Increasing level of detail of buildings for improved simulation of 4D urban digital twin

Dimitri Bulatov[1], Marie May[2], Eva Strauß[1], Francesco Mancini[2], Benedikt Kottler[1], Petra Helmholz[2]

[1] Fraunhofer Institute of Optronics, System Technologies and Image Exploitation (IOSB)
Gutleuthausstr. 1, 76275 Ettlingen, Germany. E-mail: name.surname@iosb.fraunhofer.de

[2] Curtin University, Australia

Abstract

Buildings represent a crucial component of urban morphology, and their accurate modeling is essential for a number of applications involving Urban Digital Twins. With respect to thermal simulation aiming to identify Urban Heat Islands, a trade-off between accurate modeling of a single building type and large-scale reconstruction of virtual city models needs to be found. In the proposed paper, we analyzed an Australian suburb containing approximately 1700 residential buildings with challenging roof structures. Building outlines are provided by geo-information data and converted into prismatic models of LOD1. Using airborne sensor data (digital orthophotos, high-resolution images, and digital surface models), we identified two ways to increase the LOD and thus, the accuracy of the simulation. Firstly, we used common Computer Aided Graphics software to model interactively a few selected buildings, a process denoted as geo-specific modeling. Here, the outlines were used as foundations for constructing the ground-level walls. We relied on airborne data to retrieve building heights and roof structures. Number of floors and positions of façade elements were modeled on standard typological assumptions and building practices. We developed an interface to import automatically LOD1-based data and to export LOD3 buildings into the simulation. Secondly, we reproduce these models to model other buildings of the dataset. For this so-called geo-typical modeling, a similarity measure based on the outlines was implemented. The final scene consists of triangles modeling LOD3 buildings, terrain, and trees, retrieved using machine-learning-based methods on land cover classification. Together with the semantic class, we store the geometrical and physical properties of every triangle. The environmental data (e.g., cloud coverage, air temperature) is available by means of the weather services. Surface temperature is modeled by considering conductive, convective, and radiative heat transfer. The simulation of updated LOD3 buildings shows a significantly increased realism of the temperature distribution in an urban area. It can used to verify sustainable design of appropriate morpho-typologies for a particular precinct in a given context.

Keyword: *Airborne data, building, digital twin, simulation, temperature, urban heat islands*

Introduction

Buildings are essential to serve societal needs, and their accurate modeling is important for a number of applications (Lamb, 2019). For example, nowadays, Urban Heat Islands (UHIs) became an issue of concern in city planning and so making it necessary to construct and to design buildings and their surroundings in a way to minimize the effects of trapping and radiation. Here, building models within the digital twin of the scene would contribute to the calculation of surface temperatures. Due to increasing computing power and the accuracy of the 3D models available from commercial and non-commercial providers, digital twins of urban scenes are increasingly able to provide accurate output to conditions existing or even not yet existing, such as sustainable roofing materials, and to simulate their developments according to different scenarios affecting local micro-climate. Because of this temporal dimension and the commonplace fact that temperature is always a function of its previous state, we speak of the 4D digital twin of the scene.

The previously developed model is based on the heat balance equation with terms reflecting convection, radiation, and conduction (Kottler, et al., 2019). In our opinion, it possesses an acceptable trade-off between the simplicity of the underlying model and its ability to obtain reasonable results, which could be verified using direct temperature measurements and thermal imagery as ground truth. The scene itself was retrieved using airborne sensor data, is already sufficient for automatic derivation of several important components of the 3D digital twin, such as computation of ground model (Mongus & Žalik, 2012), land cover classification (Bulatov, et al., 2019), detection of buildings and obtaining their roofing materials (Ilehag, et al., 2018). Thus, the clear advantage is that 3D scenes of large extensions can be modeled automatically. However, precisely the buildings and their 3D modeling constitute the problem here. Despite many good works on building outlining (Mousa, et al., 2019; Ortner, et al., 2007) and reconstruction from laser and photogrammetric data exist (Lafarge, et al., 2010; Bulatov, et al., 2014), the quality of reconstruction is highly dependent on model complexity as well as data quality: resolution and accuracy of 3D point clouds. Adopting the concept of Level of Details (LODs) (Albert, et al., 2003), which is well known and is being continuously refined and improved (Biljecki, et al., 2016), one can say that generation of LOD1 building models is mostly feasible in combined image and elevation data. However, even with a perfect roof model (LOD2), analysis of building walls from quasi-nadir images to detect doors and windows (LOD3) is not feasible.

