Urban Local Climate Zone classification through deep learning using spatio-temporal thermal imagery

P5 presentation

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TU Delft

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- Related work (LCZ’s, LST, deep learning)
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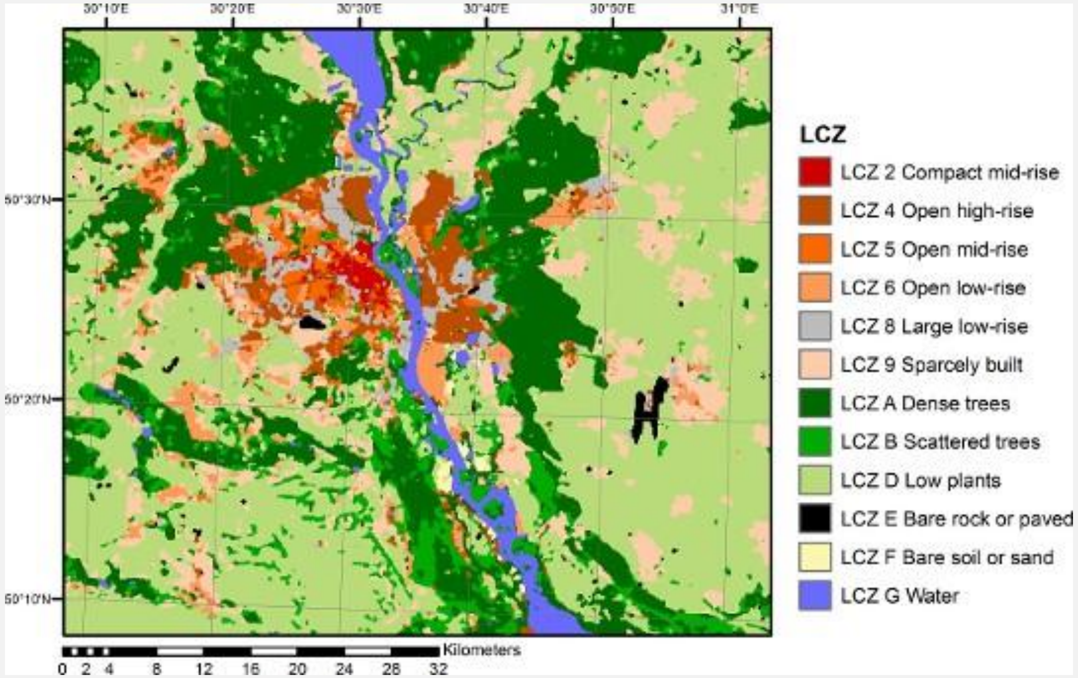
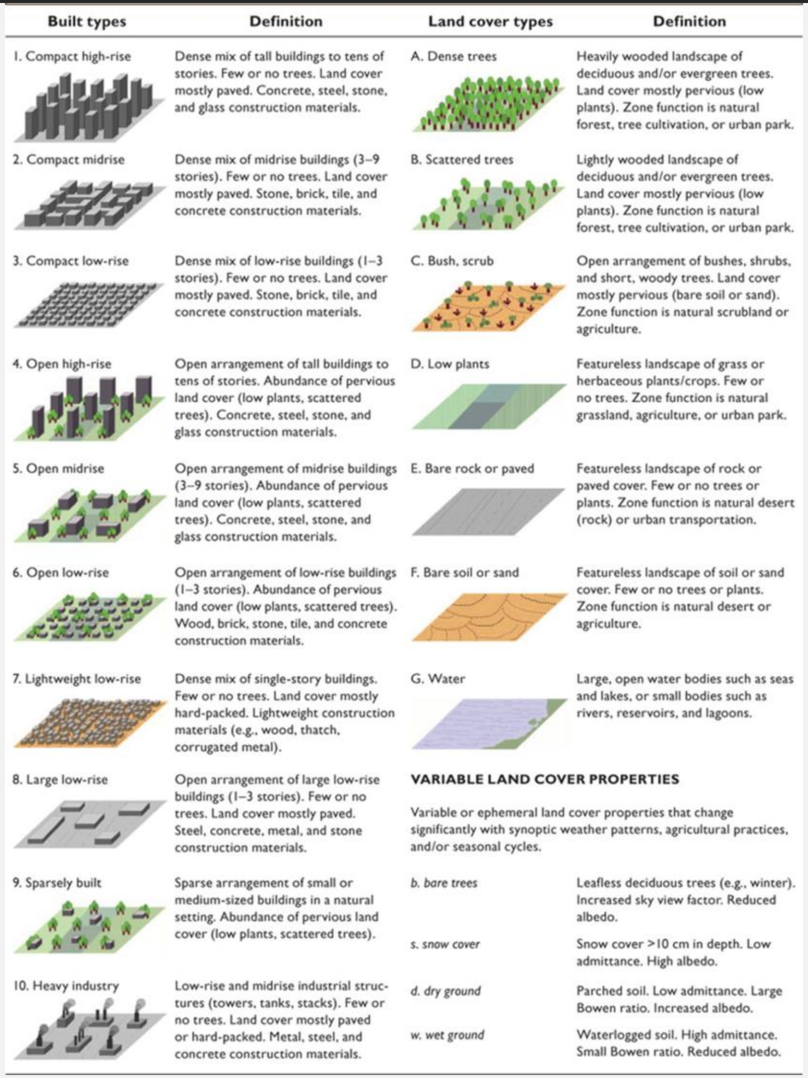
Introduction

- Increased urbanization
- Demand for understanding and characterizing urban climate
- Local Climate Zone classifications

- Spatio-temporal thermal imagery



Related work: Local Climate Zones



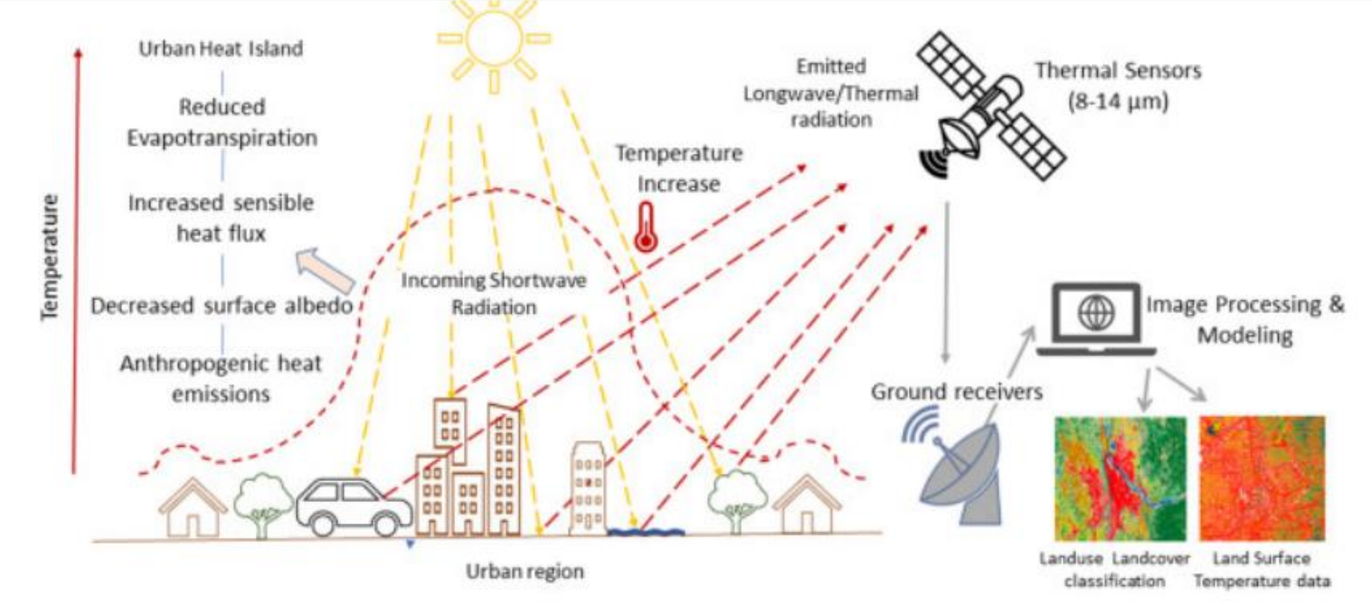
Built types	Definition	Land cover types	Definition
1. Compact high-rise	Dense mix of tall buildings to tens of stories. Few or no trees. Land cover mostly paved. Concrete, steel, stone, and glass construction materials.	A. Dense trees	Heavily wooded landscape of deciduous and/or evergreen trees. Land cover mostly pervious (low plants). Zone function is natural forest, tree cultivation, or urban park.
2. Compact midrise	Dense mix of midrise buildings (3–9 stories). Few or no trees. Land cover mostly paved. Stone, brick, tile, and concrete construction materials.	B. Scattered trees	Lightly wooded landscape of deciduous and/or evergreen trees. Land cover mostly pervious (low plants). Zone function is natural forest, tree cultivation, or urban park.
3. Compact low-rise	Dense mix of low-rise buildings (1–3 stories). Few or no trees. Land cover mostly paved. Stone, brick, tile, and concrete construction materials.	C. Bush, scrub	Open arrangement of bushes, shrubs, and short, woody trees. Land cover mostly pervious (bare soil or sand). Zone function is natural scrubland or agriculture.
4. Open high-rise	Open arrangement of tall buildings to tens of stories. Abundance of pervious land cover (low plants, scattered trees). Concrete, steel, stone, and glass construction materials.	D. Low plants	Featureless landscape of grass or herbaceous plants/crops. Few or no trees. Zone function is natural grassland, agriculture, or urban park.
5. Open midrise	Open arrangement of midrise buildings (3–9 stories). Abundance of pervious land cover (low plants, scattered trees). Concrete, steel, stone, and glass construction materials.	E. 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.
6. 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.	F. Bare soil or sand	Featureless landscape of soil or sand cover. Few or no trees or plants. Zone function is natural desert or agriculture.
7. Lightweight low-rise	Dense mix of single-story buildings. Few or no trees. Land cover mostly hard-packed. Lightweight construction materials (e.g., wood, thatch, corrugated metal).	G. Water	Large, open water bodies such as seas and lakes, or small bodies such as rivers, reservoirs, and lagoons.
8. Large low-rise	Open arrangement of large low-rise buildings (1–3 stories). Few or no trees. Land cover mostly paved. Steel, concrete, metal, and stone construction materials.	**VARIABLE LAND COVER PROPERTIES** Variable or ephemeral land cover properties that change significantly with synoptic weather patterns, agricultural practices, and/or seasonal cycles.	
9. Sparsely built	Sparse arrangement of small or medium-sized buildings in a natural setting. Abundance of pervious land cover (low plants, scattered trees).	*b. bare trees*	Leafless deciduous trees (e.g., winter). Increased sky view factor. Reduced albedo.
		s. snow cover	Snow cover >10 cm in depth. Low admittance. High albedo.
10. Heavy industry	Low-rise and midrise industrial structures (towers, tanks, stacks). Few or no trees. Land cover mostly paved or hard-packed. Metal, steel, and concrete construction materials.	*d. dry ground*	Parched soil. Low admittance. Large Bowen ratio. Increased albedo.
		w. wet ground	Waterlogged soil. High admittance. Small Bowen ratio. Reduced albedo.

