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RESEARCH BRIEF
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Multitemporal Assessment of Local Climate Zones in Cape Town, South Africa, Using LANDSAT Imagery (including an evaluation of transferability to Thohoyandou and East London)

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RESEARCH BACKGROUND

Urban areas house over half of the global population and dominate social, economic, and environmental activities, leading to significant environmental damage and health risks. Urbanisation transforms natural habitats, creating urban heat islands (UHIs) through impervious surfaces and thermal energy capture, which are exacerbated by climate change and population growth. Heatwaves and higher temperatures will amplify UHI effects, particularly impacting densely populated regions and rapidly urbanising areas in Sub-Saharan Africa.

Understanding the unique vulnerabilities of cities and identifying adaptation actions is crucial. However, spatial studies capturing the heterogeneous morphological and functional surface properties of cities, especially in African urban areas, are lacking. Addressing this, the thesis focuses on assessing Local Climate Zones (LCZs) in Cape Town using Landsat 8 imagery, aiming to enhance LCZ classification accuracy and conduct a multi-temporal analysis to understand LCZ changes over 20 years. It also explores the model's transferability to Thohoyandou and East London, providing insights for future LCZ-related research. By validating results with ground-truth data and evaluating spectral indices and post-processing methods, the study seeks to improve LCZ mapping accuracy and applicability across diverse urban and climatic conditions.

PROJECT SUMMARY

This thesis aimed to enhance Local Climate Zone (LCZ) classifications for Cape Town, Thohoyandou, and East London, addressing a research gap in urban climate mapping in African cities. It evaluated the transferability of a model trained on Cape Town data to Thohoyandou and East London, and provided a methodology for analysing LCZ changes over time, verifying the validity for Cape Town between 2001 and 2020.

KEY FINDINGS

- The **transferability of LCZ classifications to Thohoyandou and East London was low**, but high accuracies were achieved when models were trained with local data, highlighting the importance of using ground-truth data and testing transferability between cities with similar climates and urban morphologies.

- The study found that a **70% training to 30% validation data split was effective**, the inclusion of LiDAR-derived building height data could be beneficial, and a neighbourhood function as a contextual classifier improved accuracy, especially with local training areas.

- Multi-temporal analysis s**uccessfully detected general densification trends in Cape Town**, though inconsistencies hindered small-scale change detection, providing valuable insights for linking air temperature measurements to LCZ maps and better estimating the Urban Heat Island (UHI) effect.

This work advances sustainable and adaptive urban planning by offering spatial urban information and efficient LCZ classification methods.

Urbanisation, driven by economic opportunities and access to services, significantly alters local climates by changing land use, affecting temperature, humidity, and precipitation patterns. The UHI phenomenon, characterised by higher urban air temperatures compared to surrounding rural areas, intensifies with urban expansion, posing health risks like heat stress but also offering benefits such as reduced heating needs in cooler climates. UHI intensity is influenced by urban morphology, surface properties, and human activities.

To better understand UHI impacts, finer spatial distinctions beyond urban-rural divides are necessary. The framework of 17 LCZs proposed by Stewart & Oke (2012) categorises urban areas based on surface cover, structure, materials, and human activities affecting air temperatures. Remote sensing, particularly using Landsat imagery, is crucial for broad-scale data acquisition and monitoring land use and land cover changes over time. LCZ classification benefits from spectral signatures, aiding in distinguishing vegetation and built classes, and can be refined with LiDAR data to distinguish between similar impervious built classes with varying heights.