The trade-off in building modeling is, on the one hand, to represent buildings accurately, i.e., to model the course of shadows correctly, and, on the other hand, to keep the model complexity low for the simulation to run fast and for the urban planner to be able to apply numerous scenarios for scene design. To solve this problem, we are seeking an alliance with the disciplines of urban morphology and building typology to provide adequate criteria to catalog undetectable formal aspects and materials listed above to increase the quality of the semantic model. By consolidating the expertise of remote sensing and architecture, many steps of the pipeline will be carried out automatically using the available sensor data and, at the same time, semantic 3D building models of LOD3 will be created interactively and placed according to their geographic position in the scene model. Additionally to this geo-specific modeling, we propose a way to represent many other buildings in the dataset. Since the interactively created buildings are supposed to be representative for the dataset, we can reproduce their models within the dataset using a similarity function. We thus are able to simulate the temperatures of large scenes containing many buildings, such as our previously developed 3D digital twin (Bulatov, et al., 2020) of the City of Melville, Australia, which is the 1km by 2 km large dataset with more than 1720 mostly single-story individual dwellings with complex roof forms. At the same time, we increase the accuracy by replacing the LOD1 building models with more complex LOD3 structures.

After a concise summary of previous work achieved on the 3D and 4D digital twin of the scene, the main contribution of this work – namely, creating LOD3 building models – is introduced in Section 3. In Section 4, we refer to the simulation of the enriched model. Section 5 summarizes our findings and outlines the future research directions.

Previous works

Contemporary urban planning practices often focus on the land subdivision in many regions of the world. The application of this principle implies that land development is essential to plan a precinct, a neighborhood or a city, subduing other strategic components of planning, such as built form, open spaces, and green areas. The authors criticize such an approach by referring to (Moudon, 1997) and intend to reaffirm the importance of urban form to generate livable and sustainable environments. In her article, Moudon describes the importance of considering the three fundamental elements of Urban Morphology in synchronous: form, resolution and time. In our analysis, these principles were considered from a different angle. Morphological classifications of the smallest cell of the city, the individual parcel of land with its buildings and open spaces within a period, show that "the attributes of the cell and its elements reflect not only a time period of history, but the socio-economic conditions present at the time of land development and building […] Building and transformation cycles are important processes to explore for city planning and real estate development purposes, yet are rarely studied in contemporary cities" (Moudon, 1997). Moudon also lists the three possible objectives of urban morphological studies for description, prescription and assessment of design theories and their applications to city building. However, Moudon's demonstration that urban morphology is an interdisciplinary field did not encompass the intimate connection which can be established between built form and urban environmental studies, let alone applications to drive future urban developments.

This study attempts to cover this gap by analyzing the quality of morphological cells through their types, land surfaces and materials to produce environmental simulations of urban heat islands over time. In doing so, we have appropriated Moudon's three subjects of study of urban forms, but we have associated the dynamic component of time to the environmental response of a residential development area built at a particular moment in time in Melville, Perth, rather than the historical development of its urban morphology and building typology. When applied to previous (and future) developments in the same area, this method enables assessment of the environmental response of a specific building culture over time. The authors will develop this analysis in further papers, aiming to demonstrate that a specific regulatory/cultural approach to planning and design produces both specific and environmental outcomes in response to urban problems of different nature but which are, in fact, correlated as they are the product of the same governance culture. The relevance of this research to further applications within the discipline of urban morphology and urban design is twofold. Firstly, the methodology adopted in this study demonstrates the potential of systematic parametric modeling of urban form to support environmental science-based simulations of the built environment (Chapman, 2020). Secondly, such a method contributes to the definition of a precise model at scale by building on a rigorous typological study of the urban area examined. The identification of recurring characters in the geo-specific buildings of the studied precinct via typological analysis can drive an automatized selection of particular building types to generate plausible geo-typical models. This technique, once perfected, will complement or substitute traditional accurate survey methods, enabling accurate and relatively fast simulations and assessment of environmental phenomena in the urban environment at both micro and macro scale. Such environmental simulations help to assess the response of different 'plan units' or 'tissues'[1] in their ecological context from a sustainable perspective (Osmond & Hanzl, 2020). They also suggest the adoption of urban form environmental qualities to drive planning regulatory decisions.