- Steward and Oke (2012)

- Different geospatial data sources for LCZ classifications:
  - Manual sampling,
  - Multi-spectral satellite imagery,
  - Aerial imagery,
  - Ground-level imagery,
  - LiDAR data,
  - Other (derived) geospatial data.

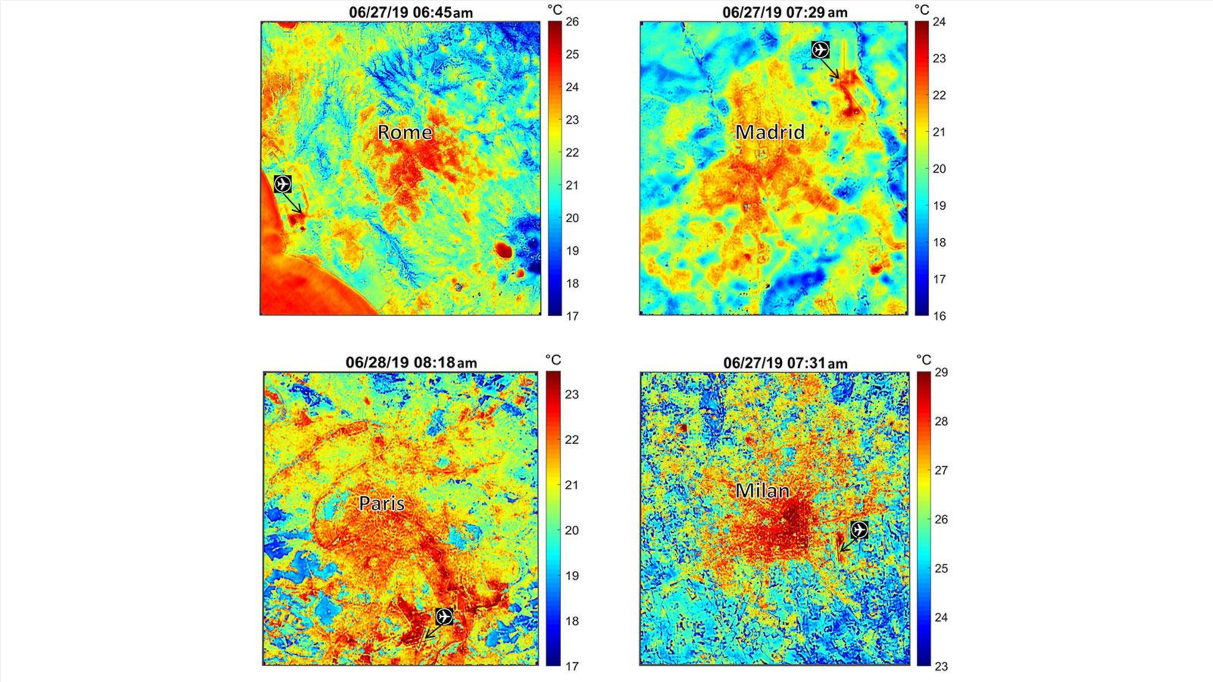
Related work: Land Surface Temperature

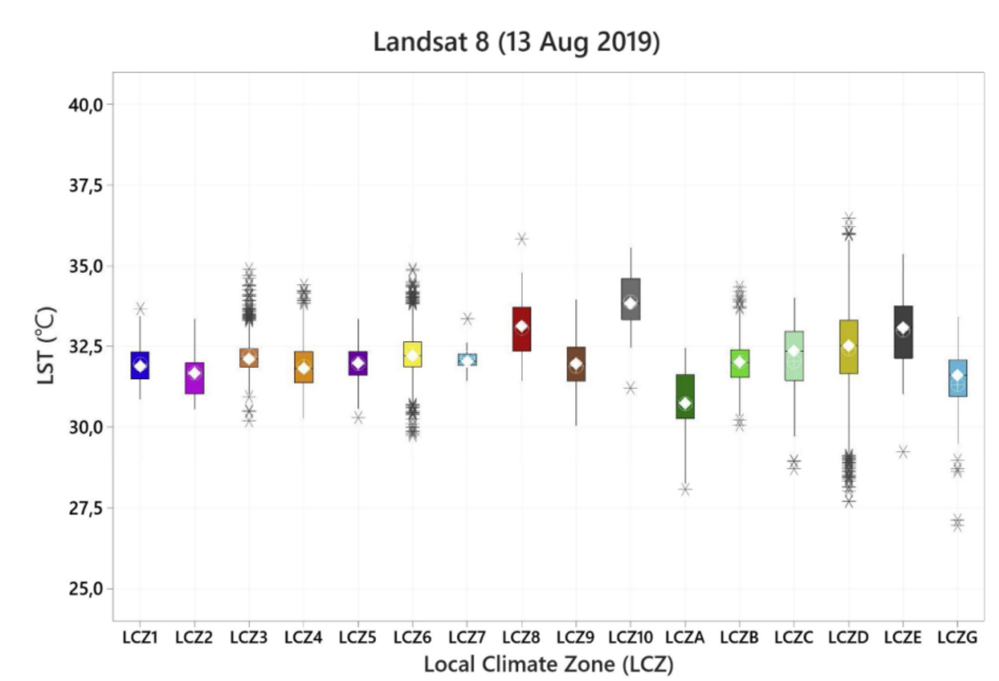
- Thermal remote sensing
- Long-wavelength infrared radiation (8-14 µm)
- ECOSTRESS (daily coverage, 70x70m pixels)



