and L5 1985. The results are slightly higher for Sentinel-2 than for Landsat 8, with a maximum difference of 3%. Natural classes achieved very high PA and UA, with most data exceeding 90% for all satellites and years, with slightly higher results for the producer's accuracies. For built-up classes, the lower accuracies are associated with *Bare rock or paved*, while higher accuracies are associated with *Compact mid-rise* and *Large low-rise* for PA and only *Large low-rise* for UA.

Figure 10 provides insight into the error matrices derived from the two LCZ maps: S2 2018 Zürich, with the highest OA at 93.36%, and L5 1985 Basel, with the second lowest OA at 78.26%. Globally, there are more 0 values for Zürich than for Basel, meaning fewer errors between classes. In the error matrix, it is possible to see which classes are mixed up during classification. For both cities, we can see a particular misclassification between *Open mid-rise*, *Open low-rise*, and *Low plants*. Despite this, the natural classes show high PA and UA in Zürich. However, the results for Basel show lower accuracies, even for natural classes. For example, there is a misclassification between *Low plants* and *Dense trees*, whereas there are 0 for Zürich.

Error matrix		(a) Ground Truth : S2 2018 Zürich									
Producer's Accuracy [%]		77.6	75.4	61.9	79.4	99.6	95.1	34.9	96.6	User's Accuracy [%]	
Class : S2 2018 Zürich	Compact mid-rise	2148	304	0	702	0	0	368	19	3541	60.7
	Open mid-rise	213	4223	1895	129	30	480	253	18	7241	58.3
	Open low-rise	0	764	4658	6	0	490	72	0	5990	77.8
	Large low-rise	302	112	0	5396	0	24	314	5	6153	87.7
	Dense Trees	0	0	97	0	82,292	808	0	3	83,200	98.9
	Low plants	0	56	767	25	268	38,400	364	25	39,905	96.2
	Bare rock or paved	99	101	110	536	0	163	740	62	1811	40.9
	Water	7	43	0	0	18	0	7	3719	3794	98.0
	Total	2769	5603	7527	6794	82,608	40,365	2118	3851	151,635	
Error matrix		(b) Ground Truth : L5 1985 Basel									
Producer's Accuracy [%]		77.3	43.5	55.6	42.4	91.3	87.3	28.3	95.5	User's Accuracy [%]	
Class : L5 1985 Basel	Compact mid-rise	1482	299	17	824	60	0	180	13	2875	51.5
	Open mid-rise	95	3002	1417	447	123	301	139	26	5550	54.1
	Open low-rise	8	1391	4039	195	185	2167	121	41	8147	49.6
	Large low-rise	92	379	551	2476	114	404	864	14	4894	50.6
	Dense Trees	0	1	153	0	27,309	1167	690	7	29,327	93.1
	Low plants	0	1550	896	941	1 098	34,470	736	153	39,844	86.5
	Bare rock or paved	239	217	164	724	589	596	1444	65	4038	35.8
	Water	0	65	28	229	423	362	924	6744	8775	76.9
	Total	1916	6904	7265	5836	29,901	39,467	5098	7063	103,450	
		Compact mid-rise	Open mid-rise	Open low-rise	Large low-rise	Dense Trees	Low plants	Bare rock or paved	Water	Total	

Figure 10. Error matrix for the LCZ maps of S2 2018 Zürich (a) and L5 1985 Basel (b). Values highlighted in green correspond to correctly classified pixels.

Table 6 presents a comparative analysis of classification accuracies across the different sensors used, with the mean values aggregated for all cities, individual sensors, and each class based on Sentinel-2 (S2) 2022 data. It can be observed that the changes depend primarily on the class, with most of them showing lower accuracy than Sentinel-2 by 2022. However, *Compact mid-rise*, *Open low-rise*, and *Low plants* have, in some instances, higher accuracies for the Sentinel-2 and Landsat 8 sensors in 2022, 2018 and/or 2017. For Landsat 5, only *Compact mid-rise* scores higher accuracy. In terms of size, the *Open mid-rise*, *Large low-rise*, and *Bare rock or paved* classes have the largest differences, not forgetting *Low plants* and *Open low-rise* for Landsat 5. The natural classes *Water* and *Dense trees* are decreasing but remain relatively stable.