Further development of such study of built form can set the basis for design simulations during the planning stage to: 1) test how different typological and morphological settings can achieve environmental balance, and 2) apply via new policies to the transformation/development of the urban realm.

Methodology

Preliminaries: Sensor data and intermediate results

A short review of available data and preprocessing steps is necessary to follow the explications on geo-typical and geo-specific building reconstruction. We are given an aerial image and DSM (digital terrain model) of GSD (ground sampling distance) of 0.5m, as well as high-resolution images in which selected buildings can be visualized. Finally, building outlines are available from an outdated cadastral map.

Following preprocessing modules, described in more detail in our previous work (Ilehag, et al., 2018; Kottler, et al., 2019; Bulatov, et al., 2020) were carried out. We obtain the ground model from the DSM and use the relative elevation together with aerial image, as features, for land cover classification into six classes (asphalt road, bare soil, water region, grass, tree, and building). The masks yielded for the building class are compared to the GIS outlines, after which the latter one is updated within an interactive procedure. Those buildings not present in the dataset anymore are deleted, newly constructed buildings, and the outlines of modified buildings are re-parametrized. The materials of building roofs are retrieved from the aerial image data using a machine learning method (Bulatov, et al., 2019). Currently, there is one material per building roof. The LOD1 building models are prismatic structures where the ground model and the building height, respectively give the position of the lower and upper base of the prism, while the sides constitute walls without doors and windows. For upgrading the LOD automatically, the inclination angle, elevation range, and approximate location of the dominant roof planes of every single building are computed using the J-Linkage procedure

[1] (Whitehand, et al., 2009) used the term plan unit to define neighborhoods through urban form; (Muratori, 1959) used the term tissue to express the same concept.

(Toldo & Fusiello, 2008). As already mentioned before and illustrated in Figure 1, mostly larger planes have been retrieved correctly while for the small planes in the presence of complex roof forms, the results were not sufficiently accurate. Therefore, we decided to model selected buildings interactively, as described in the next section.

Geo-specific modeling

Firstly, sensor data must be converted into a readable file that can be imported into the Computer Aided Drawing (CAD) programs, such as Autocad and Revit. We opted for exporting the building outlines centered on the origin of the coordinate system into VRML files because 3DsMax offers a solution of converting them into the software-proper format DWG. The conversion took place batch-wise and fully automatically using scripts. The modeling process itself takes place in Revit. This is a digital design software package for Building Information Models (BIMs) that is widely used to create 3D models and drawings with a high focus on the landscape and architecture aspects of BIM. Since the coordinates are already embedded, the BIM is easier to create. After this, we generate floors based on the building outline, as well as walls, roof, doors, and windows. To model the roof structures, we are guided by the information on roof segments' slope and elevation range. This information has been retrieved from the automatic data processing drawn into the fragment of the high-resolution airborne images provided by the supplier Spookfish, as shown in Figure 1. Finally, information not retrievable from the aerial data, such as the number of floors and positions of doors and windows, are reflected in standard typological assumptions and building practices. For example, we can suppose that each floor is three meters high to derive the number of floors from the building height.

The final step in geo-specific modeling is the import of a building model into the simulator. Again, an editable format is required. We opted for the wavefront OBJ format. An OBJ file contains a list of vertices and faces. Moreover, every face possesses attributes, namely, semantic class and normal vector. Decomposition of polygons into triangles takes place using constrained Delaunay triangulation. Overall, the simulation's data preparation takes place automatically and includes occasional re-orientation of normal vectors and simplification of building polygons (Douglas & Peucker, 1973) to save computational time. The diagram in Figure 2 shows the process of geo-specific modeling while Figure 3 visualizes the sequence steps of geo-specific modeling of an example building.

Geo-typical modeling

Using geo-specific modeling, we can model particular buildings very accurately. However, since this semi-automatic approach requires 30 minutes of human interaction per building and our aim is to model large datasets with hundreds or thousands of buildings, it would be costly to model every single building interactively. Therefore, we propose a procedure of geo-typical modeling. For every building B in dataset $\mathcal{B}$, the aim is to find the most similar building L in library $\mathcal{L}$ of previously modeled buildings and then to re-use the reconstruction from building L applying it to building B. As a perfect match is uncommon, B will look almost the same way as a building appearing somewhere else in the dataset; however, it will slightly differ in its real appearance.

