SanDyPALM v1.0: Static and Dynamic Drivers for the PALM-4U Model to Facilitate Realistic Urban Microclimate Simulations

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Abstract. This study presents SanDyPALM, an innovative toolkit designed to streamline the generation of both static and dynamic input data for the PALM-4U model, thereby facilitating urban microclimate simulations. SanDyPALM is capable of processing a diverse range of custom input data from raster and vector files, and it incorporates two novel methods—OSM2PALM and LCZ4PALM—that introduce the automated extraction of static input data from open data sources. To investigate the impact

5 of static input data on simulation outcomes, we developed static drivers from four distinct data sources. Our analysis reveals not only variations in the generated static drivers but also differences in the simulation results. Importantly, all simulations correlate well with measurements from two different weather stations, underscoring the robustness of the overall modeling approach. However, we observed variations in temperature, humidity, and wind speed that are dependent on the static input data. Furthermore, our findings demonstrate that automated processing methods can yield results comparable to those achieved

10 through expert-driven approaches, significantly simplifying workflows.

1 Introduction

Rapid urbanization and climate change are two significant factors that drive the need for a better understanding of urban climates. According to the 6th Assessment Report of the IPCC (Pörtner et al., 2022), "an additional 2.5 billion people are

15 projected to live in urban areas by 2050." The report also states that "there is at least a greater than 50 % likelihood that global warming will reach or exceed 1.5 °C in the near term, even for the very low greenhouse gas emissions scenario." In cities, the detrimental impacts of climate change will be intensified by the urban heat island phenomenon. To mitigate these adverse scenarios, urban microclimate analysis can assist urban planning in various ways. For instance, future development plans can: 1) reduce urban heating by enhancing natural ventilation, leading to healthier and more comfortable living environments; 2)

20 improve the energy efficiency of districts through optimal placement and design of buildings; and 3) promote biodiversity by tailoring temperature and humidity levels to meet the needs of local flora and fauna.

To analyze the urban microclimate, microscale modeling is considered one of the most effective methods. The PALM (PArallelised Large-eddy simulation Model for Urban applications) model system (Maronga et al., 2020) is increasingly utilized due to its accurate LES (Large Eddy Simulation) core, which is based on the non-hydrostatic, filtered, incompressible Navier-

25 Stokes equations. It incorporates an internal self-nesting capability developed by Hellsten et al. (2020), as well as an offline nesting capability implemented by Kadasch et al. (2021), which enables simulations to be driven by a mesoscale model. The PALM model system features PALM-4U, a suite of specialized components designed for detailed modeling of urban climate physics. Key components of the PALM-4U urban microclimate framework include: 1) an urban surface model (Resler et al., 2017); 2) a land surface model (Gehrke et al., 2021); 3) a radiative transfer model (Krč et al., 2021); and 4) a building indoor

30 climate model (Pfafferott et al., 2021). Since our research focuses on urban microclimate simulations, we will refer to it as the PALM-4U model throughout this manuscript.

While the PALM-4U model enables realistic urban microclimate simulations, its setup can present significant challenges. A substantial amount of input data must be collected and formatted for both the static driver, which contains all static geographic information such as terrain height, building height, and land surface classification, and the dynamic driver, which includes

35 transient initial and boundary conditions derived from mesoscale data. The PALM-4U model establishes a comprehensive standard for input data and provides checks to ensure correctness and consistency. However, the preparation of input data remains a hindrance for researchers and users of the PALM-4U model. Additionally, constraining simulations with realistic initial and boundary conditions poses another challenge. The following state-of-the-art review examines recent advancements and applications of static and dynamic drivers, referencing key literature and public software tools.

40 To create a static driver, the workflow provided by the PALM-4U environment utilizes the tool "palm_csd" along with geospatial input data that was preprocessed for the three German cities—Berlin, Hamburg, and Stuttgart—by Heldens et al. (2020) as part of the "MOSAIK" project, which was included in the first phase of the [UC²] project (Scherer et al., 2019). There are minimum requirements for basic simulations, with additional data available for more detailed and complex studies. Various sources of geospatial data were utilized: remote sensing data for building heights derived from LiDAR (Light Detection and

45 Ranging) and land cover classification from satellite imagery; municipal data collections, including building registries with detailed information and land-use maps; and open data sources such as OpenStreetMap (OSM), which provided basic building footprints and street networks. The challenge of processing large amounts of geospatial data for use in the PALM-4U model is acknowledged, emphasizing the need for further development of user-friendly, semi-automated processing tools to facilitate data preparation, as manual techniques are impractical for large city-scale simulations. A key limitation of "palm_csd" is its

50 predefined data format, primarily designed for the "MOSAIK" dataset. Adapting it to other locations or data sources requires significant effort, as the data must first be manually processed into the required format.

Besides "palm_csd", other static driver tools have been developed. The following two packages have not been published yet, but the code repositories are publicly available: The first is "palmpy" (Fluck, 2023), a Python package that creates static drivers for the PALM-4U model with a comprehensive documentation. The second tool is "rpalm" (Stadler, 2024b), an R package

55 designed to create and edit static drivers for the PALM-4U model.

To alleviate some of the existing limitations of default methods for creating a static driver, Lin et al. (2024) introduced GEO4PALM, an open-source toolkit that streamlines the processing of geospatial data from raw input to PALM-4U-ready formats. It can utilize open data sources directly and includes tools for preprocessing and visualizing data.

The "PALM-4U GUI" (Winkler et al., 2023) is a cloud-based graphical user interface (GUI) for the PALM-4U model. The code is open source and can be accessed via a code repository (Stadler et al., 2024a). The GUI provides a user-friendly way to prepare input data and simulation setups. Users can run, visualize, and analyze simulation results without requiring code writing. This method can be particularly helpful for new users or those unfamiliar with command-line interfaces, making it the easiest option for getting started with the PALM-4U modeling workflow. Input data is created via an interactive web map editor, representing the area to be simulated as a polygonal city model. Geographic data can be imported, modified, and supplemented with user-drawn objects. Settings can be configured for global parameters and for each individual map object up to Level of Detail 2 (LOD2). City models can be created from OpenStreetMap and translated into the PALM-4U input data types using the open-source package OSM2PALM (Stadler, 2024a). The optional QGIS plugin "PALMClassify" (Stadler et al., 2024b) can classify custom geodata in shapefile format into PALM-4U input data types and export them to the PALM-4U GUI.

Dynamic drivers provide transient boundary conditions to run the PALM-4U model in "offline-nesting" mode, meaning that the PALM-4U boundaries are defined using data from an external model. This approach can significantly improve the model's responsiveness to temporally varying large-scale atmospheric conditions and generally enhance the overall fidelity of the simulations. A major challenge in using dynamic drivers is the inherent errors in the weather prediction models themselves, which propagate into the PALM-4U simulations and affect their accuracy (Radović et al., 2024).

The first method to create dynamic drivers from mesoscale models was INIFOR (Mesoscale Interface for Initializing and Forcing), developed by Kadasch et al. (2021). It has become the standard tool for dynamic driver creation in PALM-4U and interfaces with the mesoscale weather prediction model COSMO (Baldauf et al., 2011). INIFOR processes meteorological data (wind, temperature, humidity) and initial soil data from the weather prediction model, preparing it for use as dynamic boundary conditions in the PALM-4U simulation. PALM-4U utilizes the prepared data to set the conditions at its borders (top, sides, and bottom), ensuring that the smaller-scale simulation within PALM-4U aligns with the larger-scale atmospheric processes.

Besides INIFOR, other methods have been developed to create dynamic drivers from mesoscale models, particularly for the Weather Research and Forecasting (WRF) model. The first was presented by Resler et al. (2021) and was used for a comprehensive study of realistic urban microclimate simulations. However, one downside of this approach is that it does not provide a surface layer model to fill the atmospheric data into the region below the first WRF model level.

Lin et al. (2021) introduced WRF4PALM—a tool designed to facilitate the conversion of mesoscale data from the Weather Research and Forecasting (WRF) model into a dynamic driver. It implements a surface layer extension to fill data below the first WRF level using a simple logarithmic fit function.

Vogel et al. (2022) presented a new method for coupling the WRF mesoscale weather model with the PALM-4U microscale model to simulate urban microclimates under realistic atmospheric conditions. The novel dynamic coupling scheme incorporates a roughness-corrected Monin-Obukhov surface layer representation (Arya, 2001), accounting for the varying roughness of urban surfaces to improve the accuracy of the initial and boundary conditions for the PALM-4U model. This scheme is

particularly important for WRF setups with relatively large vertical grid spacing near the surface. Simulations were conducted in an urban district of Berlin to test the new coupling scheme and investigate different WRF setups. The results were compared to standalone WRF simulations (without the microscale model) and actual measurements from the area. The main findings indicated that PALM-4U simulations generally showed better agreement with measurements than standalone WRF simulations,

95 especially for temperature. Refining the coupling time step or the WRF grid spacing did not significantly improve accuracy.

Radović et al. (2024) also used the WRF model to force the PALM-4U model and described the challenges of establishing ideal conditions for running accurate simulations. The study determined that the accuracy of the model's results heavily relies on the quality of the boundary conditions. It was observed that errors or limitations in WRF data can significantly affect the results generated by PALM-4U, although the influence of boundary conditions on PALM-4U simulations can vary depending

100 on the season and even the time of day. PALM-4U can, to some extent, mitigate the impact of errors in wind speed from the boundary conditions. However, its ability to handle temperature variations arising from these errors is less consistent. Overall, the study emphasizes the crucial role of carefully chosen and high-quality boundary conditions in achieving reliable results with PALM-4U.

The study of the state of the art revealed that the options for creating PALM-4U input data have been continuously increasing.

105 However, several questions remain: 1) How can the process of input data preparation be accelerated and made more user-friendly? 2) What level of detail is necessary in the input data to produce realistic urban microclimate simulations? 3) How can we develop models on coarse grids, for instance, for a large parent domain that is driven by a mesoscale model?

In this paper, we present a workflow and the necessary program code to create static and dynamic input data for PALM-4U simulations as an all-in-one solution. We primarily investigate how the level of detail in the geographic input data impacts the

110 simulation results. Additionally, we introduce two novel methods, OSM2PALM and LCZ4PALM, to generate static drivers from Open Street Maps (OSM) or Local Climate Zones (LCZ) maps anywhere in the world. This approach is particularly useful for parametric studies and for coarser grids, where real building shapes cannot be resolved, making it preferable to have an approximate but meaningful urban representation instead. In this work, we compare four static drivers from different data sources: 1) "MOSAIK"—the dataset by Heldens et al. (2020), which is already preprocessed but still needs to be converted

115 into a static driver; 2) "Custom"—our own custom preprocessing of data openly available from the municipality; 3) "OSM"—data preprocessed by our tool OSM2PALM; and 4) "LCZ"—data preprocessed by our tool LCZ4PALM. The four simulation variations were conducted, validated by tower and station measurements, and then compared to each other to address our stated research questions.