Related work: LCZ-LST

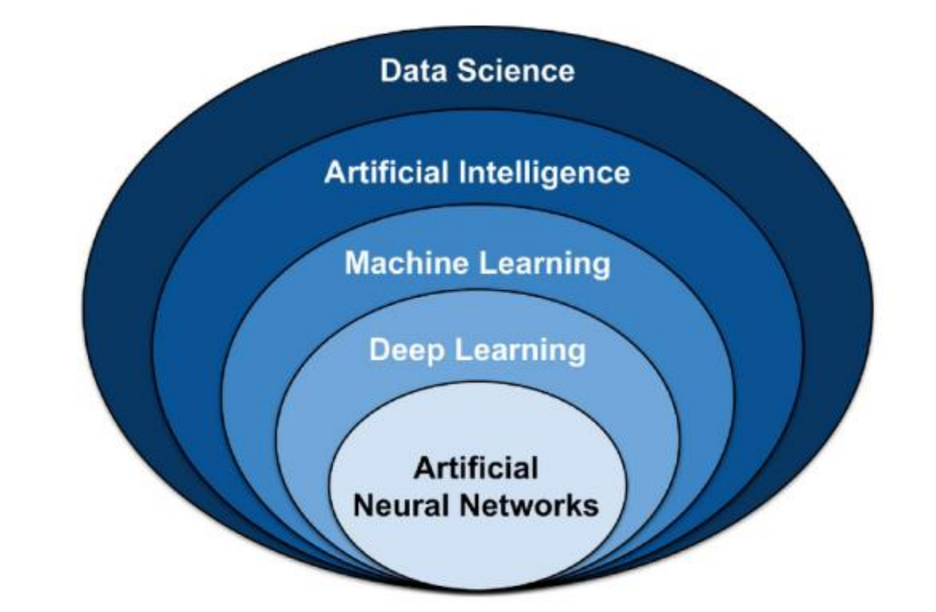
- Correlations

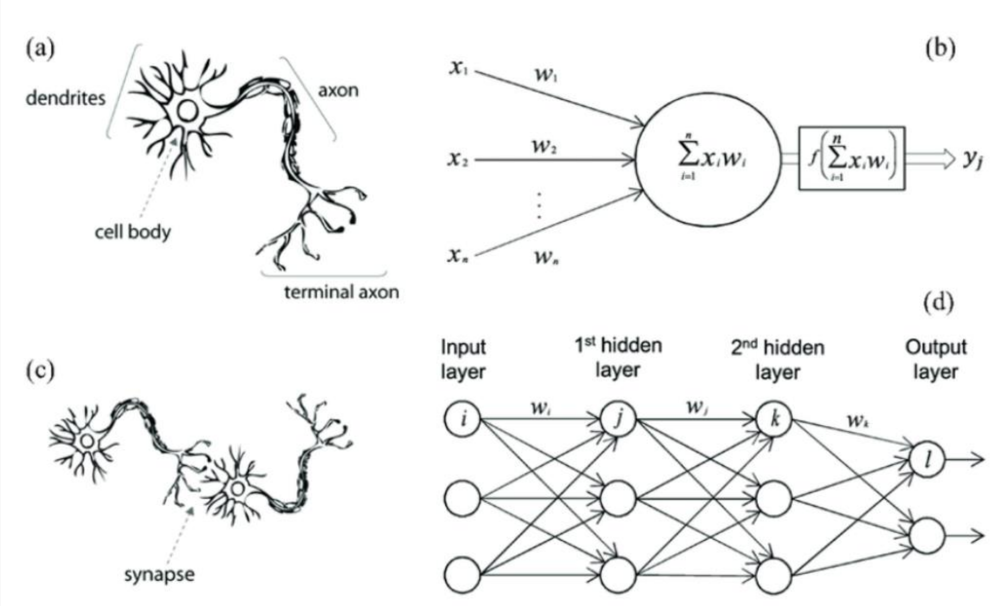


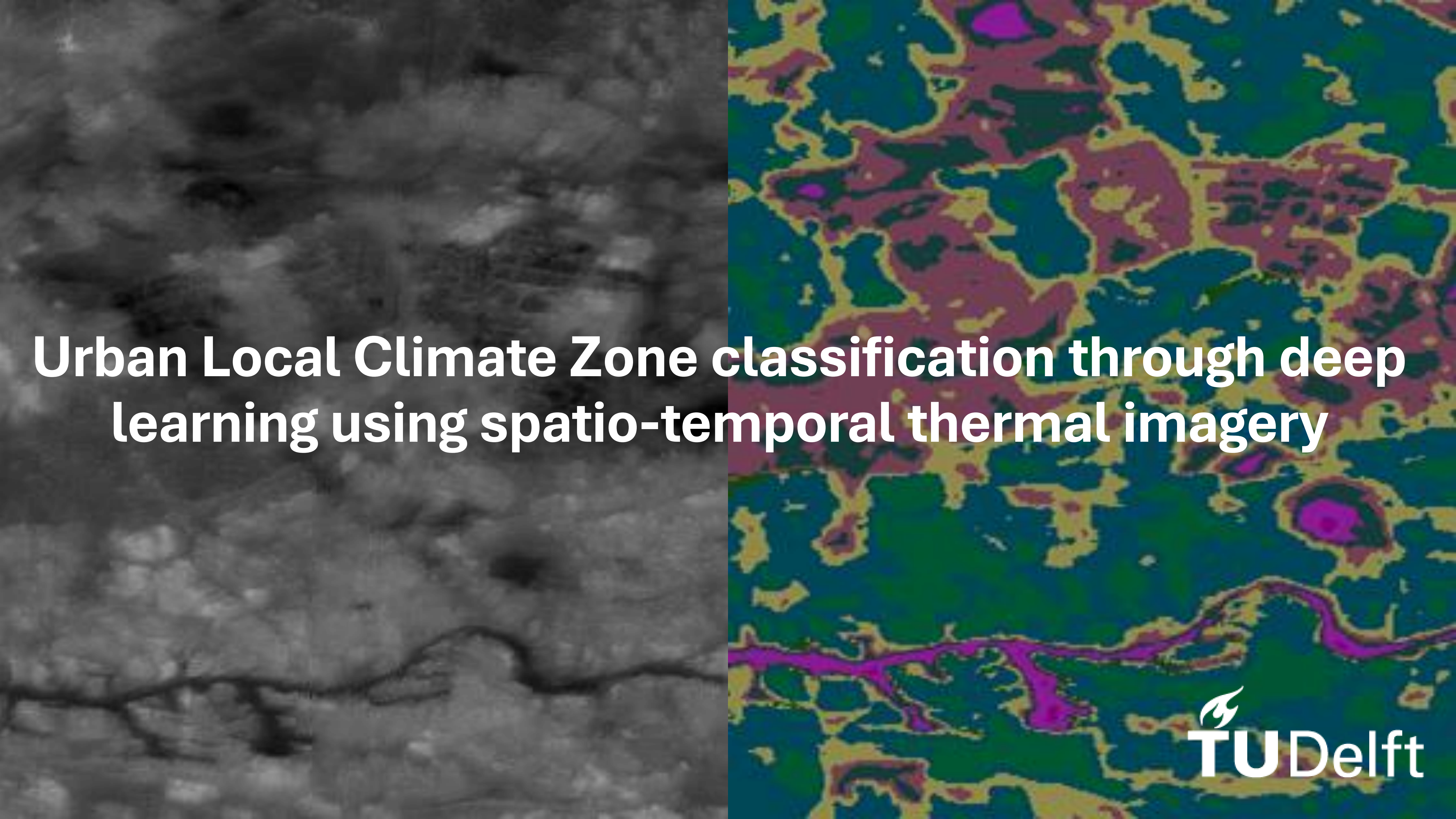


Related work: Deep learning

- Matching the level of the human brain in solving complex problems







Urban Local Climate Zone classification through deep learning using spatio-temporal thermal imagery