In the yearly comparison of the S2 and L8 sensors, UA and PA show distinct class-specific results. UA consistently demonstrates higher accuracy across most classes with Sentinel imagery, except for *Open low-rise* and *Dense trees*. Conversely, PA yields superior accuracy for *Low Plants* with Landsat 8, while Sentinel-2 outperforms in four classes, and three classes show no clear trend.

Table 6. Increase/decrease (Δ) in Producer’s Accuracy (PA) and User’s Accuracy (UA) for the average of all classifications per satellite and per class of all cities. They are compared to the average classification of Sentinel-2 in 2022 for all cities.

Class Name	Average for All Cities									
	Sentinel-2: 2022		Landsat 8: 2022		Sentinel-2: 2018		Landsat 8: 2017		Sentinel-2: 2017	
	PA [%]	UA [%]	Δ PA [%]	Δ UA [%]	Δ PA [%]	Δ UA [%]	Δ PA [%]	Δ UA [%]	Δ PA [%]	Δ UA [%]
Compact mid-rise	65.4	65.6	−0.4	−0.2	1.5	3.0	1.5	0.1	2.3	5.4
Open mid-rise	60.9	59.7	−7.3	−1.6	−0.3	4.9	−11.7	−4.2	−3.7	2.7
Open low-rise	69.9	66.1	2.2	3.4	1.2	3.6	−1.4	−0.2	2.0	−1.3
Large low-rise	81.1	79.3	−8.2	−6.3	1.1	0.4	−8.0	−7.2	0.4	−1.5
Dense trees	99.0	99.3	0.0	−1.0	0.1	−1.8	−1.0	−1.5	−2.1	−0.9
Low plants	94.0	95.6	0.2	−0.5	1.2	−0.6	−0.9	−2.9	−0.9	−3.6
Bare rock or paved	61.4	63.8	−4.3	−14.2	−11.2	−8.1	−17.7	−22.4	−15.8	−10.6
Water	99.3	99.6	−1.2	−1.0	−1.4	−0.8	−0.9	−2.6	−0.6	−1.3
Class Name	Sentinel-2: 2022		Landsat 8: 2017		Landsat 5: 2003		Landsat 5: 1992		Landsat 5: 1985	
	PA [%]	UA [%]	Δ PA [%]	Δ UA [%]	Δ PA [%]	Δ UA [%]	Δ PA [%]	Δ UA [%]	Δ PA [%]	Δ UA [%]
	PA [%]	UA [%]	Δ PA [%]	Δ UA [%]	Δ PA [%]	Δ UA [%]	Δ PA [%]	Δ UA [%]	Δ PA [%]	Δ UA [%]
Compact mid-rise	65.4	65.6	1.1	−0.1	0.6	−0.9	3.3	−3.2	8.3	0.0
Open mid-rise	60.9	59.7	−10.7	−4.9	−10.7	−5.5	−16.1	−9.0	−18.9	−8.4
Open low-rise	69.9	66.1	−7.5	−3.1	−2.5	0.1	−12.1	−7.1	−15.2	−9.5
Large low-rise	81.1	79.3	−7.6	−6.8	−17.3	−12.0	−24.7	−15.3	−31.5	−19.1
Dense trees	99.0	99.3	−3.2	−3.2	−1.6	−1.3	−5.6	−2.8	−12.2	−4.2
Low plants	94.0	95.6	−3.2	−6.5	−0.2	−4.8	−4.9	−10.6	−5.3	−16.8
Bare rock or paved	61.4	63.8	−15.2	−21.7	−31.0	−29.6	−32.4	−35.8	−33.0	−36.9
Water	99.3	99.6	−1.0	−3.5	−1.9	−2.7	−1.3	−7.0	−1.2	−5.7

