Spatio-Temporal Data Management and Enhanced Processing for Urban Heat Island Analysis supported by Digital Elevation Models

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Key words: Spatio-Temporal Data Management, Urban Heat Island, Digital Elevation Model, Urban Planning, Local Climate Zones.

SUMMARY

Reducing heat stress in cities is an emerging goal for both developing and developed regions of the world. Geodesy and earth observation can contribute to solutions, e.g. by supporting urban climate analysis and long-term strategies for city planning. However, to transfer analyses to arbitrary cities without much effort, spatio-temporal data management for cities should be used and enhanced preprocessing of climate data is necessary. Furthermore, all available data sources must be integrated to improve data analysis. In this paper, we propose a pipeline of data collection and spatio-temporal data management, for the use case of urban climate analysis. To project changes in heat exposure based on urban planning decisions, an elevation change detection analysis is provided with the help of spatio-temporal DEMs. In addition, Digital Elevation Models (DEMs) and OpenStreetMap (OSM) are used as data sources to detect errors in building segmentation to improve the segmentation process. First results are evaluated based on a case study with data from the city of Karlsruhe, Germany. We intend to support two applications of urban climate analysis: Change detection for local climate zones and mean radiant temperature determination via the Urban Multi-scale Environmental Predictor (UMEP).

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1. INTRODUCTION AND RELATED WORK

In the context of climate change and ongoing urbanization (Intergovernmental Panel on Climate Change, 2023), the UN sustainable development goals (SDGs) 3, 10, 11, and 13 are increasingly under pressure due to increasing urban heat islands. They are a well-documented phenomenon in which urban areas exhibit higher temperatures than their rural surroundings (Oke, 1973). However, urban climate itself is highly localized and significantly driven by the thermal properties of built-up surfaces, extensive surface sealing, and reduced vegetation cover, which enhance the storage of heat during the day and slow its release during the night. Thus, facing global warming and the increasing heat load in cities, there is a pressing need for targeted adaptation measures in urban landscapes (Mavrakou et al., 2018). To support this, up-to-date maps of the urban thermal environment are essential for urban planners. Urban areas are not only developing rapidly but are also continuously reshaped by construction and land-use change, making them highly dynamic. In addition, the effectiveness of implemented measures must be evaluated over time. Yet, for most cities of the globe, details of local temperatures and heat stress are unknown. It is not economically feasible to observe all necessary parameters in the required details (Adinolfi et al., 2023). Many studies make use of satellite derived land surface temperatures, but it is controversy discussed if they bear meaning for human wellbeing (Venter et al., 2021; Naserikia et al., 2024; Krikau and Benz, 2025). Hence proxies such as the Local Climate Zone (LCZ) (Demuzere et al., 2022; Stewart and Oke, 2012) classification system provide probable climatic conditions for localized zones and enables standardized comparison across the globe. LCZs divide urban and rural landscapes into 17 categories mainly based on the density and height of roughness elements.

Furthermore, human perception of the thermal environment is influenced not only by air temperature but also by factors such as wind, humidity, and solar radiation, which collectively influence the physiological response to the thermal environment. To assess human satisfaction and heat stress, a range of thermal comfort indices have been developed that integrate these factors (Migliari et al., 2022). In biometeorological approaches, the mean radiant temperature (Tmrt) is used to account for the influence of radiation on the human body. Since this parameter is difficult and expensive to measure directly (typically requiring integral radiation measurements), modelling it has become a common approach (Nazarian et al., 2021; Lindberg et al., 2018). Although this parameter is also influenced by land cover, the dominant effect comes from the amount of shading, which can account for differences of around 30 °C (Lindberg et al., 2016). A practical and accessible tool for urban climate assessment is the Urban Multi-scale Environmental Predictor (UMEP - Lindberg et al., 2018), an open-source climate modelling and analysis plugin for QGIS designed to evaluate urban climate processes and their effects on human thermal comfort (Lindberg et al., 2018). However, for accurate modelling, UMEP and comparable models themselves need a complex set of geospatial data to give meaningful and accurate results. Besides broader climate parameters to define boundary conditions, this includes information on land use, land cover, and digital elevation models.

Digital Elevation Models (DEMs) – here understood as a general term for Digital Surface Models (DSMs, representing the terrain including vegetation and buildings) and Digital Terrain Models (DTMs, representing the earth´s surface only) – provide important information about building heights, street canyon configurations, and the surrounding topography. Their significance for environmental studies is undisputed since many decades (Miller, 1958; Doyle, 1978; Weibel and Heller, 1991; Zhilin et al., 2004). Li et al. (2023) emphasized the emerging need of high-resolution Digital Elevation Models (DEMs) for environmental scenarios such as urban planning, flood simulations, and landslide predictions. The same authors presented a deep learning-based approach to increase the detail of low-resolution DEMs. On the one side, DEMs may be modelled and managed in geospatial databases as fields, i.e. images or regular grid/raster representations (Baumann et al., 1997), where each raster cell represents one elevation point. On the other side, they may be represented as geometric simplicial 2-complexes, i.e. Triangulated Irregular Networks (TINs), in object-oriented data stores (Balovnev et al., 1999; Breunig et al., 2016). Baumann et al., (1997) already proposed to store and process fields as multi-dimensional arrays of a raster database management system and to include OGC raster database services as user interface (Baumann, 2010). Furthermore, Baumann et al. (2018) have proven data cubes to be a suitable user interface to support geospatial and spatio-temporal raster data analysis. Finally, Liu et al. (2025a) stated that spatio-temporal DEMs should be directly modelled and managed in geospatial database management systems to support statistical and machine learning-based monitoring of urban planning and landslides. However, to the knowledge of the authors, spatio-temporal DEMs as well as the combination with OSM data, have not been applied so far in literature to improve the accuracy of urban local climate zones.