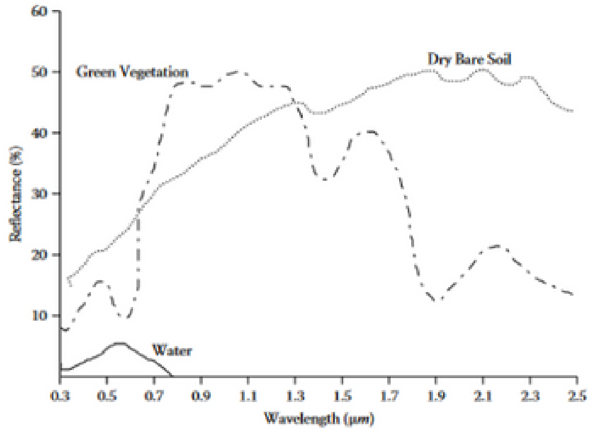

Figure 1. Typical spectral reflectance (%) of green vegetation, dry bare soil, and water (Tso & Mather, 2009)

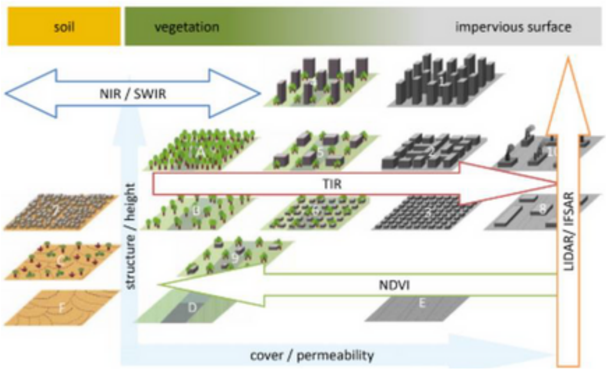

Figure 2. Observable traits that can be distinguished by remote sensing data (Bechtel et al., 2015).

RESULTS

CLASSIFICATION OPTIMISATION

The study conducted three different classifications for each year included in the temporal analysis of Cape Town, including images of every season as the work of Teerlinck (2021) proved it to be useful in LCZ classification. There were varying accuracies for different metrics. The highest Kappa value was always found in classification trends using a neighborhood function during postprocessing. However, the Overall Accuracy (OA) varied. For example, in 2001 and 2020, the highest OA was achieved without spectral indices but with the neighborhood (NH) function. Spectral indices generally improved the OA for natural classes but had mixed effects on urban classes.

TRANSFERABILITY

Thohoyandou: A summary of relevant accuracy metrics reveals that TAs from Cape Town did not successfully classify the city of Thohoyandou and its surroundings properly. However, it did succeed in delineating urban from natural LCZs. In other words, the classification map of Thohoyandou computed with Capetonian TAs, does not resemble the situation on the ground however, it did accurately distinguish between urban and natural LCZs.

RESEARCH QUESTIONS

- To what extent can **spectral indices** and a **postprocessing contextual classifier improve the accuracy** of a **supervised classification model** using Landsat 8 imagery of urban areas in South Africa?

- To what extent is the classification framework of Cape Town **transferable** to South African cities with a different climate and urbanization degree like Thohoyandou and East London? How does the model performance compare to their classifications using training areas from their own study area?

- If any, what are the **LCZ trends or oscillations in Cape Town** in the interval of 2001 and 2020 and to what extent are they confirmed by literature and satellite images?

When TAs were specific to Thohoyandou, accuracies improves significantly, especially with the inclusion of the NH function.

East London: Similar to Thohoyandou, models trained with TAs from Cape Town performed inadequately in East London. Furthermore, they failed to demarcate the urban and natural areas with an accuracy higher than 70%. The classifications using East London's own TAs had better OA and Kappa values, with the additional NH function performing best in all but one metric, that being the OA of the natural LCZs. This contradicts previous results which show an increase in the separability of natural classes when spectral indices were added.