The findings of this study indicate that the choice and quality of input data influence the accuracy of urban microclimate sim-

120 ulations using the PALM-4U model. By comparing various static drivers derived from different data sources, we demonstrate how variations in data representation can lead to differences in simulation outcomes, particularly in temperature, humidity, and wind speed. Despite these differences, all simulation test cases could be validated using measurement data, albeit with varying degrees of deviation. The introduction of the novel methods, OSM2PALM and LCZ4PALM, to generate static drivers from widely available geospatial data enhances the accessibility and applicability of urban climate modeling. Ultimately, this

125 research contributes to the development of more reliable urban climate simulations, which are essential for informed urban planning and effective climate change mitigation strategies.

2 Methodology

The methodology consists of five parts: The first section 2.1 describes the simulation test case defined for our investigation. The next section 2.2 outlines the various geographic data sources and explains how the data was preprocessed before generating

130 the static driver. Section 2.3.1 provides a detailed account of the static driver generation process, while section 2.3.2 briefly describes the dynamic driver creation. In section 2.4, we present our specific PALM-4U setup, including grid and model settings. Finally, the measured data from a tower station, which we used for validation in this study, is presented in section 2.5.

2.1 Test case

The time period of our test case spans two days, from 19 July 2022 00:00 until 21 July 2022 00:00 Central European Summer

135 Time (CEST). These two days were characterized by a heat wave with record-breaking temperatures in Germany and other European countries. According to ERA5 reanalysis data evaluated for the region around Berlin, the average temperature over the two days was $28.0\,°C$, with temperature maxima of $35.4\,°C$ on 19 July and $37.9\,°C$ on 20 July. The wind speed was relatively low, with an average value of $2.2\,m/s$, and the wind direction was predominantly southeast. The period was cloud-free, with total cloud cover not exceeding $1\,\%$ over the two-day span.

140 Our test case uses nested domains to cover an overall larger area with the parent domain while allowing a sufficiently high resolution in the nested domain around the main region of interest. The location of our test case is in the borough of "Steglitz-Zehlendorf" in Berlin, Germany. The average terrain height in the region is $46\,m$. The simulation domains are centered at the weather monitoring tower situated in the garden of the Institute of Ecology at the Technical University of Berlin (TUB). We chose this location specifically because it offers a high quantity and quality of measurements, allowing for thorough validation

145 of our simulation models. In addition to the tower, there is also a measurement station of the German Weather Service (DWD – Deutscher Wetterdienst) in "Dahlem", which is covered by the parent domain and can therefore also be used for validation.

SanDyPALM facilitates the selection of coordinates and domain size by offering a function that calculates the coordinates in both latitude/longitude and in the PALM-4U native grid, which is a local projection. It also plots the parent and all nested domain borders over a geographic map. Our test case is visualized in this manner in Figure 1.

150 The local coordinate system we use for this test case is EPSG:25833, a universal transverse mercator (UTM) projection for zone 33N. The center coordinates of our domain are $52.457227°\,N$, $13.315827°\,E$ (latitude/longitude) or $y = 5813228.0\,m$, $x = 385566.5\,m$ (EPSG:25833). In SanDyPALM, the coordinates can be specified in four different ways: 1) native PALM-4U coordinate system of the domain center, 2) latitude/longitude of the domain center, 3) native PALM-4U coordinate system of the domain lower-left corner, and 4) latitude/longitude of the domain lower-left corner.
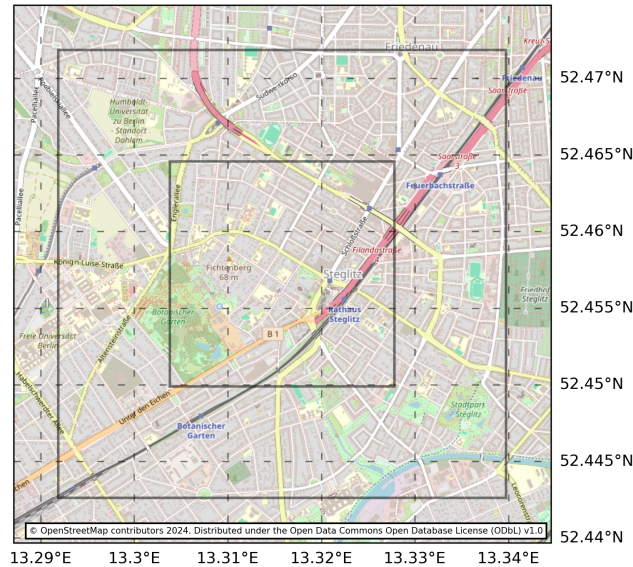
Figure 1. Open street map (OpenStreetMap contributors, 2024) of the test case with illustrations of the domain outlines of the parent and nested grids. The map also indicates two measurement locations used in this study: the TUB tower in Rothenburgstraße "Roth" and the DWD station in Botanischer Garten "Dahlem".

2.2 Geographic Data Sources

The SanDyPALM package allows input from different data representations, which mainly include: 1) raster data stored in netCDF format, 2) raster data stored in GeoTIFF files, and 3) vector data stored in commonly used formats, such as ESRI Shapefile, GeoJSON, or GeoPackage. In this work, we aim to prepare one test case with different data sources and compare how the static driver varies depending on the data source and how this affects the simulation results. We defined four data sources for our test case in Berlin. The first is the data generated within the MOSAIK project, which is readily preprocessed as netCDF raster files. The second is our own custom preprocessing of openly available data from the municipality of Berlin. The third is a dataset derived from generally available open data sources, mainly OpenStreetMap (OSM), which requires special preprocessing to convert the data types to a format compatible with PALM-4U. The last source differs from the others in that it does not represent the actual urban geometry but instead derives a virtual city solely from a 100 m LCZ map using our tool LCZ4PALM. Geographic maps of the different data sources are presented in Figure 2, where selected data types are illustrated in different colors. Table 1 summarizes the main differences between the data sources; detailed descriptions of each data source follow in the next four sections.

2.2.1 MOSAIK

This dataset originates from the MOSAIK project, for which several data sources were preprocessed for use in the PALM-4U model. This dataset was intended to be further processed and converted into a static driver by the utility `palm_csd` that is
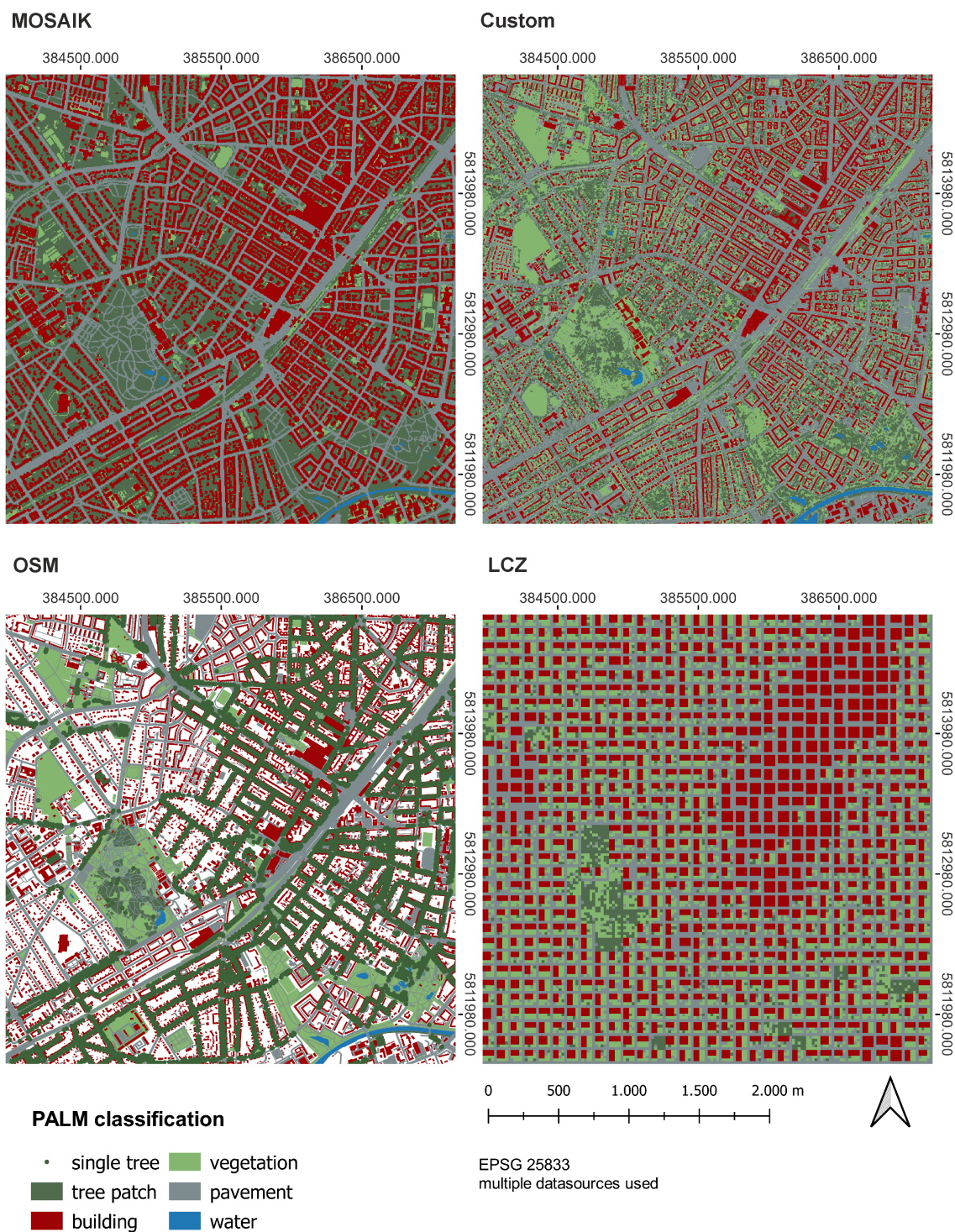
Figure 2. Geographic maps of the four different input data sources for SanDyPALM.