In this study, we introduce an enhanced processing and spatio-temporal DEM management pipeline. Results are prepared for optimal use in urban climate analysis, particularly change detection in LCZ and mapping of heat stress in UMEP. The remainder of this paper is structured as follows: In section 2 we introduce our approach for temporal DEM management demonstrating a pipeline to support local climate zone analysis. In section 3 the methodology to support spatio-temporal DEM queries, change detection, and DEM semantic segmentation is explained based on the case study of Karlsruhe, a city in southwestern Germany. The results are evaluated and the limitations and occurred problems, respectively, are discussed. Finally, section 4 summarizes the paper with conclusions, lessons learned, and an outlook on future research.

2. PIPELINE FOR TEMPORAL DEM DATA MANAGEMENT AS AN INPUT IN IMPROVED URBAN CLIMATE ANALYSIS

2.1 Motivation and Special Feature of the Approach

Due to the limited availability of urban meteorological stations, urban climate analysis and adaptation require proxy variables such as LCZs or using modeling software such as UMEP to generate high resolution maps of urban thermal comfort. Accuracy of LCZ and UMEP is mainly impacted by the accuracy of the input parameters including urban morphological inputs, such as building geometry, and surface representation. Even more, these urban morphological inputs are typically treated as static over time based on the most current available dataset (e.g. Li et al., 2024). Therefore, in contrast to existing studies, we focus on explicitly characterizing the spatio-temporal dynamics of the DEMs for urban climate analysis. As one of the key input variables, they not only provide the geometric basis for urban climate analysis (e.g., deriving terrain roughness from DTMs for LCZ classification), but also enable the representation of buildings and vegetation structures using high-resolution DSMs for detailed thermal comfort modelling. Building on this, spatio-temporal DEMs further capture the temporal evolution of urban morphology by incorporating DEM datasets acquired at different timestamps.

2.2 Enhancing Urban Climate Analysis Workflows by Integrating Spatio-Temporal DEM Management

Accordingly, our approach enhances the traditional urban climate analysis workflow by adding a new spatio-temporal DEM management (see Figure 1).

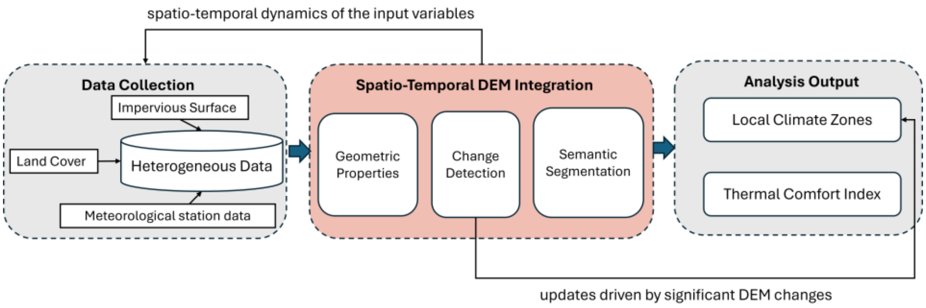

Figure 1 – The here introduced spatio-temporal DEM integration is designed to act as a central part of an enhanced urban climate analysis workflow.

As the core part of an urban climate workflow, the spatio-temporal DEM module enables the derivation of geometric properties, as well as semantic segmentation and change detection, thereby characterizing the urban three-dimensional form and its temporal evolution. Meanwhile, its spatio-temporal query capability allows the analysis to flexibly select different temporal states and dynamically align heterogeneous input variables, such as land cover, impervious surfaces, and meteorological observations. The detected changes can e.g. support dynamic updates to LCZs, triggering the recalculation of associated thermal comfort indicators when significant urban changes occur.

2.3 Details of the Spatio-Temporal DEM Pipeline

Details of the spatio-temporal DEM data management pipeline are presented in Figure 2. The DEM data used in this paper are in raster format (e.g., GeoTIFF), derived from raw point cloud measurements through interpolation and filtering processes, in the form of two products: the DSM, representing surface elevations including buildings and vegetation, and the DTM, representing the bare ground after removing all above-ground objects. Each DEM dataset covers multiple spatial subregions ($R_1, R_2, \ldots, R_n$). For each subregion, DEMs are available at multiple timestamps ($T_1, T_2, \ldots, T_n$). These DEM data then are organized as a spatio-temporal collection jointly indexed by spatial subregions R and timestamps T, with each record represented by a pair (R, T).