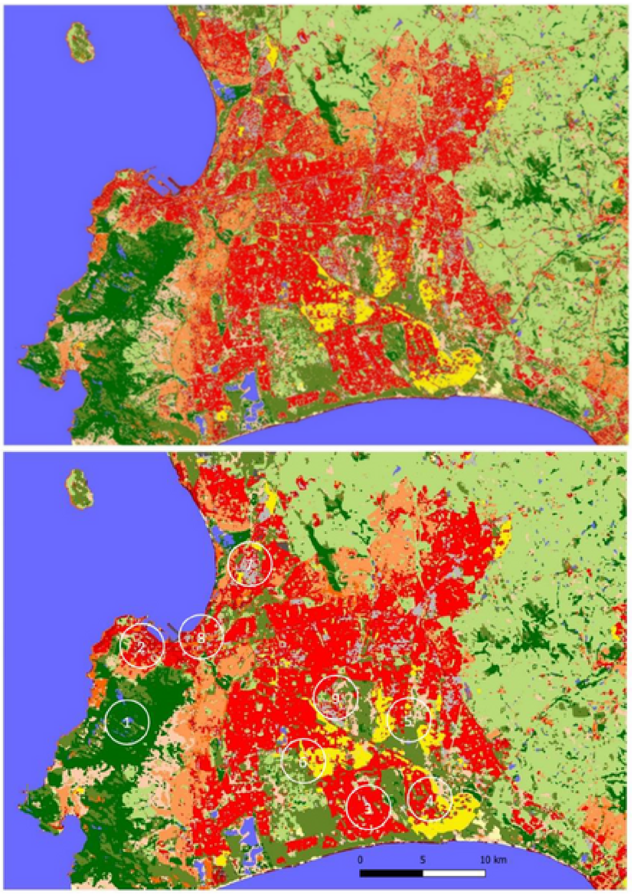

Figure 3. Cape Town classification maps for the year 2020. Top: without neighborhood function. Bottom: with NH applied during postprocessing. 1 = Table Mountain, 2 = City Bowl, 3 = Mitchell's Plain, 4 = Khayelitsha, 5= Delft & Blue Downs, 6 = Phillipi, 7 = Milnerton, 9 = Paarden Eiland, 9 = Airport.

METHODS

The study area encompasses three urban areas in South Africa: Cape Town in the Western Cape, Thohoyandou in Limpopo, and East London in the Eastern Cape. These cities represent varying degrees of urbanization and experience different climatic conditions due to South Africa's geographical diversity.

Cape Town: A major city with a semi-arid climate, climate change is causing drying in Cape Town, leading to potential water shortages. Its population is estimated to reach 5.8 million by 2035. The city is characterized by non-centralized spatial planning and several administrative centres – an artefact of apartheid era urban planning.

Thohoyandou: A small city (42.62 square km) which is the capital of the Vhembe district, characterized by a humid subtropical climate with dry winters and warm, wet summers. The population density is high at 1629 inhabitants per square kilometre.

East London: A city on the southeastern coast of South Africa in the Eastern Cape Province. The city lies on the Indian Ocean coast and hosts the country's only river port. As of 2011, Population density sits at 1600 inhabitants per square kilometre.

DATA COLLECTION AND ANALYSIS

Cloud-free Landsat 7 and Landsat 8 imagery for all four seasons was acquired from the US Geological Survey Earth Explorer tool for Cape Town, focusing on multi-temporal analysis from 2001, 2006, 2014, and 2020. The imagery was resampled to a 30-meter resolution and corrected to surface reflectance using the Semi-Automatic Classification Plugin in QGIS. This process ensured accurate physical characteristic representation. Gaps in Landsat 7 imagery due to a Scan Line Corrector failure were addressed using gap mask files and the "fill nodata" tool. The spectral indices Normalized Difference Vegetation Index (NDVI), Normalized Difference Built-Up Index (NDBI), and Enhanced Built-Up were used to enhance the distinction of greenness and built-up areas.