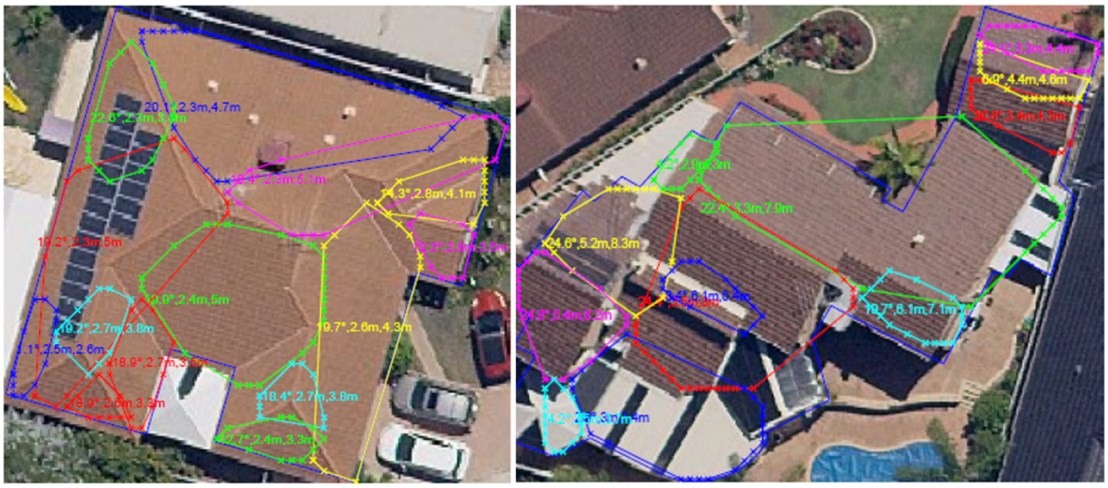

Figure *1. Fragments of high-resolution images of two example buildings from the dataset. On the left, a building with roof structure of average complexity; on the right, a building with roof structure of high complexity. The dominant planes resulting from the J-Linkage algorithm are depicted by 2D convex hulls of inlier points. The properties of plane segments serve for orientation for geo-specific modeling.*

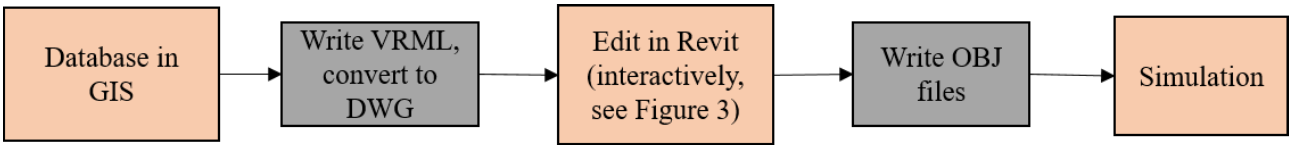

Figure 2. Overview of automatic interface for creating the geo-typical models and their integration into the simulation.