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Goal

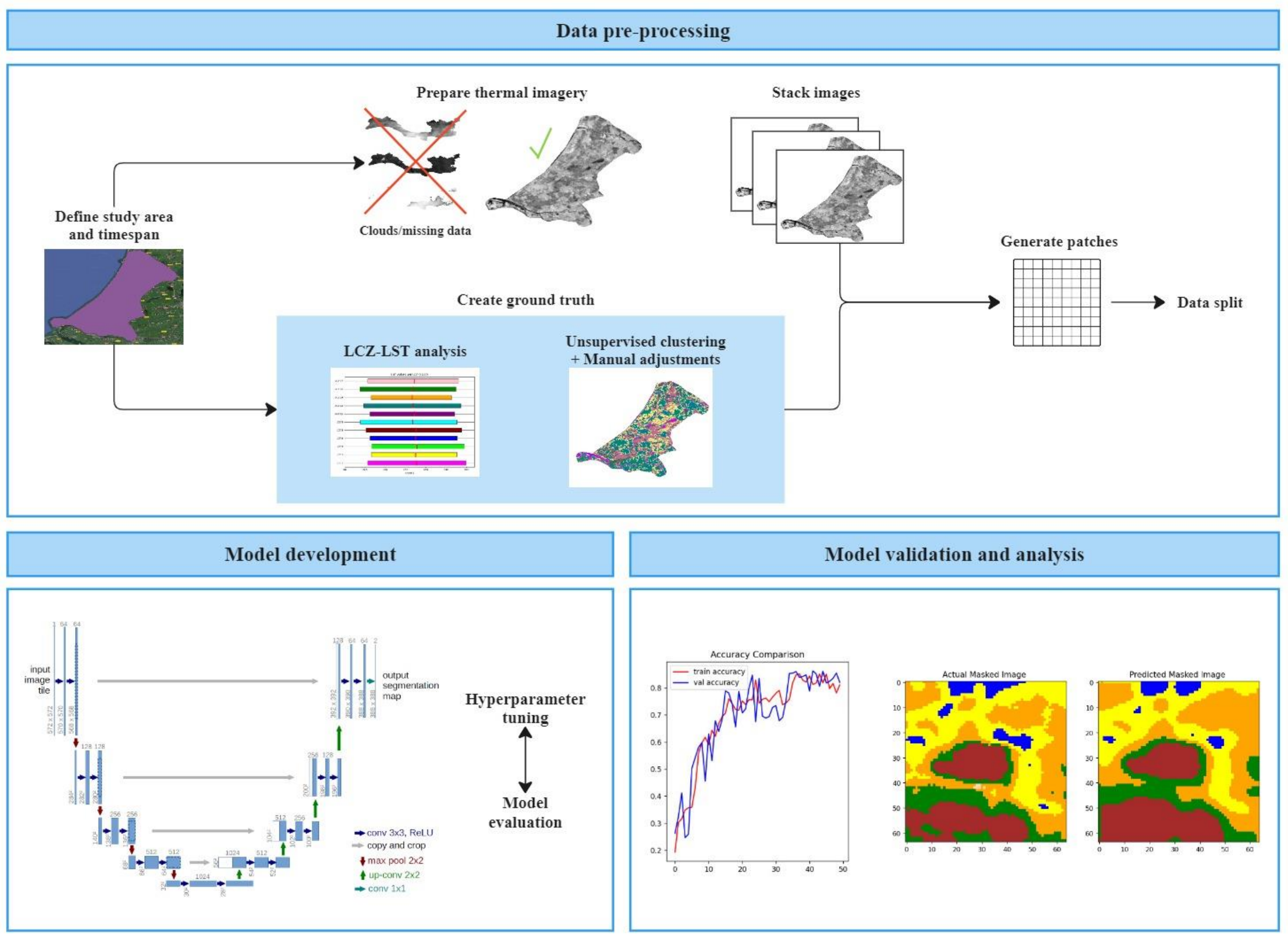
- Explore a new source for LCZ classification: spatio-temporal thermal imagery
- Gain insight in enhancing the process of LCZ classification
- Optimize the created classification algorithm

Research questions

To what extent is a CNN with U-net architecture using spatio-temporal thermal imagery suitable for the classification of urban Local Climate Zones?

- How can a representable training data set be collected?
- When it comes to the architecture of U-net, what values for the hyperparameters of the deep learning network lead to the best classification result?
- What is the impact of temporal frequency (day-night, seasonal) on the classification performance?

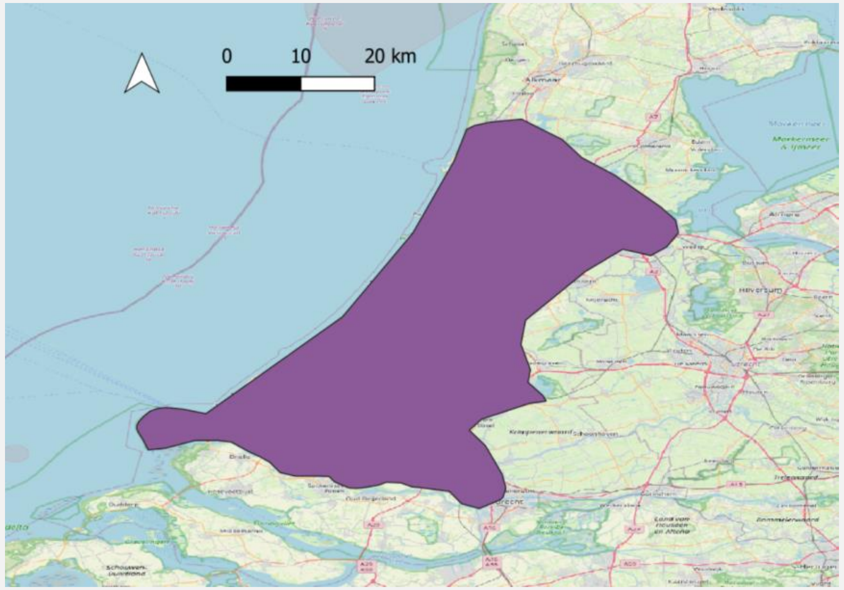
Methodology: Overview

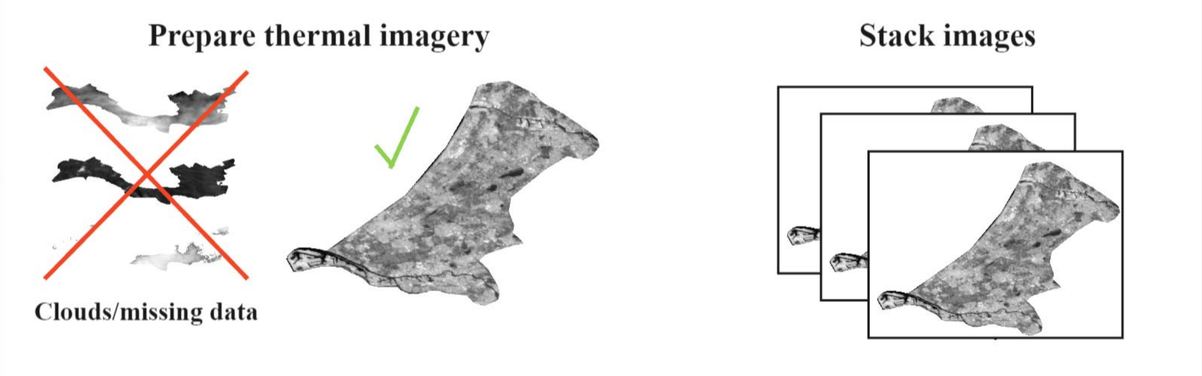


Methodology: Data pre-processing

- Study area and time span selection
- Data collection:

    - Prepare thermal imagery
    - Data split 70/15/15





Methodology: Create ground truth

- LCZ-LST analysis
- Correlations too complex for manual training data labelling
- Unsupervised clustering: ISODATA

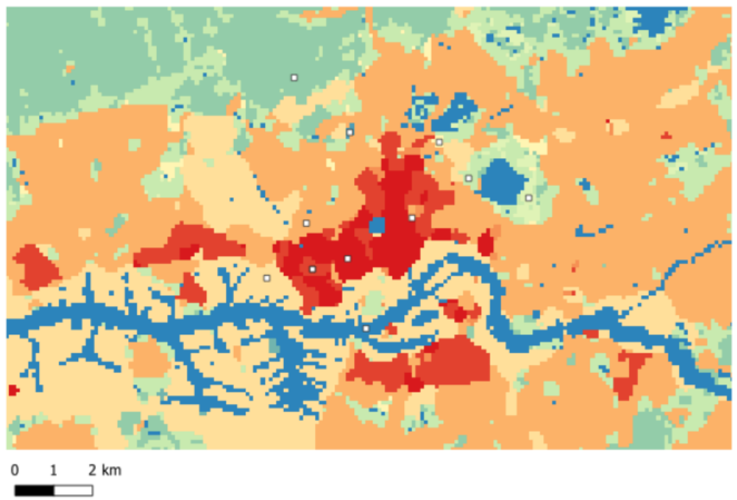
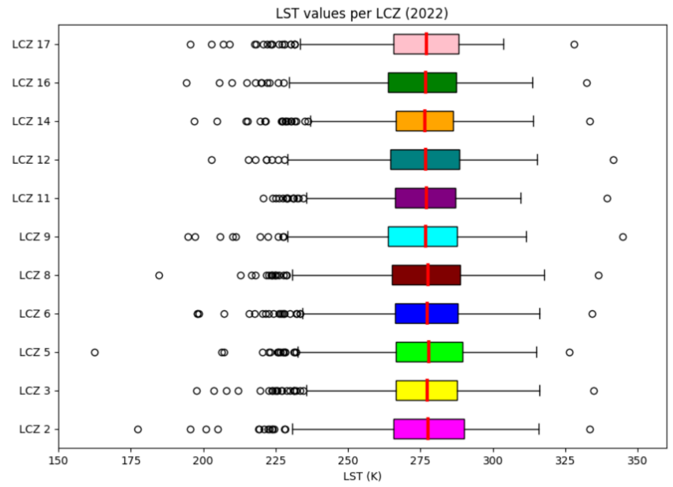
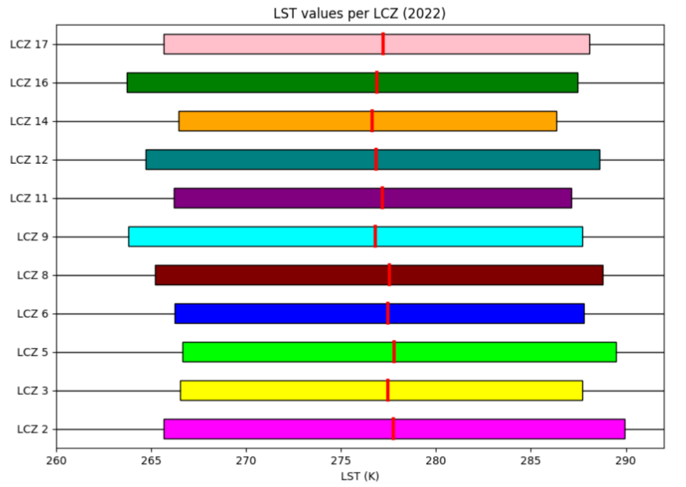