4. Discussion

Overall, the 45 LCZ maps exhibit satisfactory outcomes, displaying clear visual recognition of the different Swiss cities. While most maps achieve an Overall Accuracy (OA) exceeding 80%, only a select few surpass the 90% threshold, with an 80% OA considered as the minimal threshold for satisfactory classification. Sentinel-2 consistently demonstrates a higher OA compared to Landsat 8 when comparing results from the same year, albeit with a relatively minor difference, indicating a marginal precision gain attributed to improved resolution. Despite expectations of a substantial OA decline with Landsat 5, such a trend is not consistently observed across all cities, yet a general tendency toward decreased accuracy over time is evident across all sensors.

The singular case of Geneva in 1985, characterized by a notably low OA of 63.7%, is primarily attributed to cloud cover presence over the northwestern region of the image. These clouds disrupted the sample trainings, leading to an unknown spectral signature and then confusion for classification. Basel, on average, attains a lower OA compared to other cities, with its Landsat 5 imagery from 1985 depicting considerable confusion between classes, particularly evidenced by lower Producer’s Accuracy (PA) and User’s Accuracy (UA) for natural classes, notably *Dense trees* and *Water*, which is unusual in our results. This anomaly may be attributed to the utilization of building footprints solely from Basel-City for constructing training and testing samples, which are limited to a restricted area. Consequently, Basel’s Training Areas (TAs) were primarily sourced from Google Maps imagery, potentially leading to a decrease in accuracy.

Natural classes consistently exhibit higher and more stable accuracies across most sensors and years compared to built-up classes, owing to the distinct spectral signatures of natural features facilitating easier discrimination, in contrast to the poor spectral separability inherent in built-up classes. Notably, the class *Low plants* in Bern exhibits unique behavior in terms of Producer’s Accuracy (PA), possibly linked to the presence of cloud and snow cover, particularly notable in Sentinel-2 imagery from 2017 and Landsat 5 imagery

from 1992 and 1985, coinciding with a decline in accuracies. Build-up classes, including *Low plants*, frequently share spectral features across multiple categories, such as vegetation in *Open low-rise* and *Low plants*, or extensive concrete surfaces in *Large low-rise* and *Bare rock or paved*, as illustrated by spectral signature graphs. Moreover, natural categories demonstrate greater temporal stability compared to built-up categories, attributable to substantial landscape variations in built-up areas over time, notably evident in the dynamic nature of *Bare rock or paved* areas comprising quarries, railways, car parks, and roads, all subject to considerable changes over relatively short time spans.

Concerning the land cover of the LCZ maps, represented as a percentage of the total areas on the cumulative histograms, the main classes are *Low plants* and *Dense trees* for all cities, with *Water* for Lausanne and Geneva as an important part of Lake Geneva taken into consideration in the classification. For build-up classes, the surface areas are mainly allocated to *Open low-rise*, then *Open mid-rise* and then *Large low-rise*. *Compact mid-rise* and *Bare rock or paved* cover only a small part of Switzerland's main cities. However, this observation must be nuanced. The study areas (footprints) for each city include its suburbs, which means that the representation of different classes must be reshuffled. The result is, therefore, not solely associated with the city boundary. Globally, Sentinel-2, Landsat 8, and Landsat 5 give similar results, which means that the three sensors are reliable for LCZ classification. Admittedly, there are differences in the proportions (for S2 and L8) of certain classes in certain cities, but there is no general trend.

Concerning the temporal evolution of cities, there were no major visible changes in the LCZ maps between 1985 and 2022. However, it is still possible to identify certain trends: the built-up classes increase over time, *Open low-rise* and *Open mid-rise*, while it is mainly *Large low-rise* and *Bare rock or paved* that decrease between 1985 and 2022. Finally, *Compact mid-rise* is the most stable class over time because it mainly represents historical centers, which were built before 1985 and changed very little over time. For the natural classes, *Water* and *Dense trees* remain stable (either a slight increase or a slight decrease) between 1985 and 2022, although there are fluctuations between the two, while *Low plants* tend to decrease over time.