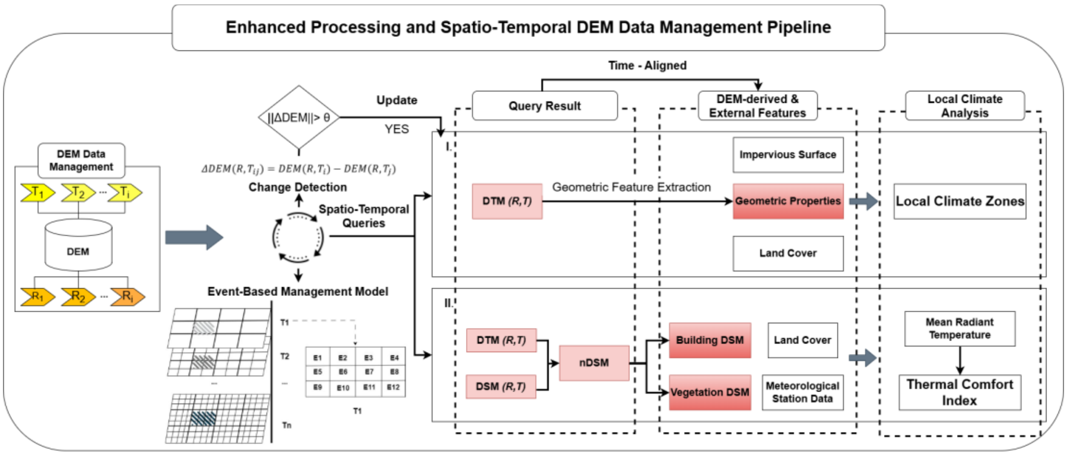

Figure 2 – Details of enhanced processing and spatio-temporal DEM data management pipeline. Our output can e.g. be used to support urban climate analysis such as change detection in LCZ and modeling of thermal comfort.

For the management of spatio-temporal DEM data, we applied an Event-Based Time-Stamping Data Model (Liu et al., 2025b). It considers DEM files from the same timestamp, e.g., the same airborne laser scanning campaign, as the same layer, which reflects global changes over time. Within each single layer, individual events E_1, E_2, …, and E_n represent collections of actions related to elevation changes for their corresponding subregions, so that detailed local changes can also be captured at the event level. To further detect temporal changes within the same spatial subregion, the elevation change is quantified as:

$$\Delta DEM(R, T_{ij}) = DEM(R, T_i) - DEM(R, T_j)$$

Where $DEM(R, T_i)$ and $DEM(R, T_j)$ represent DEMs of subregion R acquired at T_i and T_j, and $\Delta DEM\ (R, T_{ij})$ is the corresponding change between these two timestamps.

The spatio-temporal query results of DEMs are subsequently prepared for use in urban climate analysis. We particularly foresee the use of the geometric properties (e.g., terrain roughness) derived from the DTM as essential inputs for LCZ classification and change detection. In thermal comfort analysis, a detailed three-dimensional information on urban buildings and vegetation is required to properly represent shading and radiative interactions. To eliminate terrain effects, we have thus computed the Normalized Digital Surface Model (nDSM) by subtracting the DTM from the DSM (Brunn and Weidner, 1997), i.e.,

$$nDSM = DSM - DTM$$

The nDSM represents the relative height of objects above ground level, providing a reliable basis for applying height thresholds to filter non-building objects (e.g., vehicles) and to support the semantic segmentation of buildings and vegetation. These segmented layers are prepared as input in UMEP to estimate mean radiant temperature.

3. METHODOLOGY BASED ON CASE STUDY KARLSRUHE

3.1 Case Study Area

Based on nearly twenty years of airborne laser scanning data provided by the State Office for Geoinformation and Land Development (LGL) (see Table 1), Karlsruhe, a city in southwestern Germany, has experienced clear urban expansion and morphological change.

Table 1 – Laser scanning campaigns for the case study area of Karlsruhe, Germany. The LGL has conducted three Airborne Laser Scanning (ALS) campaigns, during which different regions were surveyed once within each campaign period.

ALS_name	**Year**	**Resolution**
ALS_1	2000-2005	DTM (1 m), DSM (1 m)
ALS_2	2016-2021	DTM (0.25 m), DSM (1m)
ALS_3	2022-	DTM (0.25 m), DSM (1m)

During the same period, the city has also shown stronger Urban Heat Island (UHI) effects of up to 4 K in summer at nighttime based on numbers provided by the German Weather Service (Krähenmann et al., 2018).

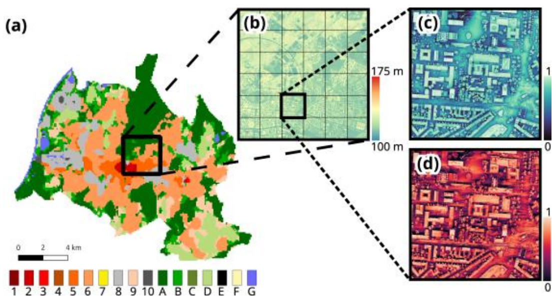

Figure 3 – A map of the Local Climate Zones (a) in Karlsruhe following Demuzer et al. (2022). The DSM (b) output of the introduced Spatio-Temporal DEM pipeline has been used as an input into UMEP to calculate the sky view factor (c) and shadow maps (d).