Figure 3.3.: Drawn polygons on LCZ map by Demuzere et al. [2019]



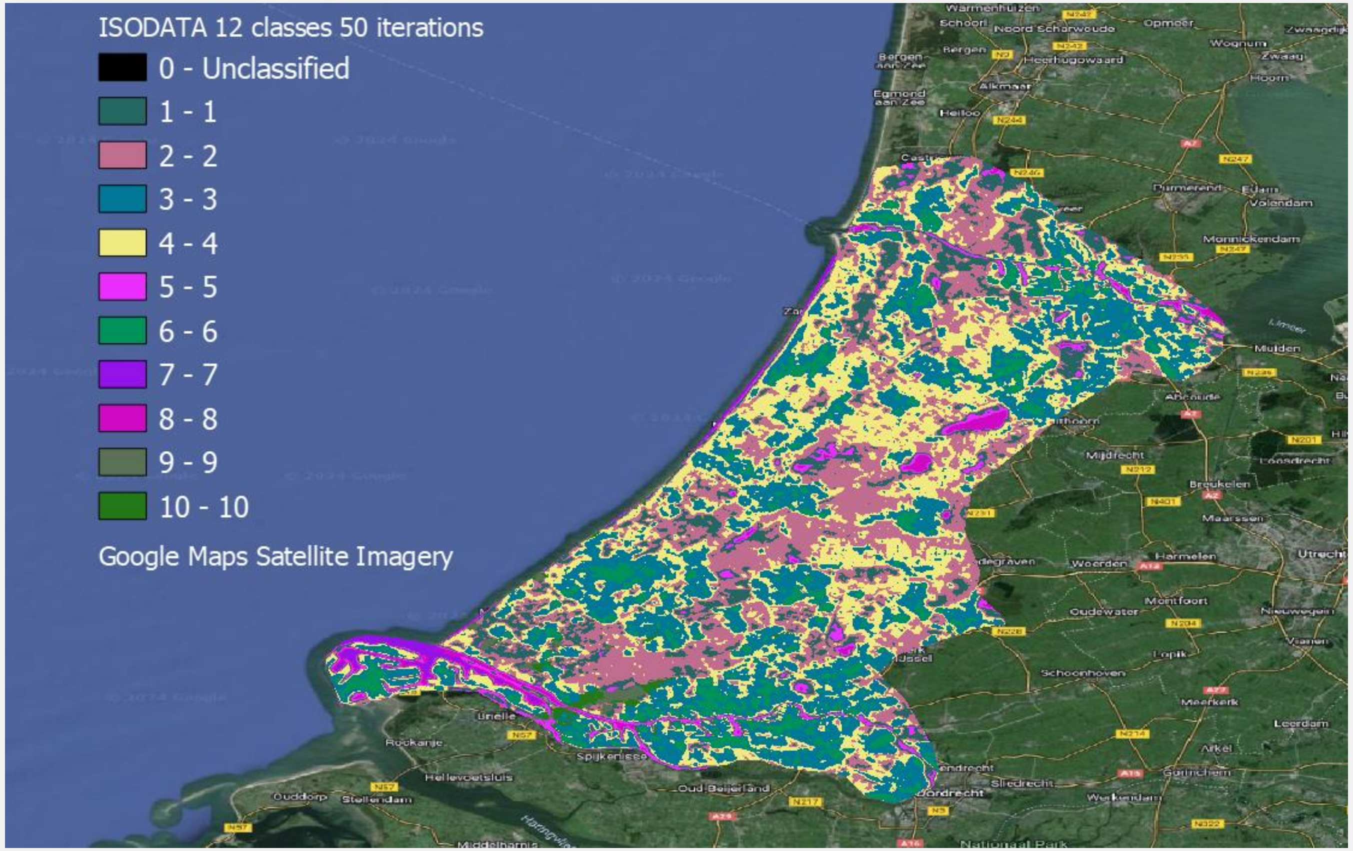


Methodology: Training data labelling

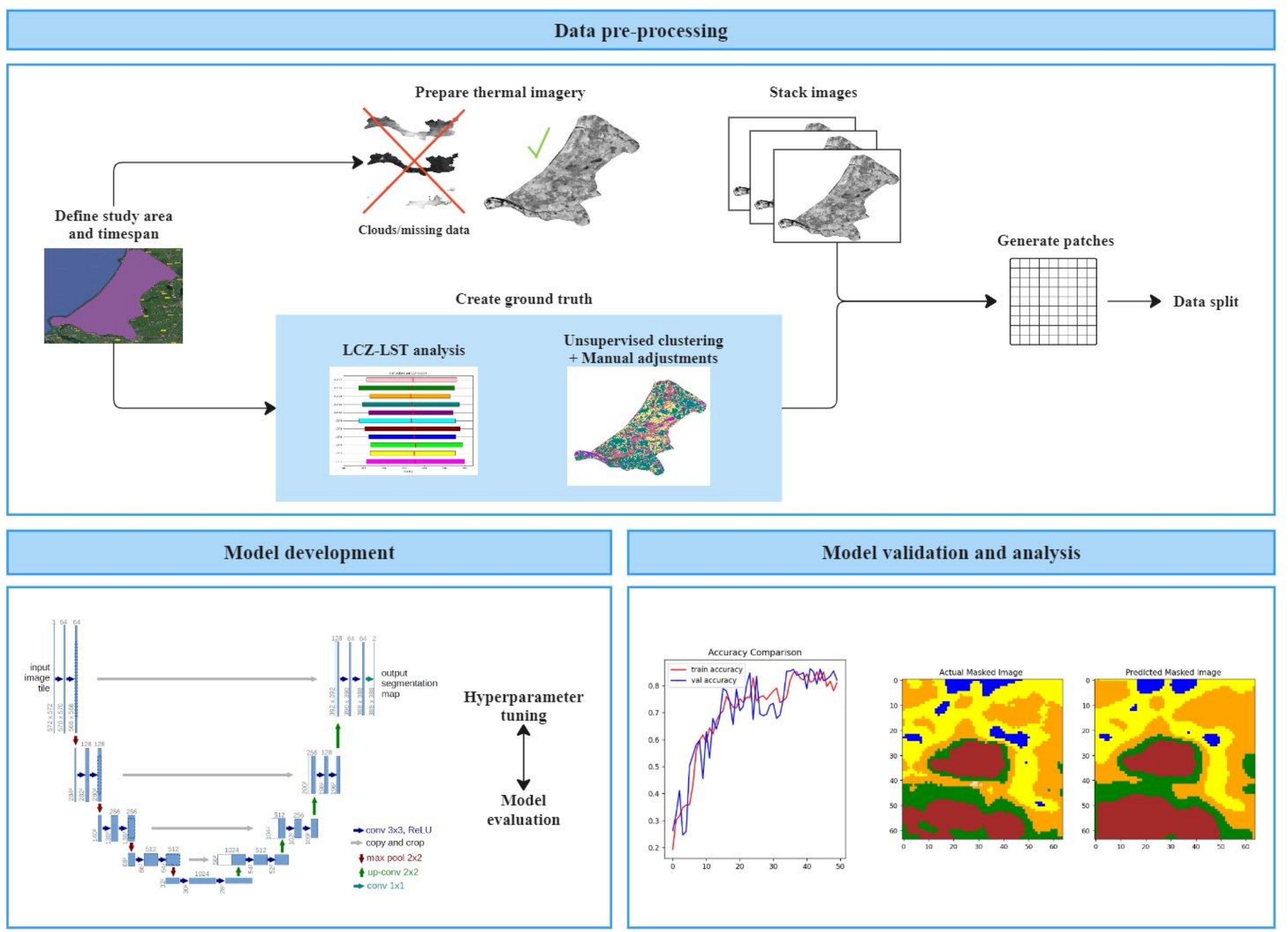
- Unsupervised clustering: ISODATA
- Clusters based on thermal behaviour