LCZ TRENDS IN CAPE TOWN

- **Urbanisation Trends:** Cape Town has experienced increased urbanization over the past 20 years, leading to changes in LCZs.
- **Densification Patterns:** Densification is notably observed in the southwest, with decreases in LCZ F, LCZ C/D, and increases in LCZ 3, reflecting urban growth.
- **Classification Observations:** Differences between classifications reveal inconsistencies, such as the sudden rise of LCZ 8 in 2014 and misclassifications in certain areas like Table Mountain.
- **Compactness Increase:** The area covered by compact classes (LCZ 1+2+3) has increased, indicating urban intensification despite a drop in 2014.
- **LCZ Conversion Flows:** Conversion flows between LCZs show shifts, with gains in compact classes from various LCZs, particularly LCZ 9 losing area to built and vegetational classes.
- **Net Loss of Natural Classes:** A net loss of natural classes is observed, compensated by gains in built areas, highlighting a balance between natural and built LCZs but suggesting potential green space losses.
- **Confirmation of LCZ Merging Choices:** The merging of LCZs was well-considered, evident from consistent trends in LCZ 1, 2, and 3, while LCZ 5 saw gains, and LCZ 6 remained stable.

The preprocessed images were used for Local Climate Zones (LCZ) classifications through a supervised pixel-based classification procedure. Ground-truth data trained the model, which was then validated with 30% of the classified training areas. Post-processing with a neighborhood function reduced grain-like structures and improved classification accuracy, maintaining a 30m scale. The transferability of LCZ classifications was tested by applying Cape Town's training areas to Thohoyandou and East London, comparing results to locally trained models. A multi-temporal analysis using the OpenLand package in QGIS identified trends in LCZ distribution and urban changes from 2001 to 2020, aiding in the exploration of urban trends and their potential climate impacts.

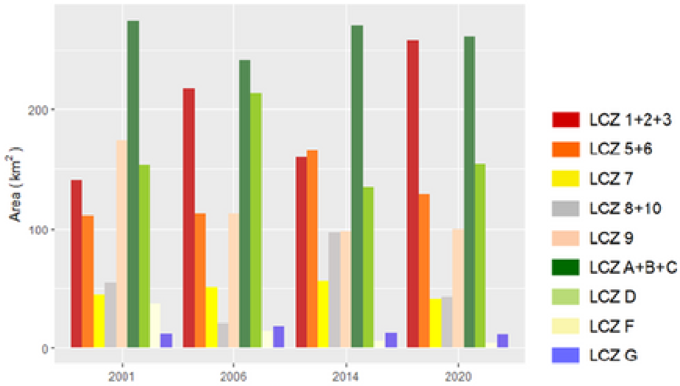

Figure 4. Changes in area coverage of LCZs in Cape Town over the last 20 years with merged classes.

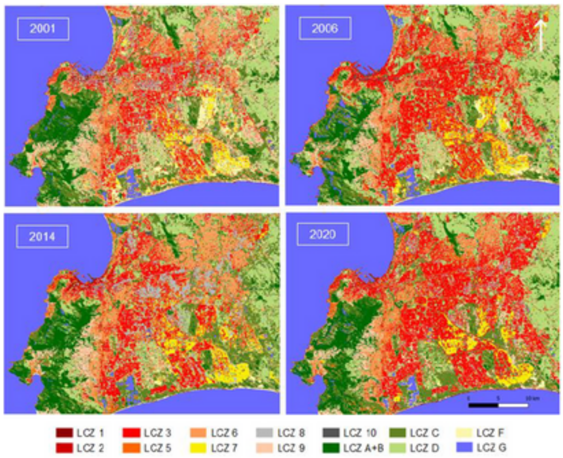

Figure 5. Cape Town classification Maps for the years 2001, 2006, 2014, and 2020

DISCUSSION

CLASSIFICATION OPTIMISATION

- The use of a contextual classifier, particularly a neighbourhood function, significantly improved classification accuracy. However, it is essential to strike a balance in the size of the neighbourhood window, as smaller LCZs could disappear and the value of urban planning and UHI information could be lost

- While NDVI played a vital role in discriminating natural classes, NDBI and EBBI did not contribute significantly to built class separability. This unexpected result may be due to an overload of bands in the raster stacks, resulting in valuable information being lost in the magnitude of pixels. To improve distinction between low-rise, midrise and high-rise, or even shrubs and trees, a layer containing height data could be added. This information is obtained using LiDAR data.