Table 1. Comparison of the four different input data sources used in SanDyPALM to generate static drivers. The following abbreviations are used: OSM: Open Street Map, DEM: Digital Elevation Model, WSF3D: World Settlement Footprint 3D

	MOSAIK	**Custom**	**OSM**	**LCZ**
Data sources	Municipality data Sentinel-2 OSM	Municipality data	OSM NASA Earth DEM WSF3D	Global LCZ NASA Earth DEM WSF3D
Source format	Vector and raster data	shape, .xyz, .txt, .jp2	XML, shape	geoTIFF
Target format	netCDF	shape	geojson	geoTIFF
Source CRS	Various/Unknown	EPSG: 25833	EPSG:4326	EPSG: 4326
Target CRS	EPSG: 25833	EPSG: 25833	EPSG: 25833	EPSG: 25833
Time period	Last updated 2019	2021-2024	Last updated Jun 2024	Last updated Oct 2023
Strengths	• tree patch LAI • tree patch heights • single trees • bridges • high-res DEM • detailed street types • detailed building types	• tree patch heights • exact building footprints • detailed building types • high-res DEM • correct construction sites	• open source • globally available • exact building footprints	• open source • globally available • ideal for coarse grids
Weaknesses	• large building footprints • overestimated vegetation	• no tree LAI • few street types	• no tree LAI • no tree heights • sparse building heights • few building types • lacking vegetation areas • low-res DEM	• no exact shapes of buildings, streets, water, vegetation etc • no tree LAI • no tree heights • low-res DEM

shipped with the PALM-4U model. However, in this work, we used SanDyPALM instead to convert this dataset into a static driver. For a detailed description of the MOSAIK dataset, we refer to Heldens et al. (2020).

2.2.2 Custom

The "Custom" dataset contains openly available data from the municipality of Berlin, specifically from the geodata portal run
175 by the Senate Department for Urban Development, Building and Housing of Berlin. The data to be used was selected after an in-depth search on the portal for information compatible with PALM-4U types.

The data was processed using our own custom processing based on Heldens et al. (2020) and the workflow proposed for "PALMClassify". This resulted in a dataset where each PALM-4U type is represented by one shapefile, including information on covered area, specific type, building height, and tree height.

180 Often, multiple input datasets represented parts of the same PALM-4U type, necessitating their combination. In some instances, new datasets had to be created; for example, the true orthophoto channels of red and near-infrared were used to calculate the NDVI (Normalized Difference Vegetation Index), which helped identify vegetation and tree areas. The topography and the digital surface model were used to create the normalized digital surface model, which provided height values for buildings and trees.

185 2.2.3 Open Street Maps

Input data for PALM-4U can also be created using open-source, globally available datasets. One such dataset is OpenStreetMap (OSM) (OpenStreetMap contributors, 2024). It contains surface classifications, building footprints with occasional building height information, and other features such as trees. Data quality varies by region, but for European cities, it is relatively high.

OSM has an open API that allows anyone to request data and, in theory, filter data on the server side to reduce the amount
190 of data received from OSM. Experience has shown that attributes and information that can help specify the PALM-4U surface classification of an OSM object can be found in any group and definition provided by OSM. This means that requesting the entire OSM chunk yields the most detailed datasets.

A Python package called OSM2PALM (Stadler, 2024a) has been developed to request and process OSM data. It primarily uses lookup tables defined by Heldens et al. (2020), with minor adjustments to existing tables and new value pairs for previously
195 unused OSM attributes. Continuous efforts are made to search for and identify unused OSM surface classifications that can be reasonably translated to PALM-4U surface types.

One caveat of OSM data is that it can be quite rich in data outside of cities, where forests, shrubs, small rivers, and other details are defined in a way that fills the domain. Inside cities, building footprints and unique features such as swimming pools and parks can be accurately represented; however, surface data is generally lacking in most urban areas. Roads can be
200 estimated and depicted using buffered line datasets, but sidewalks and especially the back and front yards of buildings typically lack surface information.

Additionally, some datasets necessary for PALM-4U are often missing in OSM, including building heights and tree heights. The script allows the user to handle missing data with multiple options. In this case, building data was used if available, or the

number of stories was used to calculate building heights. Otherwise, a default building height of 20 m was assumed. The same
205 approach was taken for tree heights, with 12 m as a fallback option.

The general workflow of the OSM2PALM script can be seen in Figure 3. All data from OSM is requested, converted into a
UTM coordinate system, and then split into three categories: multipolygons, line data, and points.
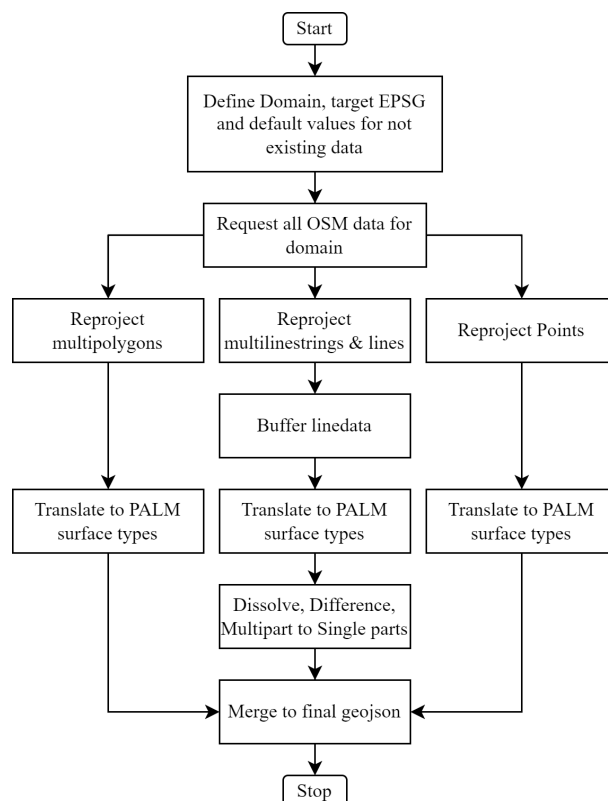
Figure 3. Workflow of conversion from OSM data to PALM-4U input data.

Multipolygons and points are translated according to a lookup table. Single values from an attribute or information from the
other_tags attribute are used to define the PALM-4U surface type as well as the value of the surface type.
210 Line data requires further processing, such as buffering, dissolving, and creating a difference. Typical line data includes
roads, train tracks, or small rivers. Finally, all datasets are merged and saved as a GeoJSON file.

2.2.4 Local Climate Zones

This dataset for the static driver is obtained using our tool "LCZ4PALM". It is a novel feature incorporated into SanDyPALM to
create a static driver using the global LCZ map provided by Demuzere et al. (2022). PALM-4U requires a detailed description
215 of urban and rural neighborhoods for accurate microclimate modeling and analysis. Unfortunately, this information is neither
readily available nor easily accessible for every region in the world, which severely limits the ability to perform microclimatic

studies. The static data is usually obtained from multiple sources and involves extensive preprocessing, as outlined in the previous sections. This problem is addressed with the help of globally available LCZ maps. LCZs are defined by Stewart and Oke (2012) as "regions of uniform surface cover, structure, material, and human activity that span hundreds of meters to
220 several kilometers in horizontal scale." LCZ is the most popular landscape classification scheme and is widely used in climate simulations and related studies. It mainly focuses on the classification of urban and rural landscapes (17 classes - 10 built classes and 7 natural classes) based on surface characteristics such as building packing densities, aspect ratio, building or tree height, sky view factor, surface albedo, anthropogenic heat emissions, and so on. This makes them highly suitable for urban microclimatic studies, typically investigations of the urban heat island effect.

225 Demuzere et al. (2022) generated a global map of LCZs at a 100 m resolution by training a random forest model using a large labeled dataset. In our tool, these LCZ maps are first reprojected onto the PALM-4U simulation domain, and the LCZs corresponding to the intended simulation region are extracted. Then, for each LCZ tile, geospatial inputs (buildings, vegetation, water bodies) that conform to the LCZ definitions are generated in a systematic approach, as shown in Figure 5. Using this method, we construct an idealized city with buildings, vegetation, and pavements, which can be used as an alternative for
230 realistic domains. This approach is mainly suitable for coarse grids, either for parent domains in nested setups or generic LCZ studies of large areas where coarse grids are needed to limit computational effort. The problem is that at low resolutions, realistic buildings, trees, and pavements are often either overestimated or underestimated. For example, narrow streets may disappear, while wider streets are stretched to fit the entire grid cell. The same applies to buildings and vegetation. This leads to unrealistic inputs that negatively impact simulation accuracy. The virtual city created by LCZ4PALM may not be accurate
235 in its details, but it represents the urban morphology on average.

The process is shown in Figure 4. The LCZ4PALM module requires several inputs, including an LCZ map that covers the desired region, a mapping of PALM-4U type probabilities to LCZ classes (building types, pavement types, vegetation types, and vegetation properties), the LCZ definitions, and, optionally, a global building height dataset. The mapping of PALM-4U type probabilities is not directly available and needs to be derived from another data source. In this study, we performed
240 an exemplary analysis using a 30 km by 30 km region around Berlin from the MOSAIK dataset by Heldens et al. (2020) to generate this data. For each LCZ class, the probability of occurrence of all PALM-4U types was derived. The resulting mapping was saved in a JSON file and is valid for Berlin and cities similar in urban morphology. The LCZ definitions used in this study were provided by Stewart and Oke (2012). For each LCZ class, they specify a range for surface fractions, which include building surface fraction (BSF), pervious surface fraction (PSF), impervious surface fraction (ISF), aspect ratio, and
245 building height. To achieve more accurate building heights, we used the global building height data "WSF3D" generated by Esch et al. (2022). Alternatively, random building heights within the LCZ range can be used. Before generating the static driver, the input data undergoes several preprocessing steps. Initially, the global LCZ map is projected onto the PALM-4U grid using a resolution specified by the user. Next, it is resampled onto an LCZ grid with a resolution of at least 100 m using a custom grid-resampling technique. This technique assigns the LCZ value with the highest occurrence to the grid cell. Finally, once the
250 LCZ grid is prepared, the code generates the geospatial information for each LCZ tile.
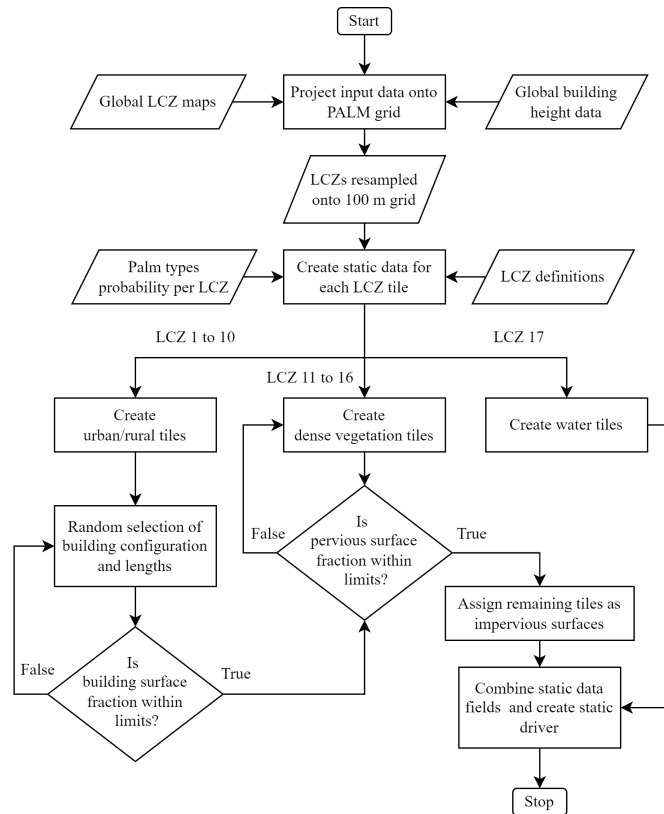
Figure 4. Process diagram of the LCZ4PALM algorithm.