Table 4.2.: Class descriptions based on aerial imagery

Class Number	Class Description
0	Unclassified
1	Dense forest/meadows, often next to water
2	Less dense forest/meadows
3	Residential area
4	Residential area with a lot of green/meadows
5	Shallow water
6	City centre/industrial area
7	Deepest water/sea water
8	Deep water
9	A few greenhouses, does not appear often
10	A few greenhouses, does not appear often

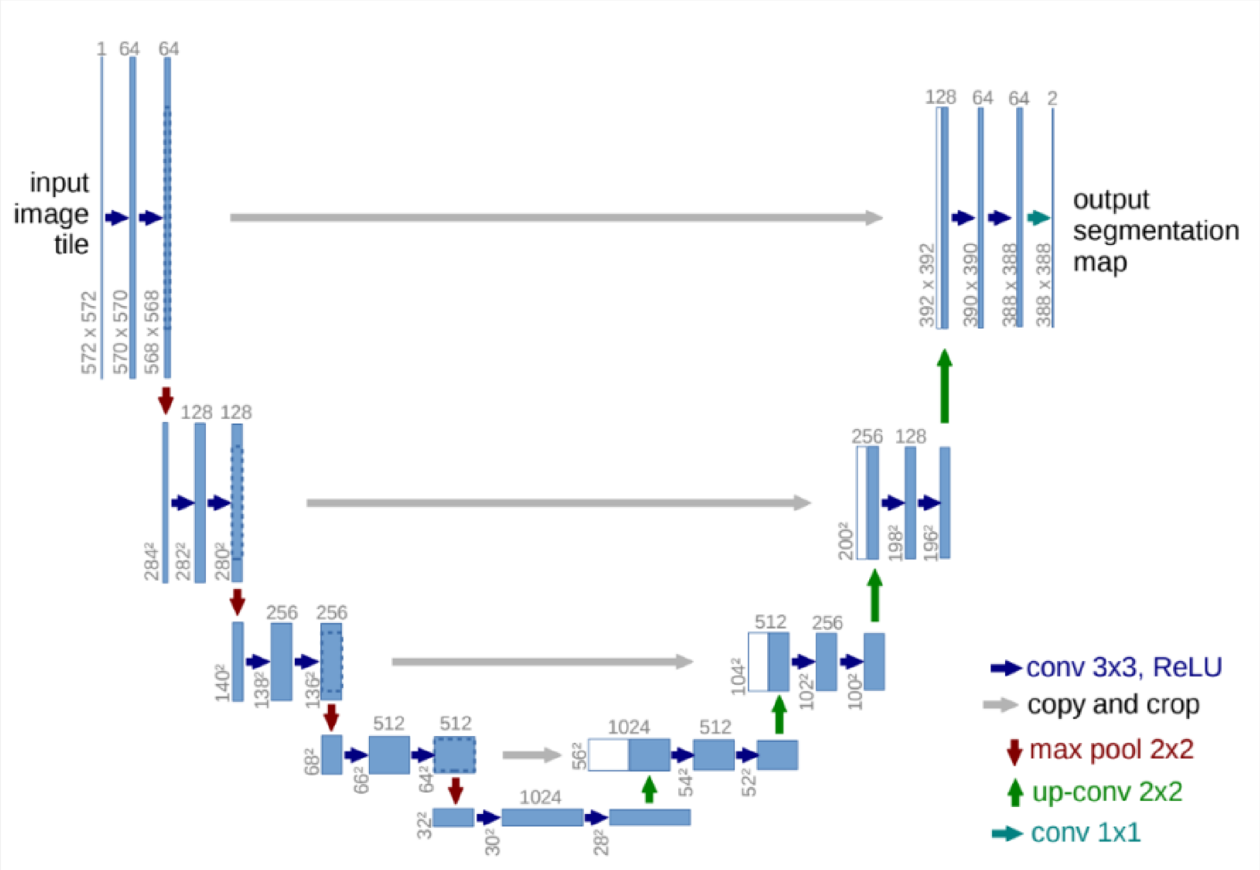


Methodology



Methodology: Model

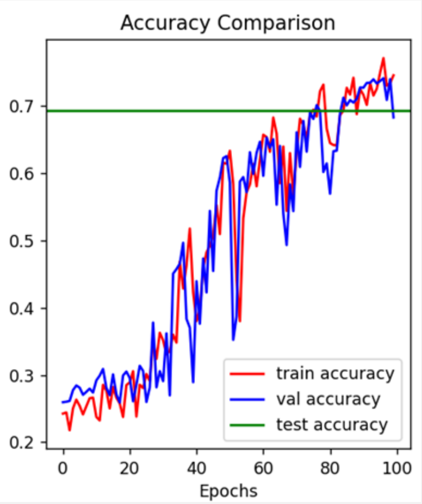
- Convolutional Neural Network (CNN) with U-net architecture
- Ronneberger et al. (2015)
- Effective for precise semantic segmentation tasks for images

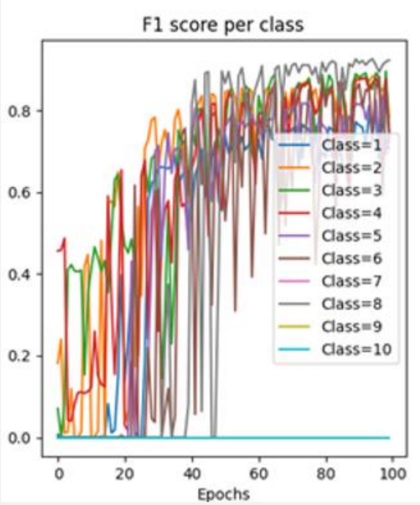


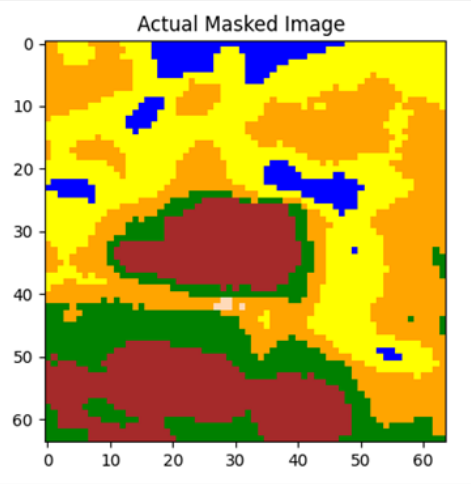
Methodology: Evaluation and analysis

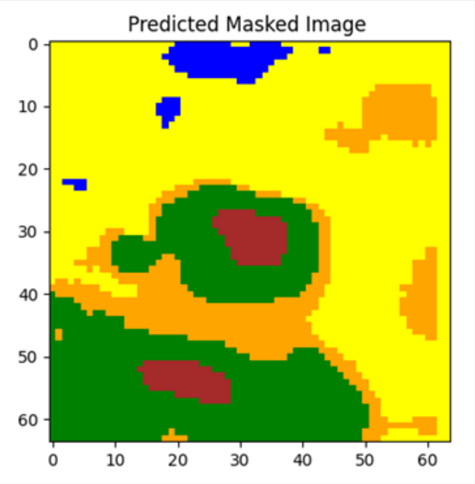
- Evaluation metrics:
  Overall Accuracy, Precision, Recall, F1-scores per class, Macro F1-score