Against this background, the spatio-temporal DEM pipeline together with its implementation in UMEP has been applied to Karlsruhe as a case study (see Figure 3).

3.2. Spatio-temporal DEM Queries and Change Detection

To achieve efficient statistical and spatio-temporal queries (see Figure 4), we stored metadata in PostGIS geodatabase, which are associated with DEM files basic information such as spatial extent, generation date and resolution. The DEM data themselves are maintained on the data server, while spatio-temporal queries are performed directly on metadata.

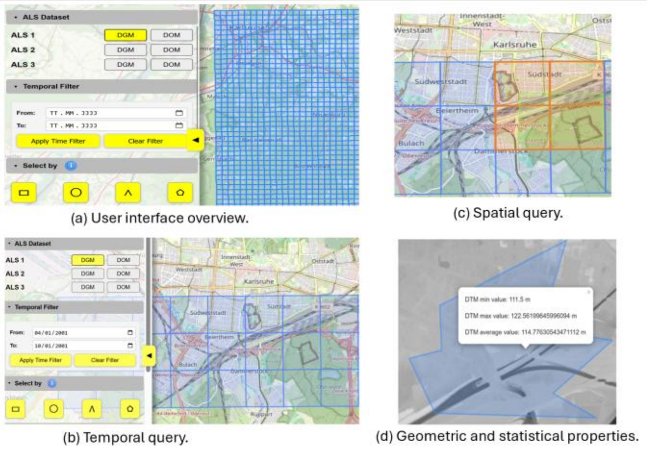

Figure 4 – Examples of spatial, temporal, and statistical data queries.

Based on the results of spatio-temporal queries, relevant DEM files are dynamically transferred to the analysis server, which provides advanced processing functionalities such as building segmentation (as described in Section 3.3) and change detection across different timestamps within the same spatial region (see Figure 5). When the user clicks on the result pixel, the elevation change value at this specific point can be acquired.

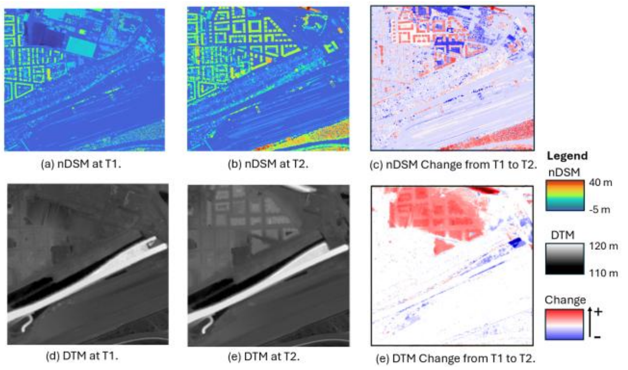

Figure 5 – nDSM change and DTM change between the timestamps T1 (2001) and T2 (2016) for a spatially selected part of Karlsruhe.

Finally, the front-end client supports users to export analysis results in multiple data formats, including raster and point cloud, with customizable output parameters such as spatial resolution and tile size to suit specific application requirements.

3.3. DEM Semantic Segmentation

3.3.1 Workflow

In this section, we describe our semantic segmentation framework, which provides the spatial inputs required for TCI calculation. The primary focus is the semantic segmentation of buildings, while vegetation areas are then obtained by excluding building regions from the DSM. The framework starts from OpenStreetMap (OSM) building footprints as initial semantic priors, while high-resolution nDSM geometric features serve as the primary basis for building identification. In addition, spectral information from orthophotos is incorporated to further distinguish buildings from vegetation.