The approach of generating a virtual urban neighborhood from LCZ classes is illustrated in Figure 5. The grid cell size is 20 m in this case. The virtual city is created in blocks of 100 m by 100 m, and for each of these blocks, a dominant LCZ class is assigned and urban surfaces are generated, while different functions are used depending on the LCZ class. For built types ranging from LCZ 1 to 10, building, pavement, and vegetation tiles are created. One row and one column of pavement tiles are always allocated in the southern and eastern borders. The available length and width of the buildings are utilized to compute the maximum number of buildings that can be accommodated without violating the LCZ class specification. This information is then used to determine the potential configurations of aligned arrays of cuboidal buildings. For instance, this could involve arrangements such as 2x3 or 2x1 building tiles, among others. From the various possible configurations, one configuration is chosen randomly, provided that it satisfies four conditions. These conditions include ensuring that the building surface fraction, total length and total width of buildings, and the length-to-width ratio of the buildings all meet the requirements of the LCZ class. The building surface fraction condition is determined based on the LCZ definitions and must fall within a specified range of minimum and maximum values. Furthermore, the total width and length of the buildings and streets should be smaller than the total width and length possible for the given tile. To prevent the presence of long and slender buildings in the domain, a

maximum length-to-width ratio of 4 is enforced. Once all of these conditions are met, the building array is generated for the

265   LCZ grid.
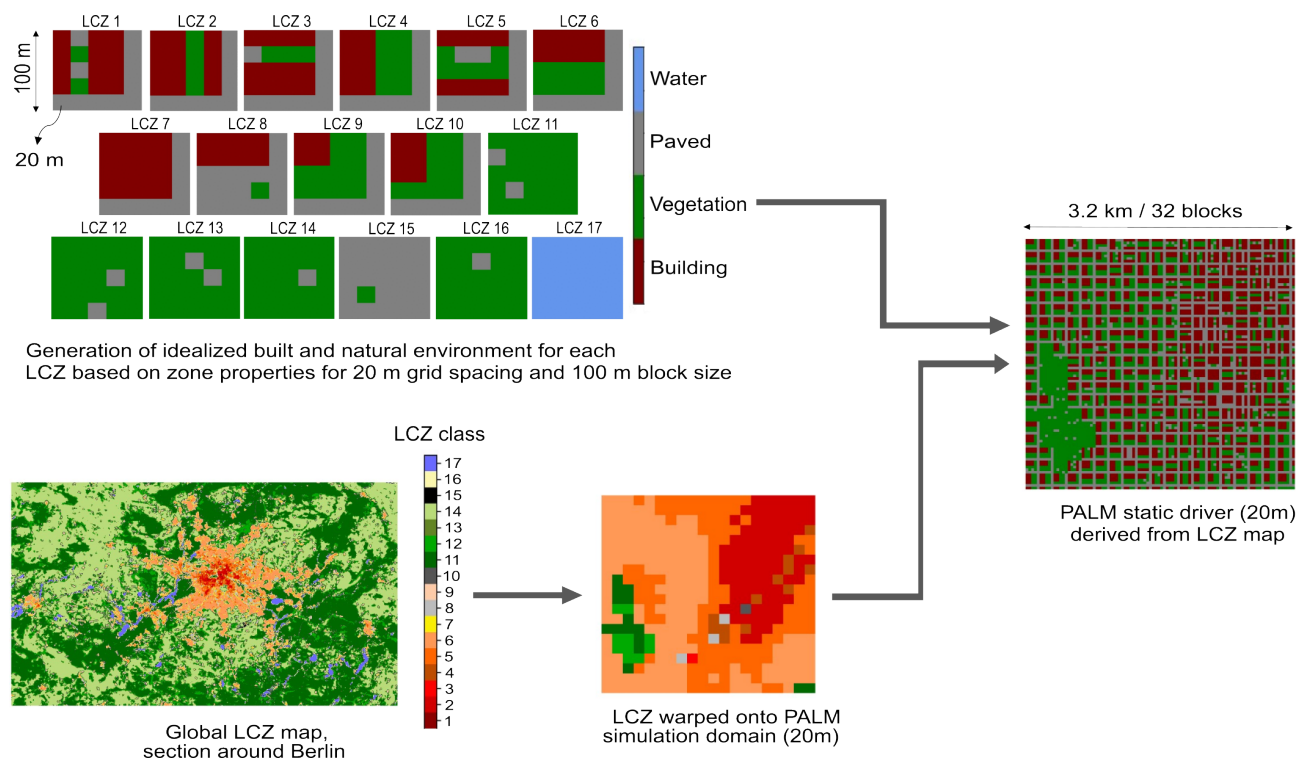
Figure 5. Creation of geospatial input data for the PALM-4U model using LCZ4PALM with global LCZ maps.

The subsequent step involves creating vegetation around the buildings up to a randomly determined limit within the permissible range. The remaining tiles that are not part of the buildings are designated as vegetation tiles until the criteria for the pervious surface fraction are met. Once the vegetation tiles are marked, each tile needs to be assigned a vegetation type, for which the corresponding vegetation properties can be further defined. This is accomplished using the data obtained from

270   the PALM-4U type probabilities per LCZ discussed earlier, which includes the vegetation type along with its probability of occurrence. For each vegetation tile, a vegetation type is randomly sampled based on its given probability and assigned to the tile. The vegetation types can be categorized as either high or low, depending on the characteristics of the vegetation present. In the case of a high vegetation type (4, 5, 6, 7, 17, or 18), additional information such as tree patch height and leaf area index (LAI) is required. The PALM-4U type probability mapping also contains the mean and standard deviation of tree heights in

275   the Berlin region for each vegetation type within each LCZ. Using this information, the tree patch height is calculated from a random normal distribution.

After creating the vegetation, the remaining tiles are utilized to create impervious surface elements (streets and pavements). Building types and pavement types are assigned to the corresponding tiles in a manner similar to that of vegetation types.

For land cover types ranging from LCZ 11 to 16, the creation of vegetation and pavement tiles follows the same process as
280   explained earlier. However, in this case, there are no buildings present. Therefore, only the criteria for pervious and impervious
surface fractions are satisfied. For water (LCZ 17), water tiles are currently created using a default type 4, which corresponds
to ponds. However, this type can also be modified to a user-defined type based on the domain. All of the data needed for static
driver generation are saved as GeoTIFF files for later processing into a static driver using SanDyPALM.

2.3   SanDyPALM package

285   The new open-source repository SanDyPALM consolidates our efforts to create static and dynamic drivers for PALM-4U using
Python code. The majority of the static driver generation code originates from the PALM-4U GUI (Winkler et al., 2023), while
the WRF dynamic driver code has been developed and utilized by Vogel et al. (2022). SanDyPALM is a package that can
generate all necessary input data for a WRF-driven microscale simulation setup. However, it can also be used to create only
a static driver for unforced PALM-4U simulations. The package comes with a default configuration and a set of tutorials that
290   explain the basic setup and guide the user through the complete process of creating a static driver from various geographic data
sources, as well as creating a dynamic driver using WRF data. Further tutorials provide basic plotting of results and conversion
of input data between netCDF, GeoTIFF, and vector formats. In addition to tutorials, we also included example case files,
where each script directs one complete generation process. All our PALM-4U setups are nested cases and relatively small,
allowing them to be run without HPC. The configuration always starts from a predefined default configuration that is modified
295   in a tutorial or case file. The final configuration is always saved together with the static and dynamic drivers to enable the user
to retrace the settings with which the drivers were generated. SanDyPALM encourages users to work in projects, where each
project contains all generated data, configuration parameters, and generated plots.

SanDyPALM also facilitates nesting and grid setup. There are separate functions that generate the PALM-4U grid and
transfer it into a geographic projection. All nested domains can be plotted together on an OpenStreetMap to inspect their sizes
300   and positioning. The grid dimensions, especially the vertical grid levels, are printed to the terminal to adjust the grid spacing
and vertical stretching parameters.

Once the domains are finished, open data can be automatically downloaded from several available data sources. There is an
interface to OSM2PALM (the code for OSM2PALM needs to be downloaded separately) that can be used to download OSM
data for the given extent of the largest domain. Another interface allows downloading the ASTER Global Digital Elevation
305   Model V003 with a resolution of $30\,\mathrm{m}$ from NASA Earth Science data (ASTER Science Team, 2019) using the Python package
earthaccess in the background. The data is freely available but requires registration. SanDyPALM provides an HTTP interface
to download other needed files into an appropriate data folder. In our tutorials, the global LCZ map (Demuzere et al., 2023)
and the World Settlement Footprint 3D (WSF3D) (Esch et al., 2022) are automatically downloaded, if desired. The LCZ map
is needed for the LCZ4PALM module, and the WSF3D map can be used in both LCZ4PALM and OSM2PALM to provide
310   approximate building height information for better accuracy.

2.3.1 Static Driver Generation

The static driver contains the physical representation of the domain in a Cartesian grid using raster data. All data fields are at least 2D, meaning they contain information for each grid point in the x and y directions. For 3D fields, the third dimension is either the z-coordinate or a dimension that accesses predefined parameterizations for some 2D datasets. The 2D variables
315   typically describe the surface of the model or the topography. Depending on the application of PALM-4U, the mandatory data fields in the static driver vary; for example, in the case of boundary layer studies, only the roughness length of the surface is needed. For an urban simulation, much more information is required, such as surface classifications, topography, and building positions and heights. PALM-4U uses four major surface classifications: vegetation, pavement, water, and buildings, each with sets of predefined physical parameters, such as roughness for heat and momentum or albedo. For each pixel in the domain, these
320   parameters can also be adjusted from the predefined values. There are two major 3D datasets that interact in the atmosphere: the 3D buildings dataset and leaf area density (LAD). The 3D buildings data define a grid of ones and zeros, where ones represent building grid points and zeros represent atmospheric grid points. These data can be used to model overhangs, gates, or bridges. The LAD dataset is used to model the 3D influence of trees, which interact with radiation and humidity in the atmosphere and act as a momentum sink. The PALM-4U Input Data Standard (PIDS) defines how these datasets, as well as further metadata,
325   need to be stored in a netCDF file.