- Compare Masked image patches to predicted masks



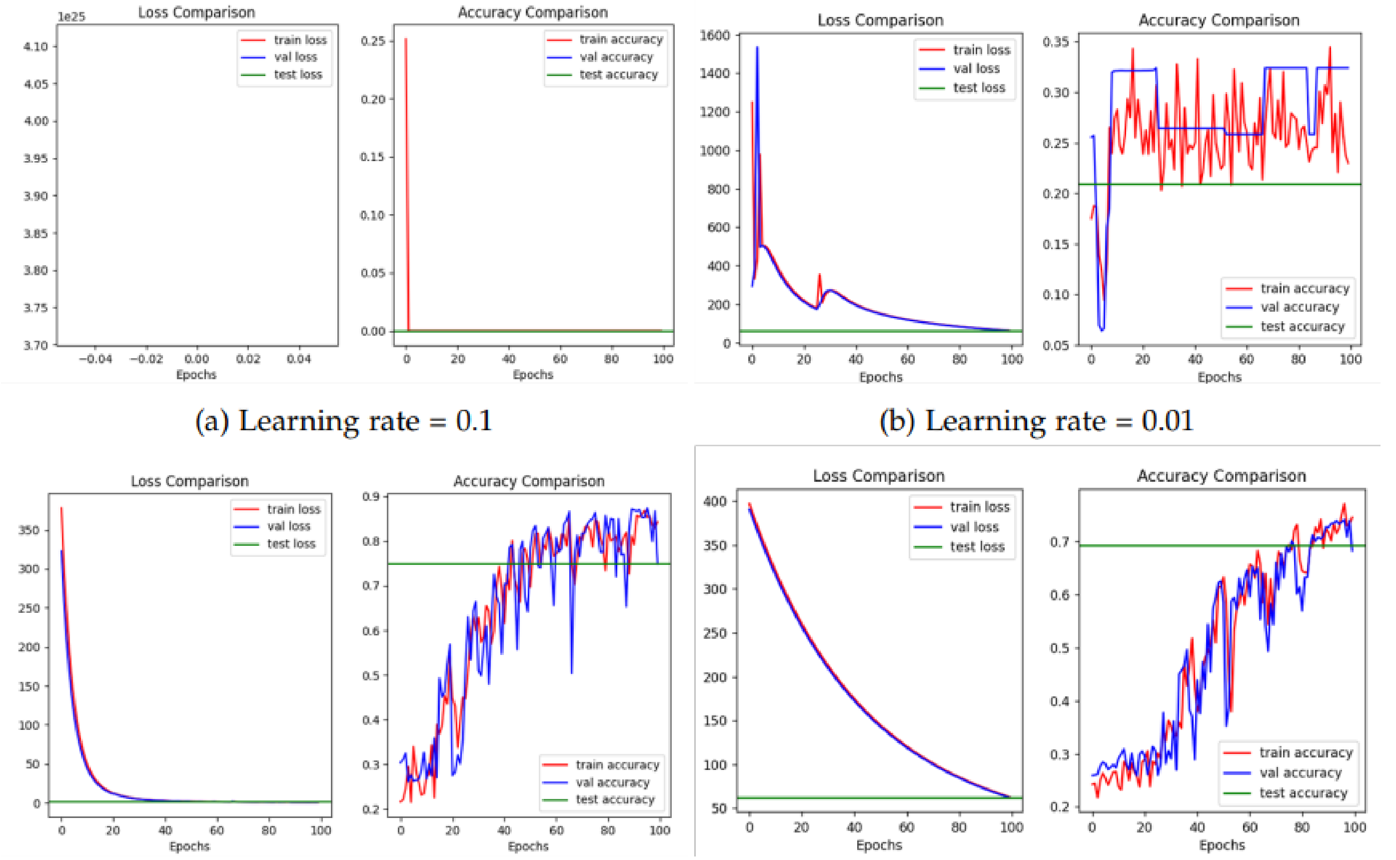






Results: Hyperparameter tuning

Learning rate



(a) Learning rate = 0.1

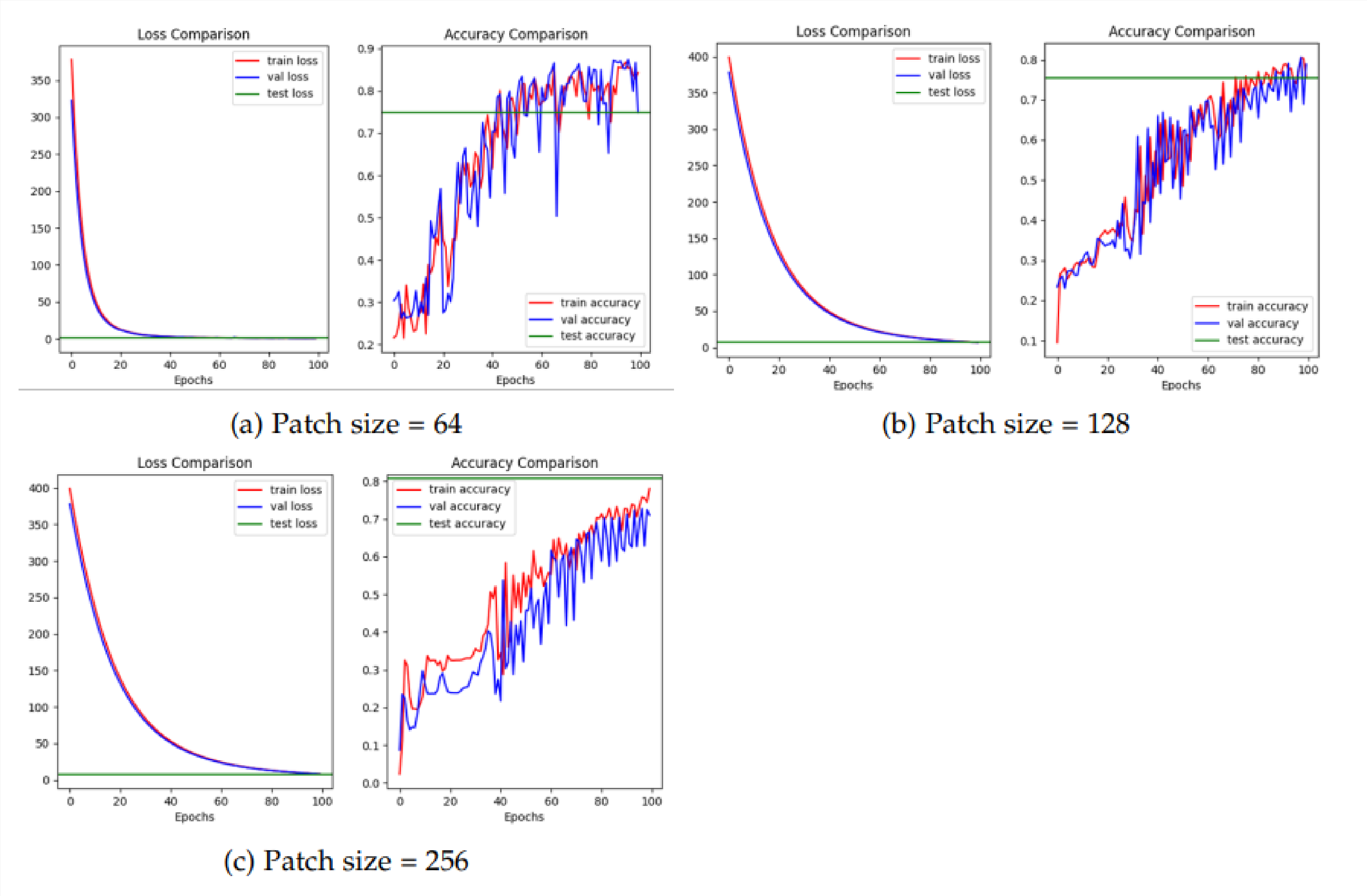
(b) Learning rate = 0.01

(c) Learning rate = 0.001

(d) Learning rate = 0.0001

Results: Hyperparameter tuning

Patch size



(a) Patch size = 64

(b) Patch size = 128

(c) Patch size = 256

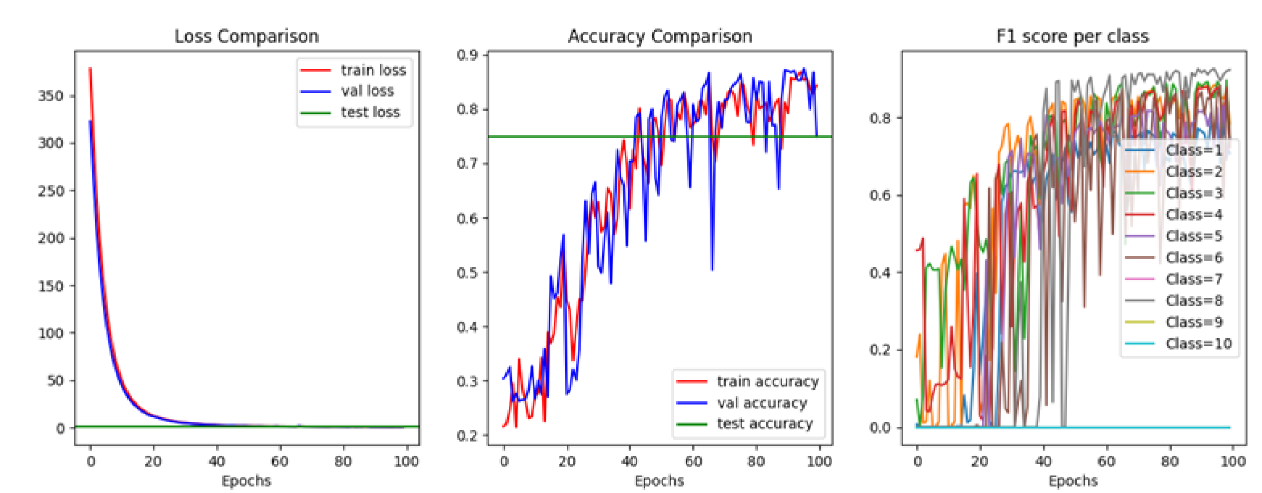
Results: Hyperparameter tuning

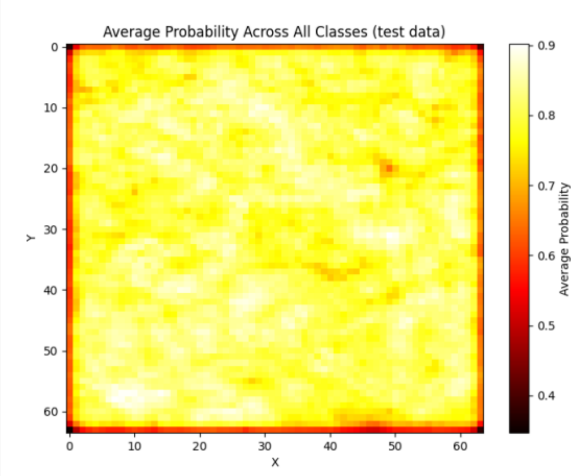
• Learning rate:	0.001
• Patch size:	64
• Loss function:	SparseCategoricalCrossentropy()

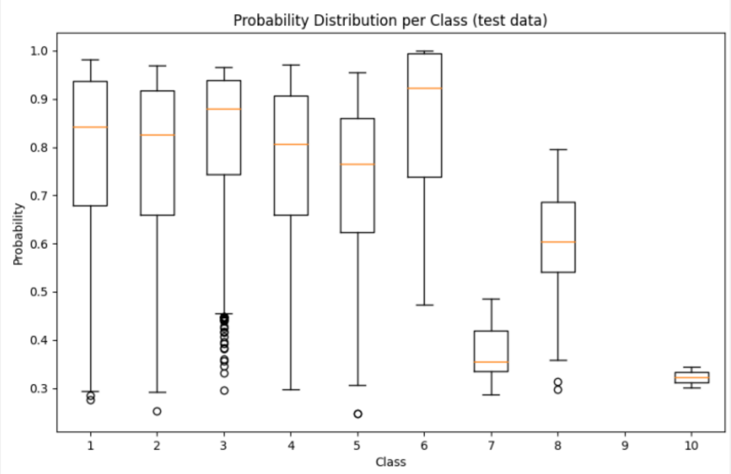
Results: Full dataset

- Test OA = 0.7484
- Test macro F1 score = 0.5903

- Edge effects
- Class imbalance







Results: Seasonal experiment

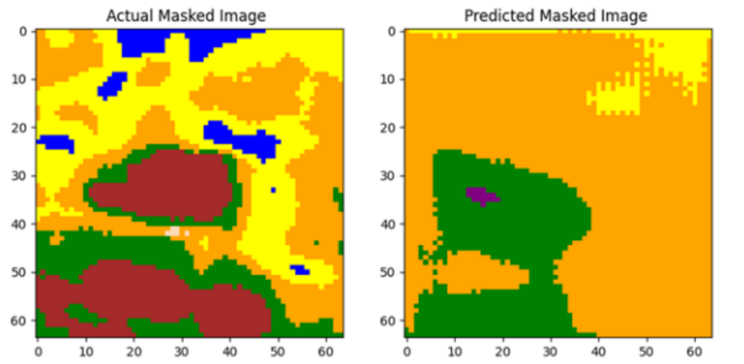
- Data was split in Spring/Summer and Autumn/Winter data set
- New data sets used for training and testing
- Significant performance differences (OA of 0.7585 and 0.5856)
- Class 1 “Dense forest/Meadows” and 4 “Residential area with a lot of green/meadows” are more difficult to distinguish when training and testing with Autumn/Winter images
- LCZ’s are differentiated better in Summer than in other seasons regarding LST (Du et al. 2020)

Class	Test F1 score per class	
	Spring/Summer	Autumn/Winter
1	0.6230	0.3374
2	0.8253	0.6245
3	0.8307	0.6596
4	0.7581	0.4392
5	0.6948	0.6781
6	0.8052	0.7308
7	0.0000	0.0000
8	0.7714	0.7011
9	0.0000	0.0000
10	0.0000	0.0000

Results: Daytime vs. nighttime

- Data was split in daytime and nighttime data set
- New data sets used for training and testing
- Significant performance differences (OA of 0.8001 and 0.4764)
- The classes that show more ”extreme” behaviour (warmer or cooler than other classes), are misclassified as classes with less fluctuations and more average values.