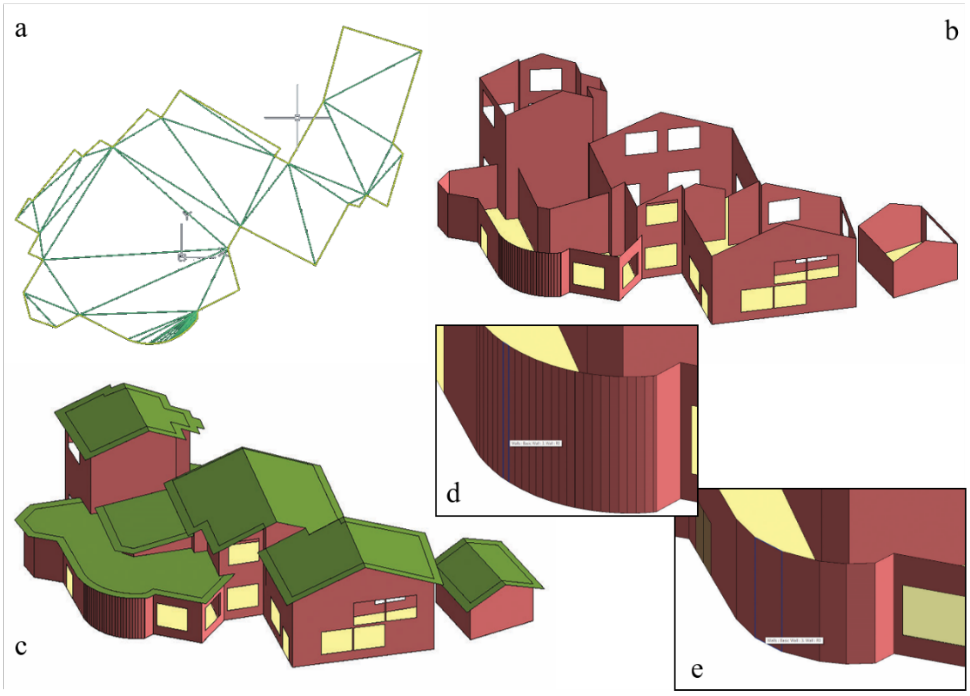

Figure 3. Modeling steps of geo-specific building from Figure 1, right. Step a: Building footprint imported in Revit. b: Walls and façade elements erected over the roof plane, c: formation of the roof structure with orientation to the dominant roof planes, d-e: optional simplification of building.

The degree of resemblance is quantified using a similarity function, which is in our case the well-known Intersection over Union (IoU) measure that assesses the overlap of two binary masks in 2D. Hereby, the binary masks are GIS-based outlines of B and L transferred into a common coordinate system. The IoU is a relatively simple choice ignoring the elevation values and roof forms, however, it can be easily implemented and also extended by several tricks: First, the outline of every building (in $\mathcal{B}$ and in $\mathcal{L}$) is rotated in the way that the longest side corresponds to the y axis. After this, it is cropped and saved as a rasterized bitplane. Additionally, we augment the number of models in the library by rotating the bitplanes by multiples of 90° and flipping them around the x-axis. For every parameter set, the comparison of bitplanes using IoU is carried out and the parameters yielding the highest score are stored. From these parameters, we determine the 2D transformation of the library building while in 3D, the offset and scale are computed using the base position and height of both buildings. Note that the material of the roof is not copied from L but preserved from B. For walls, doors, and windows, standard materials are assumed.

In Figure 4, we illustrate the results. From the multispectral image, it is hard to assess the similarity of the roof forms due to the insufficient resolution and blurring effects. Under these conditions, the fast and automatic approach to reproduce buildings according to the similarity of ground plans is sensible.

Simulation

In this section, a short overview of our simulation is provided. The newly created building meshes using the geo-specific as well as geo-typical modeling method replace the original ones (LOD1) for some instances. There are 20 geo-specific and 277 geo-typical buildings, i.e., there are almost 300 LOD3 buildings, while the total number of buildings is 1720. In a geo-specific building, the average number of vertices and faces is 138 and 209, respectively. This number exceeds by roughly 15% the one needed to create an average LOD1 building model. For LOD3 buildings, we have to assign materials to doors and windows. Without information about building façade elements, we assign wood to doors and glass to windows. From the materials, physical properties like emissivity, density, heat conduction coefficient etc. are derived. Additionally, the ground model is represented as a mesh with adaptive triangle density. Single trees are modeled separately while groups of trees are grouped into prismatic boxes having physical properties of trees. The whole scene consists of 1.9 million of triangles connecting some 1.6 million vertices.

The simulation itself is based on the heat transfer equation. The change of temperature of every face of the mesh is modelled as a sum of heat fluxes. The fluxes are either conductive, radiative, or convectional. The conductive flux is defined either along the surface or towards the object core, where an object is either a single building, a tree, or the earth. The convective flux depends on wind but is constant for every triangle. The radiative fluxes are made up by exchanging heat with the sun and the sky. They depend on whether the triangle is exposed to sun or sky, whereby a renderer for large scenes has been implemented. For a more detailed description of the fluxes and implementation, we refer to (Kottler, et al., 2019; Bulatov, et al., 2020).