SanDyPALM is able to create a static driver that follows the PIDS requirements and performs further processing for certain datasets or according to the settings of SanDyPALM. A major feature of SanDyPALM is the support for multiple types of geospatial data. Typically, geospatial data is either vector data using polygons (i.e., surfaces, lines, and points) or raster data using a grid format. SanDyPALM can read any shapefile format, GeoTIFF format, or the netCDF datasets specifically defined
330   within the MOSAIK project (Heldens et al., 2020). The data is then rastered or resampled onto the grid defined by the user and written to the static driver. Each input file needs to be assigned to a surface classification of PALM-4U or set predefined names for processing. Depending on the input file type, further information and settings must be provided. The static driver generation method is visualized in the flow chart in Figure 6.

Shapefiles are converted into raster datasets via the rasterize function of the GDAL Python package. Besides the domain
335   definition, this function also requires the attribute that is to be rastered. Optional inputs include an attribute filter as well as a rasterization parameter that specifies when grid tiles are considered inside or outside of a polygon that is to be rastered ("all touched").

GeoTIFF files are resampled onto the defined grid via the "warp" function of GDAL. Typically, the raster band of the desired dataset should be specified; otherwise, SanDyPALM takes the first band by default. If the resolution of the dataset differs from
340   the target resolution of the static driver, a resampling or aggregation algorithm can be defined in the GDAL "warp" function. The resampling algorithm needs to be chosen wisely based on the type of data and whether the data is up- or down-sampled.

The netCDF data that came from the MOSAIK project do not have their geo-referencing inside each data file; instead, additional files are needed that specify the x and y coordinates in a UTM coordinate system. SanDyPALM reads the data files
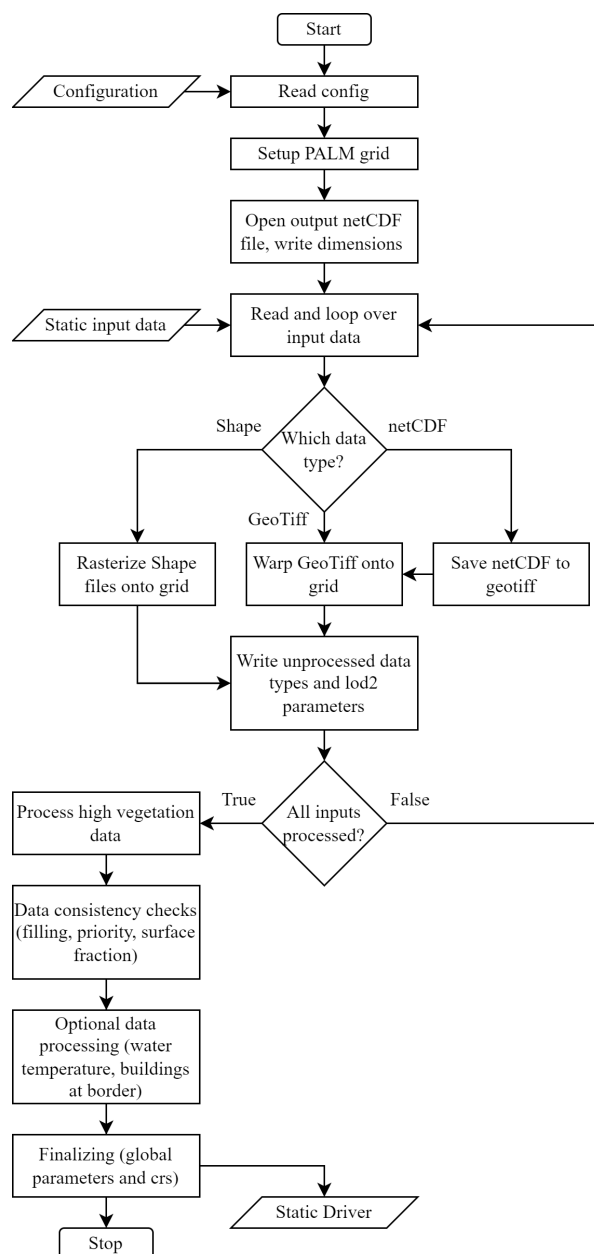
Figure 6. SanDyPALM static driver generation flowchart.

as well as the coordinate files and first creates geo-referenced GeoTIFF files; then they can be resampled using GDAL tools

345 similar to the GeoTiff files.

For an overview on the supported file types and additional inputs, see Table 2.

Table 2. Overview of supported file types and additional input parameters in SanDyPALM.

	Shape	**GeoTIFF**	**netCDF**
File types	shape, geojson, sqlite, geopackage	geoTIFF	netCDF
Mandatory input	attribute	band (defaults to 0)	variable name
Optional input	attribute_filter, all_touched	resampling algorithm	resampling algorithm

For the urban surface parameterizations, it is expected that the provided data is already translated into the PALM-4U surface types with the corresponding sub-types. Data for these parameters is converted to the grid and then saved directly onto the appropriate PALM-4U variable. Level of detail 2 (LOD2) parameters, such as roughness length of vegetation, can also be

350 adjusted from 2D input files in a separate sub-dictionary of the configuration. The position of the 2D slice inside the 3D dataset must be provided as additional input.

SanDyPALM uses a similar approach for vegetation as the static driver generation software palm_csd, which is shipped with the PALM-4U model, where the leaf area density (LAD) of larger groups of trees is treated as a tree patch. We use the leaf area distribution according to Markkanen et al. (2003), given by equation (1), which is a probability density function; therefore, we

355 define this as normalized (denoted by the overline) LAD:

$$\overline{LAD}\left(\frac{z}{h},\alpha,\beta\right) = \frac{\left(\frac{z}{h}\right)^{\alpha-1}\left(1-\frac{z}{h}\right)^{\beta-1}}{\int_0^1 \left(\frac{z}{h}\right)^{\alpha-1}\left(1-\frac{z}{h}\right)^{\beta-1} d\left(\frac{z}{h}\right)} \tag{1}$$

This equation is then discretized on the PALM-4U grid, replacing the integral with a summation over the vertical grid cells, which leads to the discretized version (denoted by the asterisk) of the normalized LAD profile given in equation (2):

$$\overline{LAD}^* = \frac{\left(\frac{z_i}{h^*}\right)^{\alpha-1}\left(1-\frac{z_i}{h^*}\right)^{\beta-1}}{\sum_{i=0}^{N_z}\left(\left(\frac{z_i}{h^*}\right)^{\alpha-1}\left(1-\frac{z_i}{h^*}\right)^{\beta-1}\right)\frac{\Delta z}{h^*}} \tag{2}$$

360 Here, z_i are the heights of the grid cell centers (above ground) and h^* is the discretized tree height of the current grid tile. The discretized tree height is calculated for each grid tile by rounding the tree height to the nearest staggered vertical position z_w (defined for vertical velocity) of the PALM-4U grid. We use these grid positions because they are also the vertical grid cell faces (or boundaries) of the non-staggered grid cells.

The discretized non-normalized LAD profile LAD^* is then obtained by multiplying by the leaf area index (LAI) and dividing

365 by the discretized tree height h^* using equation (3):

$$LAD^* = \frac{LAI}{h^*}\overline{LAD}^* \tag{3}$$

This equation is applied to every grid cell of the PALM-4U domain. The formulation is fully conservative; if we integrate over all LAD values on top of one grid tile, we exactly obtain the LAI value of that grid tile. A check is in place to ensure that this is always the case.

370 While the tree height is a mandatory input for SanDyPALM, the LAI and α parameters can be obtained from a predefined default value if no appropriate data fields are available. The default LAI value can also be automatically scaled by tree height. Therefore, instead of using one default value for all trees, we define a default value for $\frac{LAI}{h}$. From that, a more appropriate default LAI value can be derived for different tree heights. A typical default value would be $\frac{LAI}{h} = 0.2$, which means that a tree of $5\,\mathrm{m}$ height would have a default LAI value of 1, and a tree of $25\,\mathrm{m}$ height would have a default LAI value of 5. For these

375 default LAI values, the LAD is still calculated using equation (3). While this procedure is not highly accurate, it is superior to simply specifying one default LAI value.

We also implemented two different filtering strategies for LAI data fields after encountering relatively high LAI values. The first method limits the value of $\frac{LAI}{h}$ to a threshold of, for example, 0.2. As a result, for each grid cell, the value of LAI is reduced so that $\frac{LAI}{h} \leq 0.2$. Alternatively (or additionally), we can check the final values of the 3D field of LAD^* and limit

380 them to a certain value, e.g., 0.1.

SanDyPALM creates the 3D buildings data from the 2D buildings data, primarily for visualization purposes, since the PALM-4U model itself constructs the 3D buildings data. However, to be able to add custom buildings into the 3D buildings data, we need to create the 3D buildings data beforehand. If the height of the custom building exceeds the height of all other buildings in the domain, we can set a user-defined maximum height for the 3D buildings data field to ensure there is enough

385 space in the data field to add the building. This enables us to add specific buildings at a later stage after creating the static driver. For example, we used this procedure to add a custom model of the Berlin tower (Fernsehturm) in Vogel et al. (2022).

Another feature of SanDyPALM is that it performs automatic data consistency checks and allows the user to handle inconsistencies. These inconsistencies could be grid tiles that have no surface classification assigned (missing data) or grid cells having multiple classifications (overlapping data). After the initial assignment of surface parameters and building data to the

390 static driver, all grid points are checked for missing data, and a default surface classification and value are assigned to these grid points. Afterwards, all grid points are checked for overlapping data, where a user-defined priority list is applied to decide which data field is to be kept. The default setting uses the following priority (descending): buildings, water, pavement, vegetation.

A data filter checks for specific values in data fields that can be replaced with a given value. We used this functionality to replace the building type "0" in the MOSAIK data, which stands for "user-defined," for which the user would need to specify

395 all LOD2 building parameters.

Another feature in SanDyPALM is to remove buildings at the border of the domain to adhere to typical guidelines for atmospheric boundary layer studies and to avoid potential discontinuities at the inflow of the domain. Within a defined number of grid cells from the domain edge, all buildings are automatically removed and replaced by pavement. We can further decide

to remove all grid cells having the same building ID as already removed buildings, so that buildings are not cut into pieces but are removed entirely. In a nested setup, it makes sense to use this feature only in the outermost "parent" domain.

The soil type can be provided as a 2D input file, but if it is not available, a default value for the whole domain can be used. In any case, SanDyPALM handles the correct allocation of the soil type as well as the surface fraction variable. Finally, a domain-wide constant water temperature can be defined that is then applied to all water bodies in the static driver.