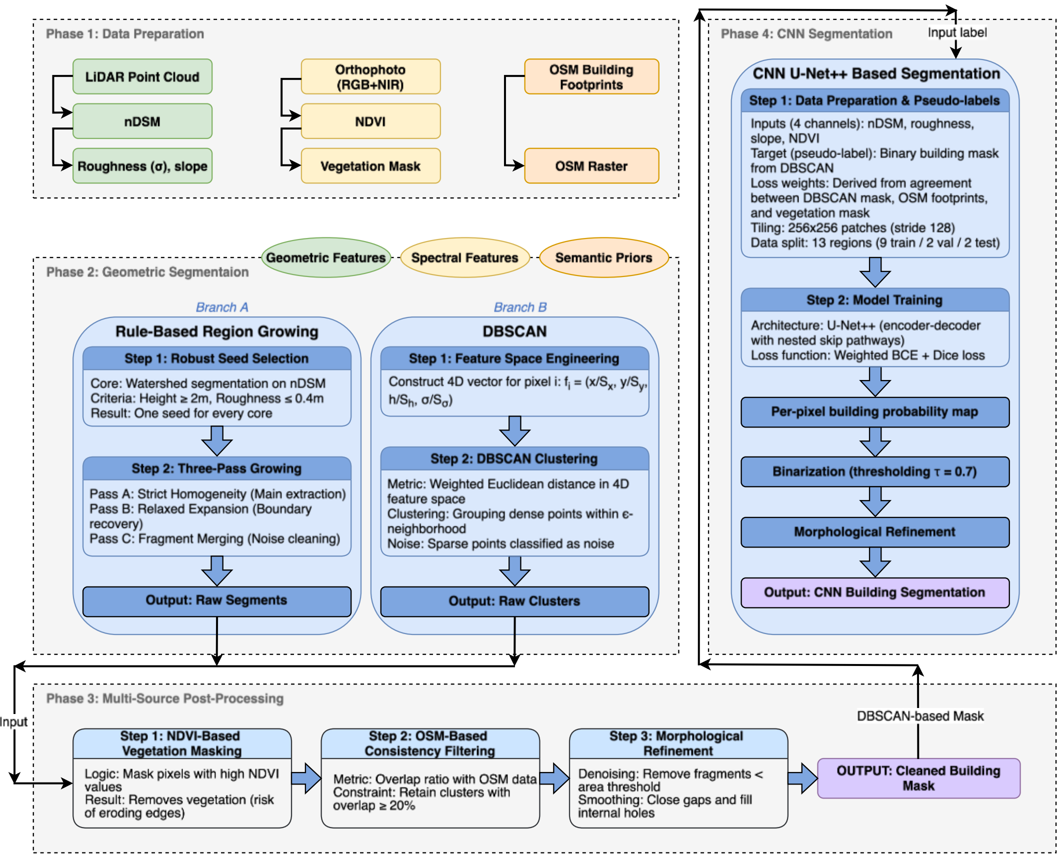

Figure 6 – DEM semantic segmentation framework: nDSM-derived geometric features, spectral vegetation information, and OSM building footprints are integrated as geometric, spectral, and semantic priors, respectively. The region growing approach identifies building seeds from the nDSM using height and roughness constraints and expands regions in multiple passes to recover building boundaries. The DBSCAN approach clusters pixels into building candidates in a normalized four-dimensional feature space (spatial coordinates, height, and local roughness) using density-based clustering. The geometric segmentation results are refined through post-processing to produce cleaned building masks, which are subsequently used as pseudo-labels for training the U-Net++ model.

Within this framework, three different segmentation strategies have been implemented: a rule-based region growing approach, a geometry-based DBSCAN clustering approach, and a deep learning approach based on U-Net++, as shown in Figure 6.

3.3.2 Evaluation

We evaluated the segmentation performance of the three approaches and compared the results against the original OSM building data as a baseline, using DEM datasets from the ALS_3 campaign (2022). Ten representative 100 × 100 m blocks across different urban and suburban settings in Karlsruhe were selected as evaluation reference data, where building polygons were manually inspected and corrected using both the orthophoto and the nDSM as visual references. In addition, 13 larger sample regions of approximately 750×750 m were used for training/validation/testing of the learning-based baseline, see Figure 7.

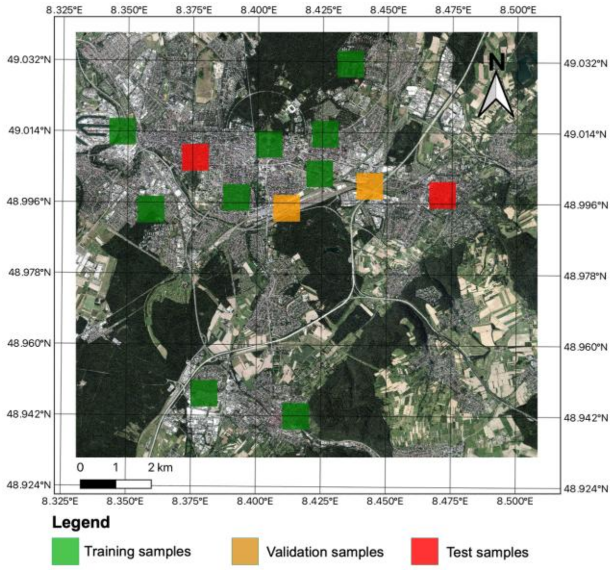

Figure 7 – Orthophoto of the study area in Karlsruhe, Germany. Training, validation, and test windows are overlaid.

As Table 2 shows, the DBSCAN approach achieves the best overall performance, with the highest mean IoU and F1-score. Both geometry-based approaches outperform the OSM baseline, while the U-Net++ model shows lower accuracy under weak supervision. Figure 8 visualizes qualitive examples comparing DBSCAN-based results and OSM building footprints with manually corrected reference data (denoted as ground truth in the figure).

Table 2 – Mean building extraction performance over ten manually corrected 100 × 100 m reference blocks.