- Variations in accuracy metrics across different time intervals were noted. These inconsistencies were attributed to changes in training/ validation sets, weather events affecting surface reflection values and differences between Landsat 7 and Landsat 8 imagery. These factors underscored the need for robustness in the analysis to account for such fluctuations.

- Comparing results with Teerlinck (2021) who used Sentinel-2 images, results show noticeable improvements (15-20%) due to field verification and better local knowledge, highlighting the importance of ground-truth data. The 70/30 training-validation split ratio also contributed to higher accuracy, aligning with machine learning best practices.

- Landsat's 30-meter resolution, while lower than Sentinel-2's, benefits the classification process by reducing computational time and minimizing misclassifications of small features like gardens. A preprocessing contextual classifier could further reduce errors by considering pixel surroundings before model training, but it requires significant computational resources. This need for high-capacity computing resources may limit accessibility and inclusivity in global LCZ research, indicating a need for alternative methods to improve classifications.

TRANSFERABILITY

The study highlighted challenges in transferring classification models across cities. These challenges stemmed from variations in LCZ characteristics due to climate differences, urban infrastructure, and land use patterns. The examples of Thohoyandou and East London suggest a large degree of variation of the same LCZ types between cities, reducing their transferability potential.

Thohoyandou's greener vegetation resulted in natural vegetation classes being predominantly predicted as LCZ A+B, without differentiation in vegetation height. Unpaved roads led to an underestimation of built classes in both Thohoyandou and East London. Combining training areas from multiple cities was proposed as a strategy to improve model generalization. Models using local training areas produced useful preliminary maps for estimating UHI gradients, but accurate UHI assessments require verified LCZ maps linked to air temperature measurements.

LCZ TRENDS IN CAPE TOWN

- **Urbanization Trends:** The multi-temporal analysis of Cape Town's LCZ trends revealed some consistencies. However, the study did capture the evolving urbanization trends in Cape Town, revealing densification patterns, especially in urban fringes. This aligns with broader trends observed in post-apartheid urban dynamics, reflecting decentralization away from the city center.

- **Merging LCZs and Temporal Analysis:** Merging LCZs into larger groups minimally affected temporal analysis quality while improving data presentation. However, it is crucial to maintain the integrity of critical LCZ distinctions as their temperature scheme and thus UHI impact was too divergent.

- **Postprocessing for Noise Reduction:** Utilising a postprocessing contextual classifier helped reduce noise in classification maps, leading to more accurate trend detection and flux analysis.

Therefore, the multi-modal temporal analysis effectively detected densification over time and space in Cape Town, despite classification inconsistencies. Noticeable differences between classifications were noted in the intervals that were likely not related to any LCZ changes. Therefore, for a model to predict LCZ composition and trends, reducing class confusion is essential.

CONCLUSION

This thesis aimed to enhance Local Climate Zone (LCZ) classifications for Cape Town, Thohoyandou, and East London, addressing a research gap in urban climate mapping in African cities. It evaluated the transferability of a model trained on Cape Town data to Thohoyandou and East London, and provided a methodology for analysing LCZ changes over time, verifying the validity for Cape Town between 2001 and 2020.

Key findings highlighted the importance of ground-truth data in improving accuracy, the efficacy of a 70% training to 30% validation data split, and the potential benefits of incorporating LiDAR-derived building height data. Although spectral indices generally increased overall accuracy and Kappa values, they decreased accuracy for built classes, indicating a need for further refinement. A neighbourhood function as a contextual classifier improved accuracy, particularly when using local training areas.

The transferability of LCZ classifications to Thohoyandou and East London was low, contrasting with high accuracies when models were trained with local data. This suggests transferability should be tested between cities with similar climates and urban morphologies. Multi-temporal analysis effectively detected general densification trends in Cape Town, though inconsistencies hindered small-scale change detection. The thesis provides valuable inputs for linking air temperature measurements to LCZ maps, enabling better estimation of the Urban Heat Island (UHI) effect. This work advances sustainable and adaptive urban planning by offering spatial urban information and efficient LCZ classification methods.

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