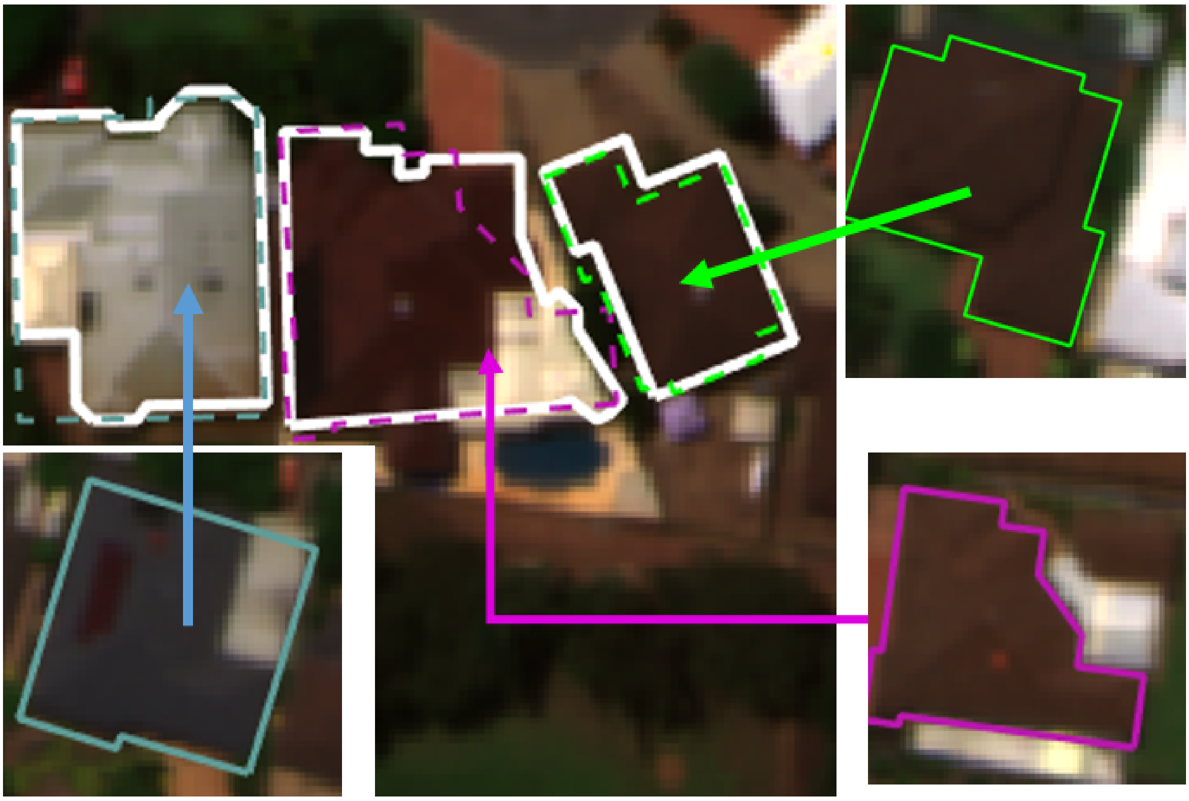

Figure 3. *Examples of geo-typical building modeling. In three smaller image fragments, the library elements are depicted. The colors of their outlines coincide with their projections into the coordinate system of the multispectral image. For the left-most building pair, please note the difference in materials.*

Figure 5 shows the results of the simulation with the LOD3 buildings for a daily cycle during summer. Windows and doors are especially visible during the evening due to their explicit modeling and very different physical materials in contrast to the surrounding materials (e.g. bricks). Triangles facing east warm up quicker in the morning due to their exposure to the early sun. In general, triangles facing towards the sun's direction are hotter than triangles faced in other directions. Therefore, these hottest points in the simulation are moving in time following the sun. Comparing the improved LOD3 buildings with the LOD1 buildings, this effect is especially visible for LOD3 roofs, as highlighted in Figure 5. Similar to the hot surfaces, thermal shadows, i.e., colder surfaces, are moving, too. Due to thermal inertia, they additionally appear and disappear respectively time-delayed compared to shadows in the visible spectrum.