2.3.2 Dynamic Driver Generation

The dynamic driver generation is the second main component for setting up a realistic urban microscale simulation using PALM-4U. Currently, SanDyPALM supports WRF as the input data source. Using the WRF model has the significant advantage of allowing a relatively fine horizontal grid spacing on the order of $1\,\mathrm{km}$, and it enables the use of an urban canopy layer scheme together with an urbanized land use/land cover map, and optionally even average building heights, to better represent urban effects in the mesoscale forcing. We believe that this leads to significantly improved boundary conditions for the PALM-4U model. The process of creating the dynamic driver is illustrated in Figure 7.

One novelty of our dynamic driver creation is the handling of mesoscale data below the first model level of the mesoscale model. Since the data in this region is not available, we need to fill it using reasonable values. As described in Vogel et al. (2022), our dynamic coupling scheme incorporates a roughness-corrected Monin-Obukhov surface layer representation, which accounts for the varying roughness of urban surfaces. As mentioned earlier, this scheme is important for WRF setups with relatively large vertical grid spacing near the surface, e.g., when using the single-layer urban canopy model (SLUCM) or the slab (or bulk) urban model in WRF. When using a small vertical grid spacing near the surface, e.g., when using the multi-layer urban canopy model in WRF (BEP, BEM), a simple linear interpolation can be used instead.

The dynamic driver generation can utilize the building height data in the static driver to derive the urban morphological parameters needed in the aforementioned roughness-corrected Monin-Obukhov surface layer representation. Additionally, the terrain height can be read from the PALM-4U static driver to adjust the atmospheric data from WRF to the PALM-4U terrain height. To achieve this, the WRF level heights are shifted by the amount that the WRF terrain deviates from the PALM-4U terrain. However, this shifting is limited to the surface so that we do not shift the atmospheric layers throughout the entire boundary layer. Therefore, we can specify a vertical distance for this transition region. The WRF level heights will then be fully shifted at the reference height, which is either the WRF first (half) model level height or a user-defined reference height to which the WRF data is interpolated. At the specified distance above the reference height, the WRF level heights will remain untouched. All level heights in between will be linearly shifted. This produces a smooth transition region and limits the level height shifting to a small area close to the surface. The procedure is illustrated in Figure 8.

2.4 PALM-4U setup

This section provides a short summary of our most important PALM-4U model settings, which include offline nesting, the choice of grid, the solver, and the setup of the urban physics modules.
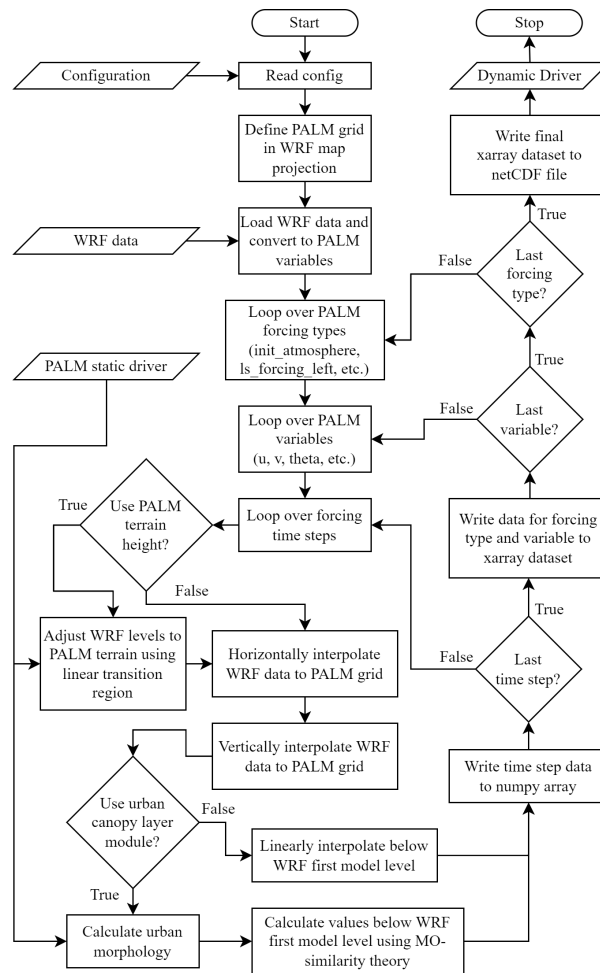
Figure 7. SanDyPALM dynamic driver generation flowchart.

We used release 23.04 of the PALM model system from the Institute of Meteorology and Climatology Hannover, which can be obtained from their code repository (PALM model system developers, 2023).

The PALM-4U model is forced by mesoscale data using the offline nesting capability. The mesoscale data is the result of a WRF downscaling simulation using three nested domains with spatial resolutions of 9 km, 3 km, and 1 km, and a temporal resolution of 1 h. The WRF model was itself forced by ERA5 global reanalysis data (Hersbach et al., 2018a, b) with a spatial resolution of 0.25° in both latitude and longitude, which at the given latitude equates to approximately 28 km by 17 km, respectively, and a temporal resolution of 1 h. The WRF mesoscale simulation used here is similar to the setup described in Vogel et al. (2022), which employed the multi-layer urban canopy model named Building Effect Parameterization (BEP) for urban representation. The dynamic driver was created using the method described in Vogel et al. (2022). The nesting setup is illustrated in Figure 9.
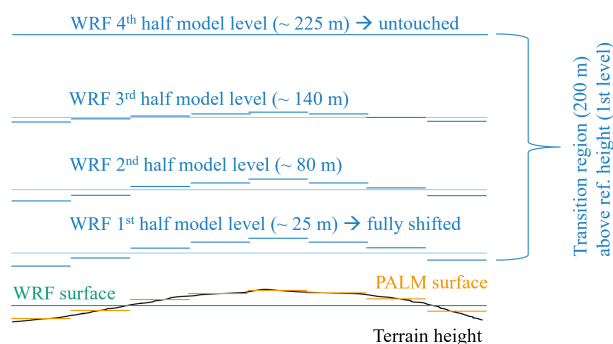
Figure 8. Adjustment of WRF mesoscale level heights based on the difference between WRF and PALM-4U surface heights, which account for actual terrain elevation at different horizontal resolutions. The adjustment procedure employs a linear transition region. This example is illustrative and does not represent the actual level heights utilized in this study.
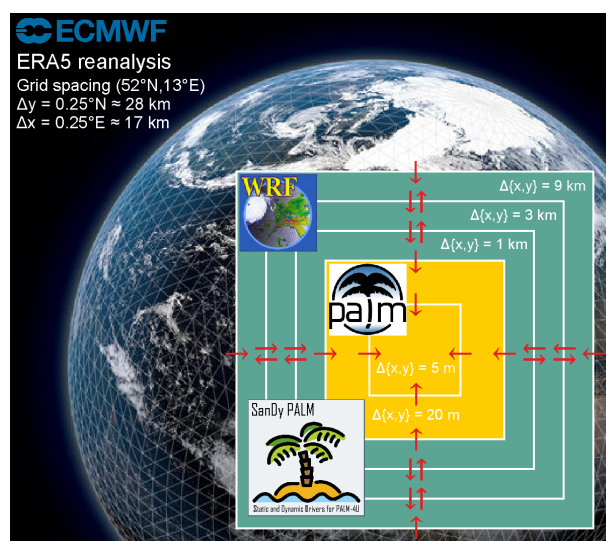
Figure 9. Nesting setup utilizing ERA5 for global boundary conditions, WRF for mesoscale forcing, and PALM-4U as the microscale model.

The nesting mode of the PALM-4U internal grid nesting is set to one-way nesting, meaning the data is only transferred from the parent to the nest, but the refined results from the nest are not transferred back to the parent. This is the recommended setting. The parent domain has a coarse horizontal grid size of $dx = 20\,\mathrm{m}$ by $dy = 20\,\mathrm{m}$ and an extent of $L_x = 3.2\,\mathrm{km}$ by $L_y = 3.2\,\mathrm{km}$. The nested domain has a finer grid size of $dx = 5\,\mathrm{m}$ by $dy = 5\,\mathrm{m}$ and an extent of $L_x = 1.6\,\mathrm{km}$ by $L_y = 1.6\,\mathrm{km}$.

445 The vertical grid size is $dz = 5\,\mathrm{m}$ in both cases; however, in the parent domain, we used vertical grid stretching. The stretching starts $10\,\mathrm{m}$ above the nested domain, which has a height of $L_z = 640\,\mathrm{m}$. Since the urban boundary layer is approximately at a maximum height of $2045\,\mathrm{m}$ in our case, this means that the grid stretches throughout the boundary layer; however, the stretching is very gradual, using a small stretching factor of 1.0183. Although a uniform grid is recommended for Large Eddy Simulations (LES), this grid has the advantages of a small vertical grid size at the surface, which allows for the evaluation

450 of near-surface measurements, a uniform grid transition between the parent and nest near the surface, and a relatively small vertical grid cell count. Throughout the boundary layer, the vertical grid size increases gradually and reaches about $dz = 30\,\mathrm{m}$ at the maximum boundary layer height. In the upper damping layer above the urban boundary layer, the grid size further increases up to $dz = 40\,\mathrm{m}$ at the domain top at $z = 3088\,\mathrm{m}$. The grid parameters are summarized in Table 3.

Table 3. Grid specifications in the PALM-4U model for the parent domain (using vertical grid stretching) and the nested domain (without vertical grid stretching).

Grid parameter	x – direction	y – direction	z – direction
Parent			
Domain size	3200 m	3200 m	3088 m
Number of grid points	160	160	256
Grid size	20 m	20 m	5 m
Stretching factor	-	-	1.0183
Starting height	-	-	650 m
Max grid size	-	-	40 m
Nest			
Domain size	1600 m	1600 m	640 m
Number of grid points	320	320	128
Grid size	5 m	5 m	5 m

In the last third of the vertical height of the grid, starting at $z = 2050\,\mathrm{m}$, we employed Rayleigh damping with a damping

455 factor of 0.1. According to the PALM-4U model documentation, this forces horizontal velocities, temperature, and humidity to their respective mean values provided by the mesoscale model. The damping is weak at the starting height and increases towards the top. The Rayleigh damping is intended to decrease gravity waves that might otherwise travel unhindered through the domain and reflect at the top of the domain.

As the solver for the Poisson equation for perturbation pressure, we used the multigrid method with 2 iterations of the w-cycle per time step and 2 iterations of the Gauss-Seidel method on each grid level. For the multigrid solver, the number of grid points needs to follow certain rules to achieve enough grid coarsening levels, and the performance of the solver is optimal when this number is 5 or higher. In our case, the grid of the parent domain allows for 5 coarsening levels, and the grid of the nested domain allows for 6 grid coarsening levels. In the case of parallel computing, these conditions need to hold for each partitioned subdomain.