Given the minor differences in accuracies observed among satellites and years for classes that are stable over time, it appears that distinctive sensor characteristics play a less significant role compared to landscape evolution. Moreover, while the literature suggests the potential contribution of additional bands, such as red-edge bands in Sentinel-2, to improved accuracy, disentangling this effect from the influence of superior spatial resolution remains challenging.

Switzerland has experienced significant urbanization in recent decades. Between 1985 and 2018, the extent of settlement and urban areas in the country expanded by nearly one-third. Notably, residential areas increased by approximately 61%, a rate that is twice as fast as population growth during the same period. However, the pace of settlement expansion has slightly decelerated over the last 30 years. To efficiently mitigate UHI and enhance local climate resilience, policies promoting sustainable urban development, such as green building standards, extensive public transportation systems, and the creation of urban green spaces, can influence the observed changes [34].

By 2018, settlement and urban areas occupied a total of 3,271 square kilometers in Switzerland, representing 8% of the nation's total land area—an expanse comparable to the size of the canton of Vaud. Among these settlement areas, residential zones constituted the largest category, accounting for 35% of the total settlement area in 2018. Residential zones include not only buildings and garages but also associated features such as driveways, open spaces, lawns, and gardens. These zones correspond to the “Open mid-rise” and “Low-rise” classes in the Local Climate Zone (LCZ) classification system, which exhibited the most significant increases among the mapped LCZ categories.

The expansion of built-up areas has predominantly occurred at the expense of agricultural land. Approximately 90% of the new settlements and urban areas that developed between 1985 and 2018 were established on former agricultural land. In contrast, only

about 10% of these areas were developed on land previously covered by forests, woods or classified as unproductive. This trend can be attributed to the proximity of existing settlements to agricultural areas, which lack the legal protection afforded to forests, where deforestation must be offset. Unproductive lands, which are largely situated in remote locations, have been minimally impacted by the expansion of the built environment.

4.1. Benefits

LCZ classification was conducted using the semi-automatic classification plugin with a precise and scientifically validated methodology. The decision to employ the random forest algorithm with 100 trees was made to obtain more reliable results and reduce the risk of overfitting. This specific algorithm is used widely, as most studies follow the WUDAPT LCZ mapping method, which uses the RF algorithm [22].

This work has resulted in the generation of 45 LCZ maps through a remote sensing approach for the main cities in Switzerland. To the best of our knowledge, a comprehensive and comparative study encompassing various Swiss cities has not been conducted to date. This initiative has allowed us to identify several trends in the urban landscape of Switzerland. Classification into local climate zones provides a more detailed analysis of the territory, facilitating more reliable comparisons, particularly for climate studies. These LCZ maps, when combined with climatic analyses, can serve as a foundational resource for planners and designers, aiding in prioritizing efforts to mitigate UHI effects and implementing urban cooling strategies.

The use of remote sensing allows for rapid, cost-effective, efficient, and consistent processing of a large amount of data and proves to be relevant to producing these tools useful for climate-related studies. This can contribute to the uniform implementation of these tools across various cities, promoting a consistent and integrated approach within the scope of climate studies, particularly for the implementation of climate action plans.

This work, made possible by the LCZ system, facilitates a comparative analysis among different major cities of Switzerland (“inter-urban analysis”) as well as within a single city, considering its land cover and temporal evolution over different years (“intra-urban analysis”). Such analyses provide invaluable insights into the dynamics of urban environments and their response to temporal changes, thereby informing informed decision-making processes concerning urban planning and climate resilience strategies.