- At night the LST values are more similar to each other

Class	Test F1 score per class	
	Daytime	Nighttime
1	0.7594	0.0513
2	0.8505	0.5874
3	0.8296	0.6596
4	0.7842	0.1409
5	0.7143	0.5035
6	0.7273	0.0000
7	0.0510	0.0000
8	0.7690	0.0000
9	0.0000	0.0000
10	0.0000	0.0000

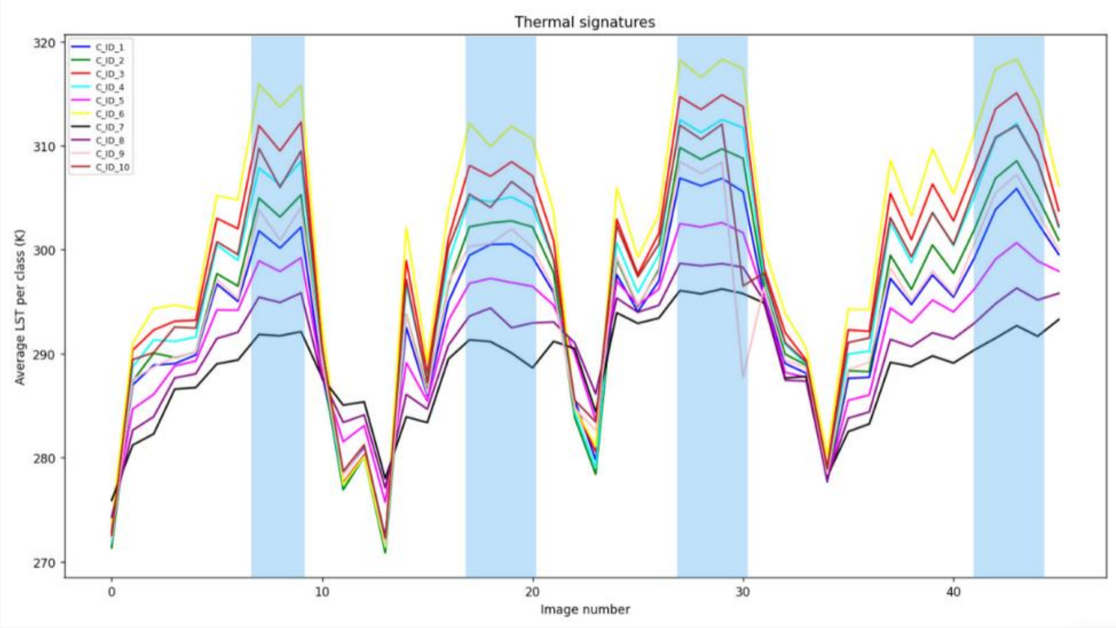


Results: Extreme analysis

- High LST values but ensuring variability can yield superior performance compared to the full dataset

Selection of images	number of images	Test accuracy
Maximum	1	0.260
Maximum per peak	4	0.285
All peaks	14	0.834

Table 5.7.: Test accuracy values for different image selections



Conclusion

To what extent is a CNN with U-net architecture using spatio-temporal thermal imagery suitable for the classification of urban Local Climate Zones?

Conclusion

- How can a representable training data set be collected?
  - Unsupervised clustering
  - Clusters based on thermal behaviour
  - Representable for this application

Conclusion

- When it comes to the architecture of U-net, what values for the hyperparameters of the deep learning network lead to the best classification result?
  - Hyperparameters adopted from Bathia (2021)
  - Hyperparameter values experimentally selected (learning rate, loss function, patch size)

Conclusion

- What is the impact of temporal frequency (day-night, seasonal) on the classification performance?
  - Summer/Spring
  - Daytime
  - Variability and thermal images with large contrast

Conclusion

To what extent is a CNN with U-net architecture using spatio-temporal thermal imagery suitable for the classification of urban Local Climate Zones?

Suitable for this application (hyperparameters, training data)

Good starting point

Recommendations

- Take weather conditions into account
- Integration of other thermal imagery sources
- Integration with other geospatial data

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