In the urban surface model, the inner temperatures of walls, roofs, and windows are set to 298.15 K. To facilitate model spin-up and reduce atmospheric simulation spin-up time, we employed a wall/soil spin-up with a duration of 24 h and a time step of 10 s. In the OSM case, a smaller time step was necessary due to a metal surface type with high heat conductivity, which led to instabilities. The spin-up period corresponds to the 24 h interval from 18 July 2022 00:00 to 19 July 2022 00:00 (CEST), immediately preceding the simulation start time. The PALM-4U model performs the wall/soil spin-up with a sinusoidal atmospheric temperature variation over time, specified by the mean and amplitude of daily temperature variation. The mean value $\overline{\theta}_{\mathrm{spinup}} = 299.15\,\mathrm{K}$ and amplitude $\tilde{\theta}_{\mathrm{spinup}} = 9.0\,\mathrm{K}$ for atmospheric temperature during the wall/soil spin-up were approximately derived from mesoscale model results for the spin-up period.

For global radiation input, we used the "external" setting, where shortwave and longwave downwelling radiation are read from the dynamic driver. This approach has the advantage of considering clouds resolved by the mesoscale model in the radiation input. To resolve radiation within the urban canopy, the radiative transfer model (RTM) is used in PALM-4U. The radiation time step is set to 60 s. In the plant canopy model, the canopy drag coefficient is set to 0.2, and plant canopy transpiration is enabled. To create dynamic boundary conditions, the offline nesting mode is used. To generate turbulence at the boundaries, the synthetic turbulence generator is activated with an adjustment time step of 1800 s.

2.5 Measurement data

For the validation of the different PALM-4U model simulation runs, we used measurement data from two different stations. The locations of the stations are illustrated in Figure 1.

The first station is a weather monitoring tower situated in the garden of the Institute of Ecology at the Technical University of Berlin (TUB) on Rothenburgstraße (Fenner et al., 2014). The exact coordinates are 52.457232° N, 13.315827° E, and the terrain height is 46.5 m. The meteorological data generated by the tower is openly available on the website of the Urban Climate Observatory (UCO) (Scherer et al., 2024). This station is at the center of our inner nested PALM-4U domain. From the many quantities available, we evaluated temperature, humidity, and wind. The available measurement heights are 2 m, 5 m, 10 m, 20 m, 30 m, and 40 m. However, wind speed and direction are only available at heights of 10 m to 40 m, while humidity is only available at 2 m and 5 m. For simplicity, we evaluated only the heights of 5 m and 40 m for temperature, 5 m for humidity, and 10 m and 40 m for wind speed.

The second station is the weather monitoring station "Dahlem" from the "Deutscher Wetterdienst" (DWD), which is located in the botanical garden in Berlin-Steglitz. The data was obtained from the DWD Open Data-Server (Deutscher Wetterdienst, 2024). The coordinates of this station are 52.4537° N, 13.3017° E, and the terrain height is 51 m. This location is only covered

by our outer parent domain. The station features temperature and humidity measurements at a height of $2\,\mathrm{m}$ and wind speed measurements at a height of $36\,\mathrm{m}$.

3 Results and discussion

In this study, we present a novel method for generating static and dynamic drivers for the PALM-4U model, with an emphasis on static geographic data. Our results focus on two primary aspects: the impact of using various data sources to create static drivers and the subsequent effects on the PALM-4U simulation outcomes. To achieve this, we compared the most relevant static driver variables from our four approaches, both visually and statistically. Additionally, we evaluated how the use of different static drivers influences PALM-4U simulations by running simulations for each case and comparing them against measurements and one another. This comparison is crucial for understanding the implications of data source selection on simulation accuracy and reliability.

3.1 Comparison of static drivers

Referencing Figure 2, it is evident that the input data sources differ substantially in their representation of building footprints, vegetation, and pavement. We further investigate these variations in the final processed static drivers, focusing on the most significant variables. The static driver variables are categorized into continuous and categorical types. For continuous variables, we examined terrain height (Figure 10), building height (Figure 11), tree height (Figure 12), and Leaf Area Index (LAI) (Figure 13). For categorical variables, we evaluated building type (Figure 14), vegetation type (Figure 15), and pavement type (Figure 16).

In addition to qualitative differences, a quantitative comparison containing several statistics was performed. For continuous variables, statistics (mean, standard deviation, minimum, and maximum) were calculated over the valid grid tiles only (excluding no-data values); the results are shown in Table 4. For categorical variables, the distribution of the observed types was calculated as a percentage of the total number of grid tiles (including no-data values); the results are given in Table 5. Types that do not occur are omitted in the table. To identify the valid types of a variable, we refer to the figure of the specific type for a legend connecting the type number to a text description. The table also lists no-data values to compare the number of grid cells lacking specific types. Calculations were performed separately for parent and nested domains.

For terrain height, despite the four cases, there are only two main data sources: the terrain height for MOSAIK and Custom originates from municipal data, while OSM and LCZ utilize a remotely sensed Digital Elevation Model (DEM). The MOSAIK terrain height was slightly post-processed, resulting in negligible differences from the municipal terrain height. The terrain height presented here is relative to the origin of the z-coordinate ($origin_z$) of the parent domain, with $origin_z \approx 32\,\mathrm{m}$ for MOSAIK and Custom, and $origin_z \approx 26\,\mathrm{m}$ for OSM and LCZ. The remotely sensed DEMs (OSM and LCZ) exhibit higher average and maximum values compared to the municipal DEMs (MOSAIK and Custom). Additionally, the remote sensing DEMs (OSM and LCZ) have a larger range of values, are generally noisier, and lack the detail found in the municipal DEMs (MOSAIK and Custom).
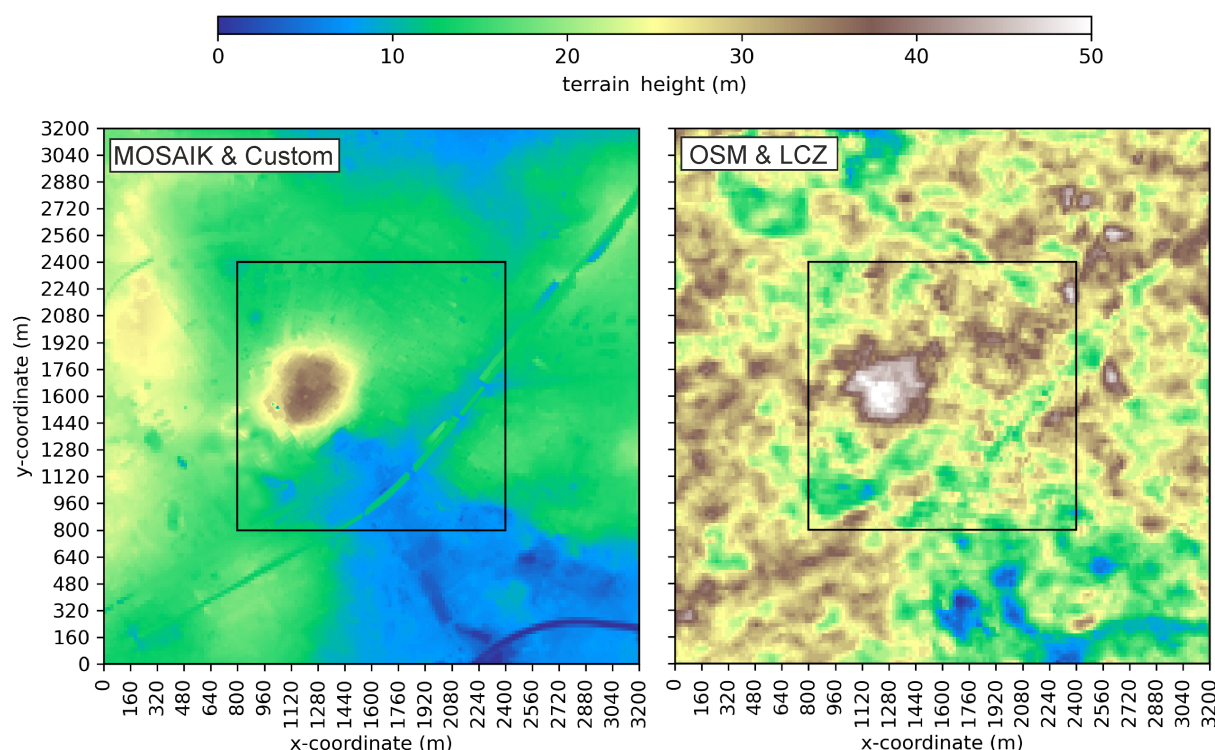
Figure 10. Comparison of terrain height for the different static drivers.

Regarding building height, the MOSAIK data shows larger building footprints compared to the Custom and OSM cases. All three datasets struggle to resolve building footprints at the coarser scale of the parent domain. The LCZ method does not accurately capture the exact building footprints at either scale but maintains consistency across them. Building heights are similar in MOSAIK and Custom, while OSM and LCZ exhibit comparable heights. OSM combines available heights with WSF3D data, which can result in occasional anomalies due to gaps filled by WSF3D data. In contrast, LCZ relies solely on WSF3D, leading to more consistent building heights.

Tree heights vary significantly across the datasets. MOSAIK features extensive tree cover, while Custom has fewer trees. OSM includes only individual trees with no tree patches, and LCZ shows sparse tree coverage. Generally, tree heights in MOSAIK are larger than those in Custom, although there are regions where the reverse is true. OSM lacks specific tree height data, so default constant heights were used. In contrast, LCZ tree heights align with those in MOSAIK, as their distribution was derived from the same data source.