From a broader perspective, integrating LCZ and UHI data can significantly contribute to enhancing urban policymaking and public health strategies by providing a detailed, spatially explicit understanding of how different urban areas experience heat. This integration allows policymakers to identify heat-prone zones with precision, enabling targeted interventions such as increasing green spaces, optimizing building materials, or enhancing cooling infrastructure in the most vulnerable areas. For public health, this approach helps pinpoint communities at greater risk of heat-related illnesses, allowing for better resource allocation, such as cooling centers or emergency services, and the development of heatwave response plans tailored to specific neighborhoods. Overall, the combined use of LCZ maps and UHI data supports more informed, equitable, and effective strategies for mitigating heat impacts and improving urban resilience.

4.2. Limitations

Our proposed methodology, while robust in several aspects, is subject to certain limitations:

1. Despite the decrease in the risk of overfitting with the random forest algorithm, the number of training samples (65) remains relatively low, which can cause overfitting. This may occur if the TAs do not cover all situations and, therefore, the spectral signatures of the corresponding classes, allowing good classification of the training and testing areas, but perhaps not in a general way on the image. This is why good overall accuracy results can sometimes be overestimated.

2. Landsat satellites have a long historical record, while Sentinel-2 satellites offer higher temporal, spatial, and spectral resolution, so it is difficult to say why the accuracies remain similar for all sensors. For instance, the additional red-edge bands in S2 provide additional information regarding the spectral signature. This augmentation is anticipated to enhance the discrimination between classes, consequently resulting in an improvement in OA. However, it is crucial to acknowledge that the entirety of the training and testing samples was derived exclusively from Sentinel-2 data. This exclusive reliance on S2 data for sample creation imposes limitations on the extent of the differences in properties observed across sensors.
3. The cloud coverage limitation of 20% could be lowered to mitigate its impact on the classification. Ref. [13] suggests minimizing cloud coverage to 5% or less, depending on meteorological conditions. Additionally, the presence of snow may have decreased the accuracy of some LCZ maps, as seen for Lugano. This decision was made because, with a threshold lower than 20%, some images could not be obtained, especially in the Lugano region, where cloud cover is often present.
4. During preprocessing, no radiometric calibration was conducted since the datasets (surface reflectance) were already atmospherically corrected. However, implementing radiometric enhancement may enhance the capacity to differentiate between classes. Thus, conducting experimentation to evaluate the efficacy of incorporating this step in improving results is warranted.
5. Overall, Producer, and User accuracy metrics in remote sensing classification can be limited as they provide general measures of classification performance but do not fully capture class-specific errors, spatial distribution of misclassifications, or the impact of imbalanced class distributions. Accuracy metrics could have been enhanced using additional metrics such as Cohen's Kappa or F1 score, but they were not available in the version of the plugin we used.
6. Data acquisition limitations arise from the unavailability of building height information for certain cities/cantons. Integrating height data facilitates improved class differentiation associated with height-related classes, thereby potentially enhancing accuracy [12,35]. It has been demonstrated that building height can lead to an improvement of approximately 10% in the classification of LCZ urban classes (e.g., open low-rise) [12]. Therefore, enhanced data consistency across cities would overcome this limitation.
7. Produced maps were verified based on our knowledge and the historical evolution of these cities. To further enhance the results, proper ground-truthing should have been used, for example, mobile applications like EarthTrack or Collect Earth [36].
8. To better understand the differences in LCZ changes, it would be beneficial in the next iteration of this work to conduct a detailed comparative analysis of the urban characteristics and climatic conditions in the selected cities.
9. Differences in urban morphology, climate, and socioeconomic factors across regions significantly impact the scalability of the applicability of LCZ classification schemes to other cities/regions. Urban morphology, including building density, height, and street layout, varies widely, influencing how LCZs are identified and their thermal characteristics. Climatic differences, such as varying humidity, temperature ranges, and seasonal patterns, affect the definition and relevance of certain LCZ types, as some may be more applicable to temperate zones than to tropical or arid regions. Socioeconomic factors also play a role, as cities in wealthier regions may have more resources for green spaces or modern materials, whereas cities in developing regions may exhibit informal settlements with distinct thermal properties. These variations require adaptations or refinements of the LCZ classification to ensure accurate representation and effective application in different contexts.