Method	IoU	Precision	Recall	F1-score
OSM baseline	0.844	0.934	0.900	0.905
Region Growing	0.881	0.931	0.944	0.936
DBSCAN	0.894	0.956	0.933	0.943
U-Net++ (CNN)	0.732	0.835	0.853	0.844

However, there are still some limitations in our approach. First, we apply currently only a binary classification of buildings and vegetation to elevated targets in the DSM, so the classification results may include other land-cover types. Moreover, the vegetation DSM representation is simplified. Lindberg and Grimmond (2011) have discussed the influence of distinguishing canopy and trunk zones on radiation calculations in UMEP. Based on this, the simplified representation may overestimate vegetation shading. In addition, it is difficult to distinguish between buildings and vegetation when dense tree canopies occlude building roofs.

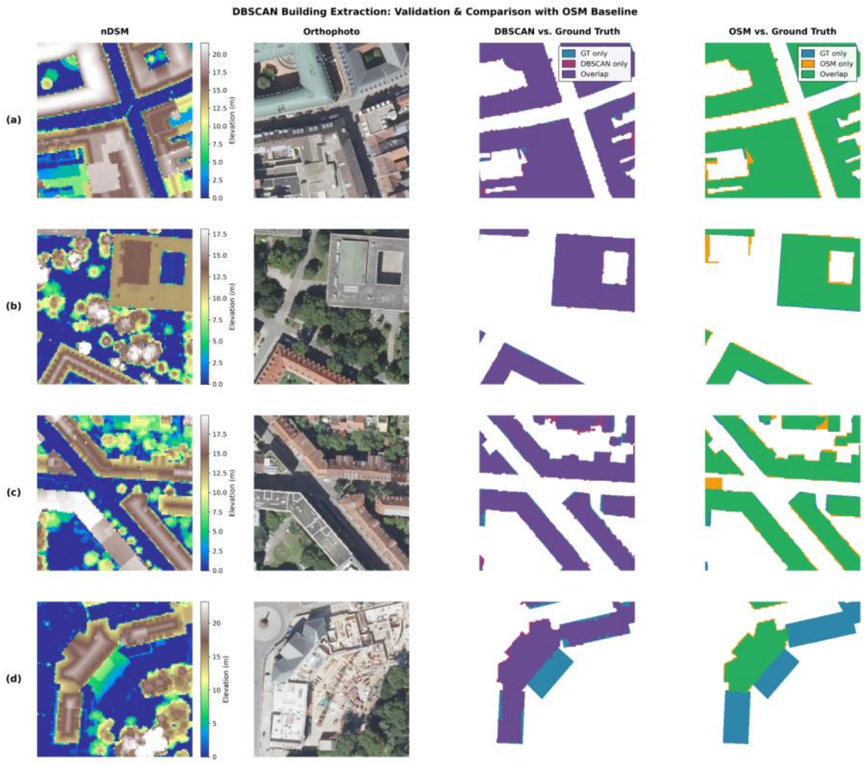

Figure 8 – DBSCAN building segmentation on four reference blocks. In (a), DBSCAN slightly adjusts the building outlines along block boundaries by a few pixels, correcting small edge shifts. In (b), several thin, spike-shaped OSM polygons with clearly non-building geometry, likely resulting from random OSM drawing errors are removed. (c) shows a case where an OSM footprint incorrectly extends over part of a road; DBSCAN largely suppresses this region and retains the actual building´s roof. In (d), DBSCAN recovers a building that is clearly visible in the nDSM but partly absent in OSM, although one wing of the roof is still missing.

Finally, the performance of the CNN-based approach is constrained by weak supervision, as the pseudo-labels derived from geometric segmentation contain noise and systematic biases, indicating that, in the absence of high-quality annotated data, the advantages of deep learning methods cannot be fully exploited.

4. CONCLUSIONS AND OUTLOOK

In this paper, we presented a pipeline for spatio temporal DEM data management aimed at the use in urban climate analysis. To project changes in heat exposure based on urban planning decisions, a spatio-temporal DEM management system has been developed that supports change detection analysis. In addition, semantic segmentation of DEMs has been implemented to distinguish buildings from vegetation for use in mean radiant temperature determination. First results have been evaluated based on a case study with data from the city of Karlsruhe, Germany.

The lessons learned by this study are: DEM and OSM data have been proven to be valuable additional data sources to detect errors in building segmentation from images and thus to improve the entire segmentation process. Furthermore, change detection of buildings and vegetation has been proven to be a suitable instrument for city development analysis examining the past and the future of cities. In the future, change detection will be a key element to examine historically developed heat islands as well as the development of future heat islands e.g. due to construction measures in cities. By leveraging temporal DSM information, future studies will e.g. be able to generate more reliable LCZ maps. Currently most studies rely on the static results of a global random forest approach (Demuzer et al. 2022, see Fig 3a). Our tool clears the path for visualisation of structural changes and their climatic impacts, providing a comprehensive understanding of urban dynamics and their effects on heat distribution and microclimatic conditions.

By implementing the proposed pipeline with existing models of heat stress such as the UMEP (Lindberg et al., 2018), future studies will be able to directly project changes in urban climate extremes based on proposed urban planning decisions. This will further support predictive heat island analysis. Already we can link our pipeline to UMEP in order to more accurately present the dominant features in urban heat stress modeling (Figure 3 b-d). Based on change detection of the built and natural environment, the presented pipeline enables a detailed assessment of urban transformation over time. It allows not only the identification of areas with significant structural modifications but also the quantification of their impacts on local climate and thermal comfort.