Conclusions

We presented a pipeline for thermal modeling large scenes and tested this pipeline for a primarily residential area of an Australian city potentially affected by UHIs. This work focuses on building modeling, whereby we differentiated between geo-typical and geo-specific types of modeling. The geo-specific modeling uses 2D and 3D sensor data but takes place interactively. Depending on the human workforce, a library containing dozens or hundreds of buildings can be created. The library elements, rotated, scaled, and flipped in different ways, allow to reproduce an arbitrary number of buildings in a scene. The similarity function used for geo-typical modeling is referred to bitplanes only, without consideration of 3D. New cost functions, considering

3D data, must be tested in the future. After updating building models in the simulation, the temperature distribution of large meshes can be computed, resulting in clearly visible improvement by LOD3 over LOD1 buildings. This visual impression confirms the benefit of a higher level of detail in the context of simulation-based urban morphology. Quantitative analysis of temperature curves, to be accomplished in future work, allows for the identification of UHIs.

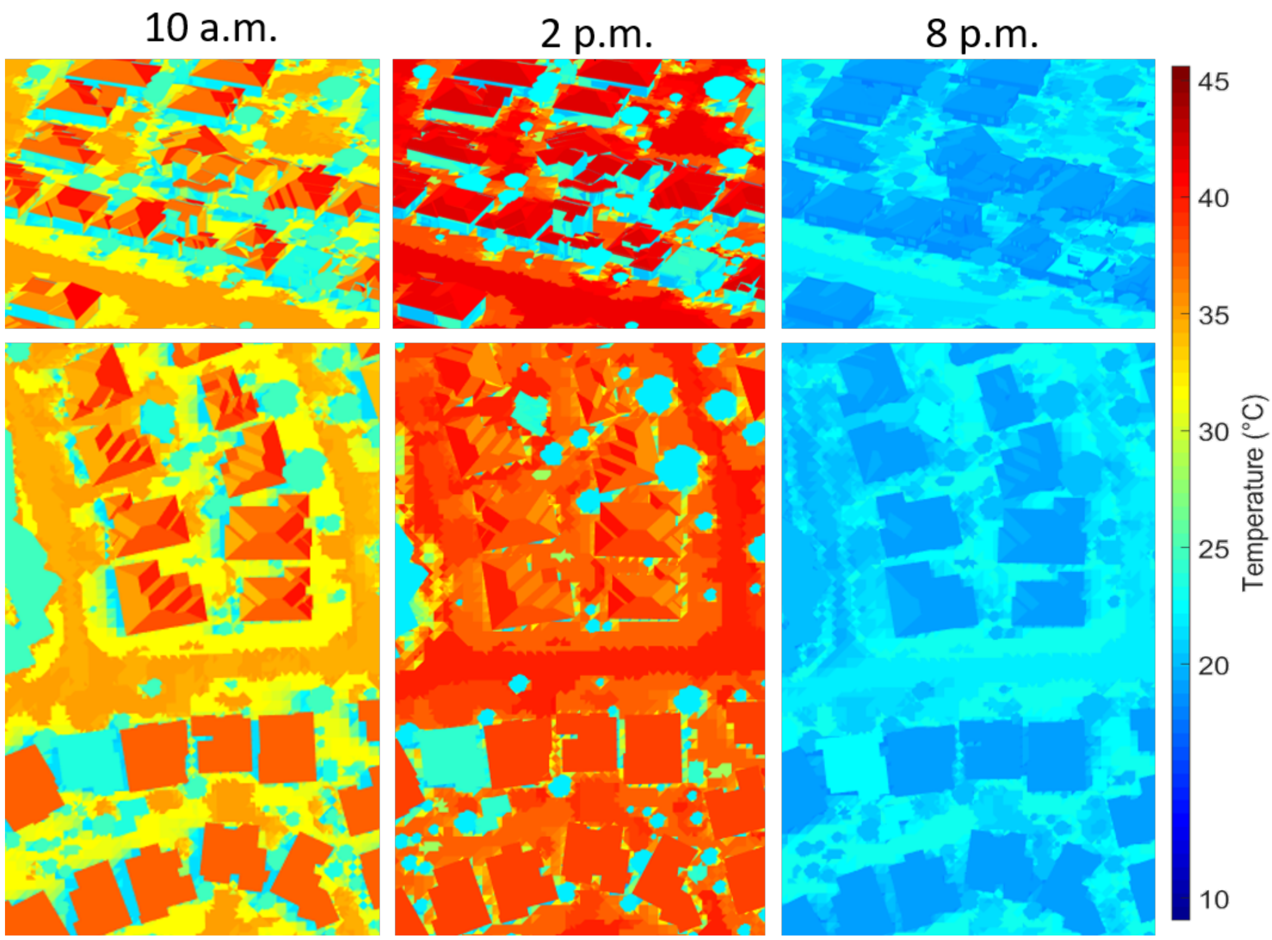

Figure 5. *Comparison of LOD1 buildings and LOD3 buildings in the thermal simulation. Top images: Side views of the 4D digital twin, bottom images: top views with LOD3 buildings in the upper part and LOD1 buildings in the lower part.*