4.3. Perspectives

These results are encouraging, yet further work is needed to strengthen them and improve the discrimination of classes that have lower accuracies. Subsequently, the following ideas are proposed:

1. To enhance the results, it would be beneficial to generate additional training zones while ensuring consistency with those collected during this study to refine the spectral signatures of each class. To achieve this, different confusion matrices allow us to highlight where the greatest confusions lie. Particular care is needed in their selection, as they are the key to achieving high LCZ classification accuracy [37]. More generally, to minimize the risk of confusion between classes, according to [38], the establishment of a standardized method for the detection and delineation of LCZs in urban areas in a consistent manner worldwide is essential.
2. Moreover, to reduce the biases of visually identifying LCZ classes, it is possible to use (semi-)automated procedures to reduce the subjectivity of interpretation when creating training samples [39–41].
3. Enhancing the consistency of LCZ maps with reality and mitigating noise can be achieved through post-processing operations such as a 3-pixel filter, akin to methodologies employed in the World Urban Database and Access Portal Tools (WUDAPT) [42], or by employing noise-smoothing techniques such as a classification sieve algorithm with a 5-pixel threshold [12].
4. When building height data become available for all cities, it would be relevant to conduct the LCZ classification again.
5. For a more dynamic analysis conducive to informing urban planning and policymaking, generating annual LCZ maps, despite the potentially limited changes in the urban landscape over short intervals, would offer a nuanced perspective. Additionally, facilitating access to these maps through visualization/tracking services would empower urban planners and decision-makers with direct access to pertinent information.
6. Considering cloud coverage, revisiting the threshold applied in this study (20%) could be beneficial. Alternatively, implementing a function to mask pixel-wise clouds, cloud shadows, and snow from image collections while retaining the 20% threshold would help mitigate the influence of atmospheric artifacts on classification outcomes [43].
7. One challenge in using Google products is the potential dependence that users can encounter. Therefore, we recommend the future development of LCZ products for Switzerland to use as a national asset. LCZ classification process could be facilitated by integrating the methodology into the Swiss Data Cube [44], a repository and processing infrastructure of Analysis Ready Data (ARD) Landsat and Sentinel-2 data required for LCZ classification for all Swiss cities [45]. The challenge lies in finding a solution for the TA, either by producing them manually in advance or utilizing existing ones.
8. To better account for the spatiotemporal variability of LCZ classes, it would be valuable to explore the potential of time-series analysis based on Satellite Image Time-Series Analysis (SITS), which has already been demonstrated to improve traditional land cover classifications [46–48].
9. Other possibilities to improve the LCZ classification would be to (1) enhance the spectral characterization of LCZ classes using hyperspectral data with enhanced spectral resolution [12,49] or (2) explore the use of very high-resolution satellites (e.g., Pleiades, WorldView) with object-based approach (OBIA) that could improve classification accuracies [50].
10. There are also studies that combine an algorithm, such as Random Forest, with deep learning models, such as convolutional neural networks (CNN) [3]. Combining them could enhance accuracy, particularly in improving the classification of specific LCZs (building/tree combinations).