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REFERENCES

Adinolfi, M., Raffa, M., Reder, A., Mercogliano, P., 2023. Investigation on potential and limitations of ERA5 Reanalysis downscaled on Italy by a convection-permitting model. Clim Dyn 61, 4319–4342. https://doi.org/10.1007/s00382-023-06803-w

Aghamolaei, R., Azizi, M.M., Aminzadeh, B., Mirzaei, P.A., 2020. A tempo-spatial modelling framework to assess outdoor thermal comfort of complex urban neighbourhoods. Urban Climate 33, 100665. https://doi.org/10.1016/j.uclim.2020.100665

Balovnev, O., Breunig, M., Cremers, A.B., 1999. GeoToolKit: Opening the Access to Object-Oriented Geodata Stores. M.F. Goodchild, M.J. Egenhofer, R. Fegas, and C.A. Kottman (eds.): Interoperating Geographic Information Systems, Kluwer Academic Publishers, Boston, pp. 235-248.

Baumann, P., 2010. The OGC Web Coverage Processing Service (WCPS) Standard, Geoinformatica, 14(4)2010, pp. 447-479.

Baumann, P., Furtado, P., Ritsch, R., Widmann, N., 1997. The RasDaMan Approach to Multidimensional Database Management. Proc. 12th Annual Symposium on Applied Computing (SAC'97), San Jose/USA, February 28 - March 2, 1997.

Baumann, P., Misev, D., Merticariu, V., Pham Huu, B., 2018. Datacubes: Towards Space/Time Analysis-Ready Data. J. Doellner, M. Jobst, P. Schmitz (eds.): Service Oriented Mapping - Changing Paradigm in Map Production and Geoinformation Management, Springer Nature, Lecture Notes in Geoinformation and Cartography, pp. 269-299.

Breunig, M., Kuper, P.V., Butwilowski, E., Thomsen, A., Jahn, M., Dittrich, A., Al-Doori, M., Golovko, D., Menninghaus, M., 2016. The Story of DB4GeO - A Service-Based Geodatabase Architecture to Support Multi-Dimensional Data Analysis and Visualization. ISPRS Journal, Vol. 117, pp. 187-205.

Brunn, A. and Weidner, U., 1997. Extracting buildings from digital surface models. International Archives of Photogrammetry and Remote Sensing, 32(3 SECT 4W2), pp. 27-34.

Budhathoki, N.R. and Haythornthwaite, C., 2013. Motivation for open collaboration: Crowd and community models and the case of OpenStreetMap. American Behavioral Scientist, 57(5), pp. 548-575

Colaninno, N., Salvati, A., Lopez-Besora, J., Morganti, M., 2025. District-scale cumulative heat stress mapping using very-high-resolution spatiotemporal simulation. Sustainable Cities and Society 130, 106498. https://doi.org/10.1016/j.scs.2025.106498

Demuzere, M., Kittner, J., Martilli, A., Mills, G., Moede, C., Stewart, I.D., van Vliet, J., Bechtel, B., 2022. A global map of local climate zones to support earth system modelling and urban-scale environmental science. Earth System Science Data 14, 3835–3873. https://doi.org/10.5194/essd-14-3835-2022

Doyle, F.J., 1978. Digital Terrain Models: An Overview. Photogrammetric Engineering and Remote Sensing, Vol. 44, No. 12, December 1978, pp. 1481-1485.

Intergovernmental Panel on Climate Change (IPCC). 2023. Climate Change 2023: Synthesis Report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Edited by H. Lee and J. Romero. Geneva: IPCC. https://doi.org/10.59327/IPCC/AR6-9789291691647

Krähenmann, S., Walter, A., Brienen, S., Imbery, F. and Matzarakis, A., 2018. High-resolution grids of hourly meteorological variables for Germany. *Theoretical and Applied Climatology*, *131*(3), pp.899-926.

Krikau, S., Benz, S.A., 2025. Temporal and spatial patterns of heat extremes in Hesse, Germany. Environ. Res. Commun. https://doi.org/10.1088/2515-7620/adce59

Landesamt für Geoinformation und Landentwicklung Baden-Württemberg (LGL), 2025. Digitale Geländemodelle (DGM) [Open GeoData]. Datenlizenz Deutschland – Namensnennung – Version 2.0. Available at: https://www.lgl-bw.de/Produkte/3D-Produkte/Digitale-Gelaendemodelle/ (accessed 15 September 2025).

Li, X., Wang, G., Zaitchik, B., Hsu, A., Chakraborty, T., 2024. Sensitivity and vulnerability to summer heat extremes in major cities of the United States. Environ. Res. Lett. 19, 094039. https://doi.org/10.1088/1748-9326/ad6c64

Lindberg, F. and Grimmond, C.S.B., 2011. The influence of vegetation and building morphology on shadow patterns and mean radiant temperatures in urban areas: model development and evaluation. *Theoretical and applied climatology*, *105*(3), pp.311-323.