Acknowledgements

The 2020 SPUR Accelerator Program Landgate, Curtin Research grant enabled this research and the participation in the conference. The data was acquired in cooperation with the City of Melville.

References

1. Albert, J., Bachmann, M., & Hellmeier, A. (2003). *Zielgruppen und anwendungen für digitale Stadtmodelle und digitale Geländemodelle [In German].* Erhebungen im Rahmen der SIG 3D der GDI NRW.
2. Biljecki, F., Ledoux, H., & Stoter, J. (2016). An improved LOD specification for 3D building models. *Computers, Environment and Urban Systems, 59*, 25–37.

3. Bulatov, D., Burkard, E., Ilehag, R., Kottler, B., & Helmholz, P. (2020). From multi-sensor aerial data to thermal and infrared simulation of semantic 3D models: Towards identification of urban heat islands. *Infrared Physics & Technology, 105*, 103233.

4. Bulatov, D., Häufel, G., Lucks, L., & Pohl, M. (2019). Land cover classification in combined elevation and optical images supported by osm data, mixed-level features, and non-local optimization algorithms. *Photogrammetric Engineering & Remote Sensing, 85*, 179–195.

5. Bulatov, D., Häufel, G., Meidow, J., Pohl, M., Solbrig, P., & Wernerus, P. (2014). Context-based automatic reconstruction and texturing of 3D urban terrain for quick-response tasks. *ISPRS Journal of Photogrammetry and Remote Sensing, 93*, 157–170.

6. Douglas, D. H., & Peucker, T. K. (1973). Algorithms for the reduction of the number of points required to represent a digitized line or its caricature. *Cartographica: The International Journal for Geographic Information and Geovisualization, 10*, 112–122.

7. Ilehag, R., Bulatov, D., Helmholz, P., & Belton, D. (2018). Classification and representation of commonly used roofing material using multisensorial aerial data. *ISPRS – International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, XLII-1*, 217–224.

8. Kottler, B., Burkard, E., Bulatov, D., & Haraké, L. (2019). Physically-based Thermal Simulation of Large Scenes for Infrared Imaging. *VISIGRAPP (1: GRAPP)*, (S. 53–64).

9. Lafarge, F., Descombes, X., Zerubia, J., & Pierrot-Deseilligny, M. (2010). Structural approach for building reconstruction from a single DSM. *IEEE Transactions on Pattern Analysis and Machine Intelligence, 32*, 135–147.

10. Mongus, D., & Žalik, B. (2012). Parameter-free ground filtering of LiDAR data for automatic DTM generation. *ISPRS Journal of Photogrammetry and Remote Sensing, 67*, 1-12. doi:https://doi.org/10.1016/j.isprsjprs.2011.10.002

11. Moudon, A. V. (1997). Urban morphology as an emerging interdisciplinary field. *Urban morphology, 1*, 3–10.

12. Mousa, Y. A., Helmholz, P., Belton, D., & Bulatov, D. (2019). Building detection and regularisation using DSM and imagery information. *The Photogrammetric Record, 34*, 85–107.

13. Muratori, S. (1959). Studi per una operante storia urbana di Venezia [*In Italian*]. *Palladio, 1959*, 1–113.

14. Ortner, M., Descombes, X., & Zerubia, J. (2007). Building outline extraction from digital elevation models using marked point processes. *International Journal of Computer Vision, 72*, 107–132.

15. Toldo, R., & Fusiello, A. (2008). Robust multiple structures estimation with j-linkage. *European conference on computer vision*, (S. 537–547).

16. Whitehand, J. W., Samuels, I., & Conzen, M. P. (2009). Conzen, MRG 1960: Alnwick, Northumberland: a study in town-plan analysis. Institute of British Geographers Publication 27. London: George Philip. *Progress in Human Geography, 33*, 859–864.