11. More advanced methods such as CNN, Recurrent Neural Networks (RNN), and attention-based models are achieving even better results. However, they are more computing-intensive and usually require more training samples [51,52].
12. Current LCZ classification methodologies often rely on periodic updates and remote sensing to account for urban development and land use changes; however, improvements could include more real-time monitoring and the integration of predictive modeling to anticipate future changes.
13. While remote sensing data is a powerful tool for studying urban climates, it presents several ethical challenges, particularly around privacy, data accessibility, and equitable use. Addressing these concerns requires careful consideration of how data are collected, analyzed, shared, and used, with a focus on protecting individual privacy, ensuring fair access, and promoting environmental justice. Transparency, community engagement, and accountability are key to using remote sensing data ethically in urban climate studies.
14. Successful implementation of region-specific LCZ classification and UHI mitigation strategies requires collaboration between urban planners, climatologists, and geographers to accurately map and understand local climate zones. Additionally, partnerships with public health experts, engineers, and local governments are essential for designing, implementing, and sustaining effective mitigation interventions tailored to the unique needs of each region.
15. The broader application of the LCZ classification approach in urban climate research includes its use as a standardized tool to enhance the spatial resolution and precision of studies related to air quality, flood risk analysis, and green infrastructure planning. By categorizing urban areas based on their physical and thermal properties, the LCZ framework allows for more accurate assessments of microclimatic conditions, which can inform targeted interventions and policy decisions in these domains.

These LCZ maps provide an analytical tool that can be integrated into various datasets. For instance, it is feasible to compare these maps with LST maps to assess the magnitude and distribution of UHI and to investigate the influence of morphology and urban fabric on this phenomenon.

Given the dynamic nature of urban environments, LCZ maps should ideally be updated every 3 to 5 years to maintain their relevance and accuracy. Urban landscapes can change rapidly due to new developments, infrastructure projects, or changes in land use, which can alter the characteristics of existing LCZs or create new ones. Regular updates ensure that the maps reflect these changes, enabling urban planners, policymakers, and researchers to base their decisions on current data. Additionally, because climate change and technological advancements influence urban morphology and microclimates, periodic updates allow the incorporation of these factors, ensuring that LCZ maps remain effective tools for urban planning, environmental monitoring, and public health strategies.

5. Conclusions

In the context of climate change and population growth, LCZ maps have emerged as valuable tools for adapting to UHI in cities, which play a pivotal role in mitigating climate change. Urban planners and policy/decision-makers should prioritize ensuring thermal comfort for the entire population within cities while also facilitating the necessary conditions to implement the required measures. The creation of 45 LCZ maps for the main Swiss cities provides an efficient, distributable, cost-effective, and homogeneous tool that can aid in the implementation of climate action plans for each municipality/canton.

This study highlights the potential of the proposed methodology to classify the major Swiss cities into Local Climate Zones, enabling their use for mitigating climate impacts and adapting to them. Our initial results indicate good and similar performance for Sentinel-2, Landsat 8, and Landsat 5 imagery, with marginal superiority in performance for S2. This improvement was less than anticipated, considering the spectral and spatial differences of these sensors. Furthermore, for the temporal evolution, it was observed that the built-up

classes experiencing the most significant increase within and around cities are *Open low-rise* and *Open mid-rise*, while *Large low-rise* and *Bare rock or paved* tend to decrease, and *Compact mid-rise* stays stable over time. For natural classes, it was observed that *Water* and *Dense trees* remained stable, while *Low plants* tended to decrease. Regarding overall accuracy, it usually exceeds the 80% threshold, with classes that are better classified than others (e.g., *Water* and *Dense trees* giving good results compared to *Bare rock or paved*); we observe a general trend of decline over time, primarily explained by changes in the landscape that no longer align as closely with the reference data.

This work represents a preliminary effort to create and utilize LCZ maps for major cities in Switzerland. To advance further, it is crucial to enhance and automate the methodology, particularly with respect to TAs, and seamlessly integrate it into the Swiss Data Cube. Additionally, there is the potential to extend the analyses by incorporating climate data, particularly for studying the urban heat island effect. Facilitating the dissemination of these tools through a visualization/tracking service for authorities and urban planners is a key aspect of future development.

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/urbansci8030120/s1>. Figure S1. Cumulative histogram for Lausanne; Figure S2. Cumulative histogram for Bern; Figure S3. Cumulative histogram for Basel; Figure S4. Cumulative histogram for Geneva; Table S1. Summary tables for UA and PA for each year, each satellite, and each city.

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