Lindberg, F., Onomura, S., Grimmond, C.S.B., 2016. Influence of ground surface characteristics on the mean radiant temperature in urban areas. Int J Biometeorol 60, 1439–1452. https://doi.org/10.1007/s00484-016-1135-x

Lindberg, F., Grimmond, C.S.B., Gabey, A., Huang, B., Kent, C.W., Sun, T., Theeuwes, N.E., Järvi, L., Ward, H.C., Capel-Timms, I., Chang, Y., Jonsson, P., Krave, N., Liu, D., Meyer, D., Olofson, K.F.G., Tan, J., Wästberg, D., Xue, L., Zhang, Z., 2018. Urban Multi-scale Environmental Predictor (UMEP): An integrated tool for city-based climate services. Environmental Modelling & Software 99, 70–87. https://doi.org/10.1016/j.envsoft.2017.09.020

Li, Z., Zhu, X., Yao, S., Yue, Y., García-Fernandéz, A.F., Lim, E.G., Levers, A., 2023. A large scale Digital Elevation Model super-resolution Transformer. Int. Journal of Applied Earth Observation and Geoinformation 124 (2023) 103496, Elsevier, p. 1-17.

Liu, R., Kuper, P.V., Breunig, M., 2025a. Implementation of Database-Supported Analysis for Spatio-Temporal Digital Terrain Models. 28th AGILE Conference on Geographic Information Science “Geographic Information Science responding to Global Challenges”. AGILE GIScience Ser. 6, 36, pp. 1-7, https://doi.org/10.5194/agile-giss-6-36-2025.

Liu, R., Kuper, P., Grombein, T., Naab, C., Al-Doori, M. and Breunig, M., 2025b. Towards Integrated Data Management and Analysis for Spatio-Temporal Digital Terrain Models. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, pp.543-550.

Maronga, B., Gryschka, M., Heinze, R., Hoffmann, F., Kanani-Sühring, F., Keck, M., Ketelsen, K., Letzel, M.O., Sühring, M., Raasch, S., 2015. The Parallelized Large-Eddy Simulation Model (PALM) version 4.0 for atmospheric and oceanic flows: model formulation, recent developments, and future perspectives. Geosci. Model Dev. 8, 2515–2551. https://doi.org/10.5194/gmd-8-2515-2015

Mavrakou, T., Polydoros, A., Cartalis, C., Santamouris, M., 2018. Recognition of Thermal Hot and Cold Spots in Urban Areas in Support of Mitigation Plans to Counteract Overheating: Application for Athens. Climate 6, 16. https://doi.org/10.3390/cli6010016

Migliari, M., Babut, R., De Gaulmyn, C., Chesne, L., Baverel, O., 2022. The Metamatrix of Thermal Comfort: A compendious graphical methodology for appropriate selection of outdoor thermal comfort indices and thermo-physiological models for human-biometeorology research and urban planning. Sustainable Cities and Society 81, 103852. https://doi.org/10.1016/j.scs.2022.103852

Miller, C.L., 1958. The theory and application of digital terrain model. Thesis (M.S.). Massachusetts Institute of Technology, Dept. of Civil and Sanitary Engineering, http://hdl.handle.net/1721.1/67142.

Naserikia, M., Nazarian, N., Hart, M.A., Sismanidis, P., Kittner, J., Bechtel, B., 2024. Multi-city analysis of satellite surface temperature compared to crowdsourced air temperature. Environ. Res. Lett. 19, 124063. https://doi.org/10.1088/1748-9326/ad8be4

Nazarian, N., Lee, J.K., 2021. Personal assessment of urban heat exposure: a systematic review. Environ. Res. Lett. 16, 033005. https://doi.org/10.1088/1748-9326/abd350

Oke, T.R., 1973. City size and the urban heat island. Atmospheric Environment (1967) 7, 769–779. https://doi.org/10.1016/0004-6981(73)90140-6

Silvela, J. and Portillo, J., 2001. Breadth-first search and its application to image processing problems. *IEEE Transactions on Image Processing*, *10*(8), pp.1194-1199.

Stewart, I.D. and Oke, T.R., 2012. Local climate zones for urban temperature studies. *Bulletin of the American Meteorological Society*, *93*(12), pp.1879-1900.

Venter, Z.S., Chakraborty, T., Lee, X., 2021. Crowdsourced air temperatures contrast satellite measures of the urban heat island and its mechanisms. Science Advances 7, eabb9569. https://doi.org/10.1126/sciadv.abb9569

Weibel, R., Heller, M., 1991. Digital terrain modelling. Geographic Information Systems, Principles and Applications, Longman, pp. 269-297.

Zhilin, L., Zhu, C., Gold, Ch., 2004. Digital terrain modelling: principles and methodology. CRC press.

Zhong, X., Voogt, J., Bailey, B., Zhang, X., Krayenhoff, E.S., 2026. Evaluating high-resolution mean radiant temperature within an urban street canopy: Resolving spatiotemporal variations with LiDAR/thermal infrared scanning and data-driven simulation. Building and Environment 287, 113819. https://doi.org/10.1016/j.buildenv.2025.113819

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