For tree Leaf Area Index (LAI), MOSAIK, Custom, and LCZ exhibit similar values due to the LAI limiting process during SanDyPALM processing. The original LAI values in MOSAIK were significantly higher, requiring moderation to prevent excessive humidity spikes near vegetation. The variation in LAI for Custom arises from height-dependent default calculations.
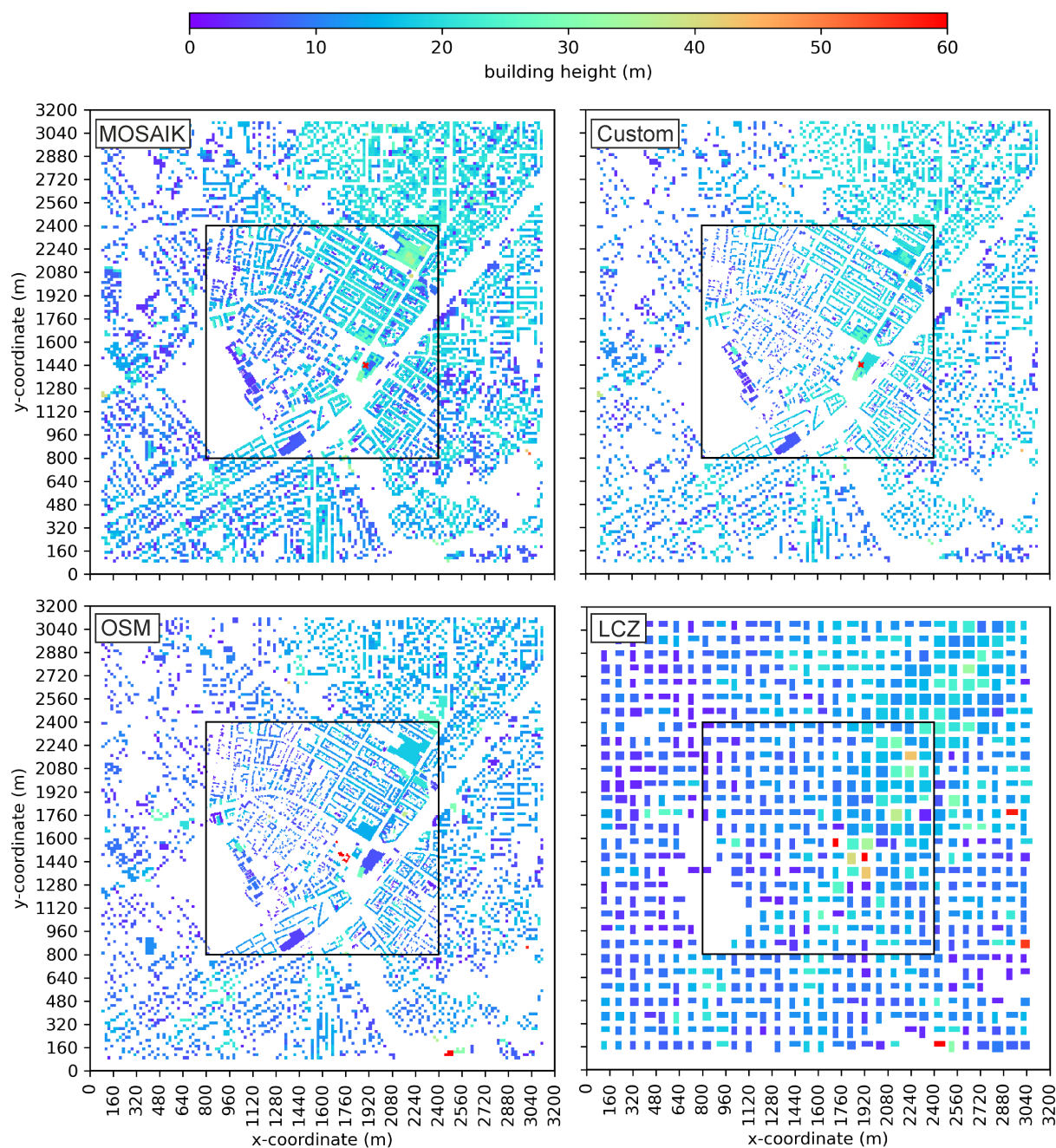
Figure 11. Comparison of building height for the different static drivers.
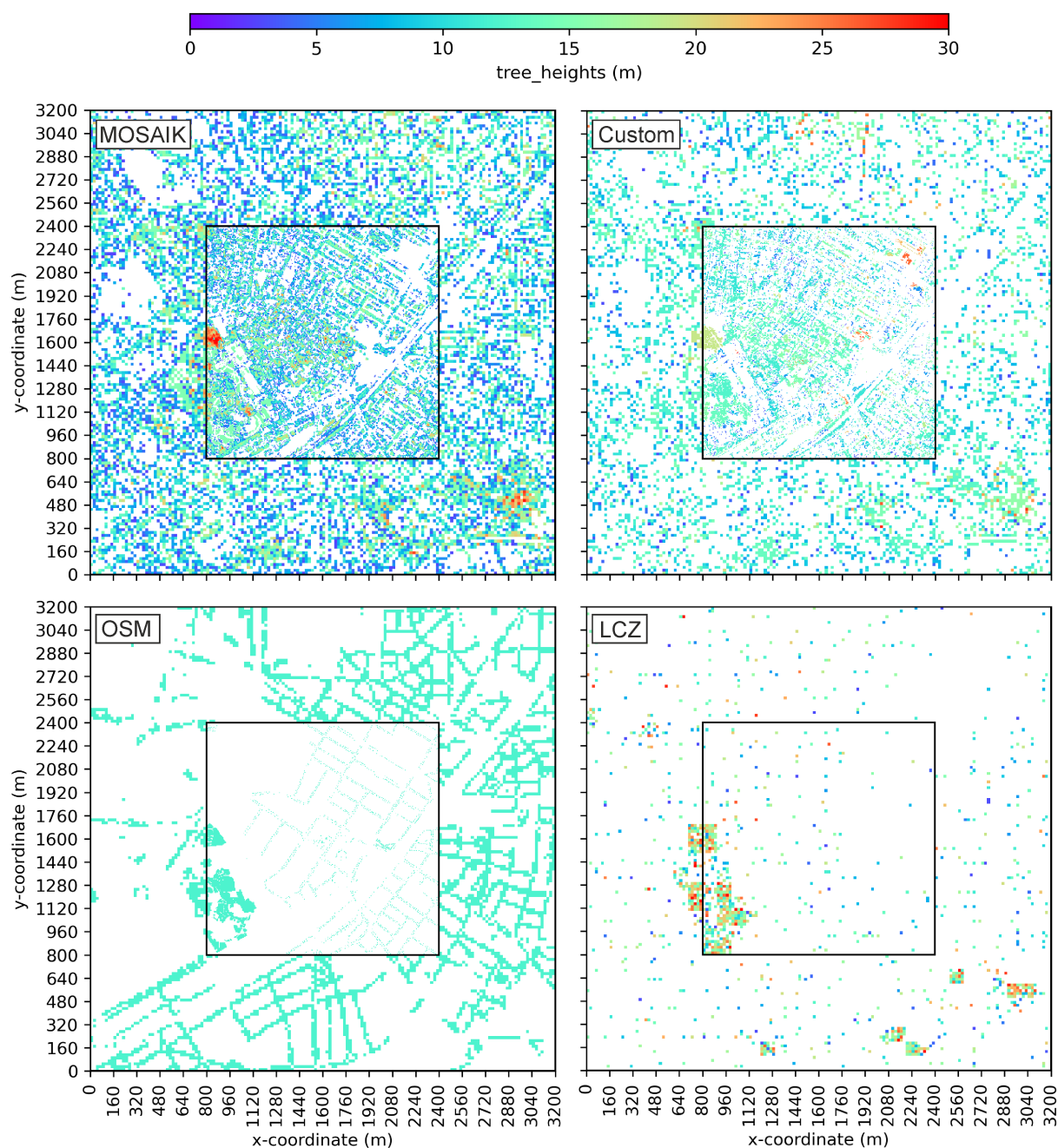
Figure 12. Comparison of tree height for the different static drivers.
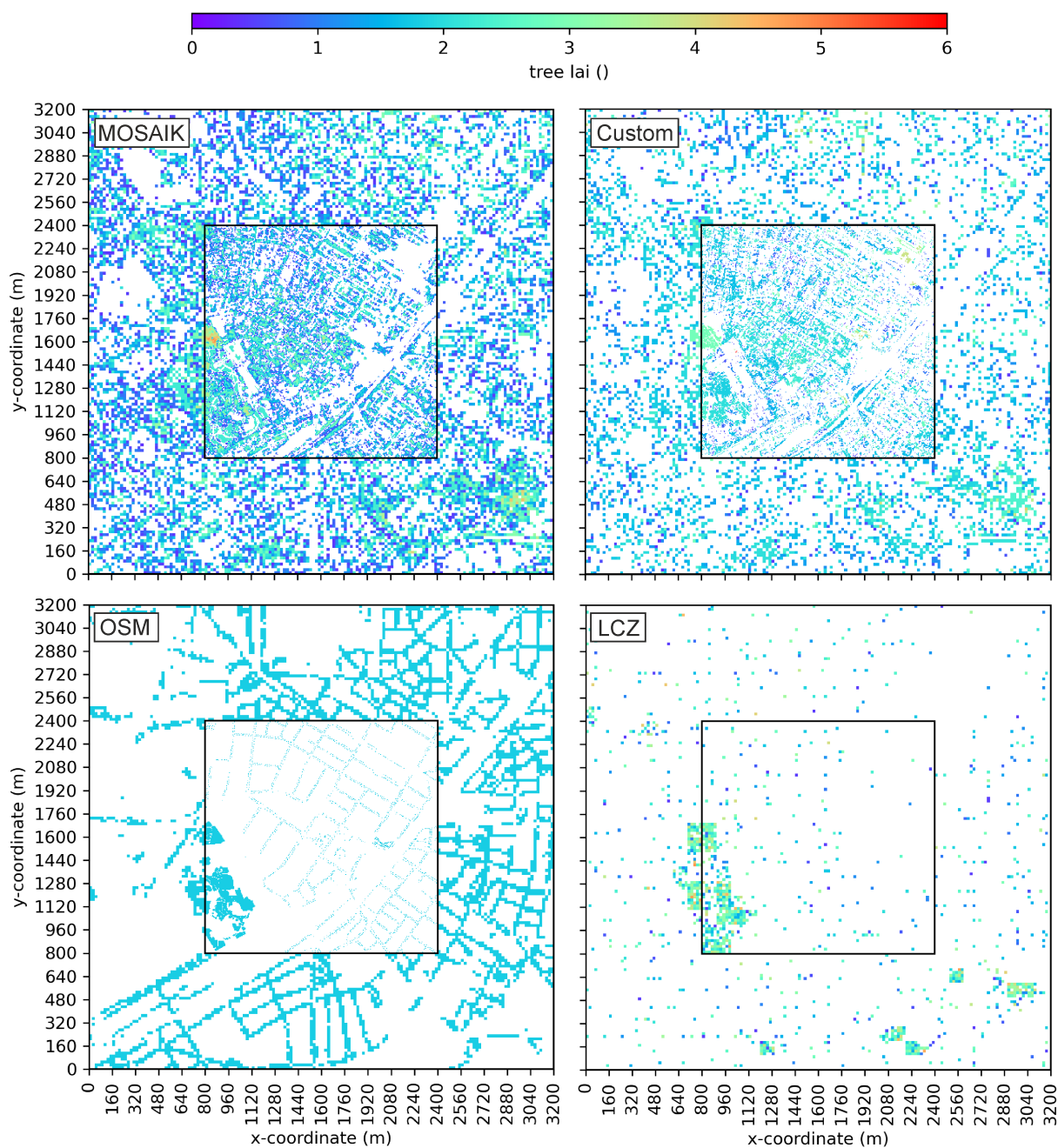
Figure 13. Comparison of leaf area index (LAI) for the different static drivers.
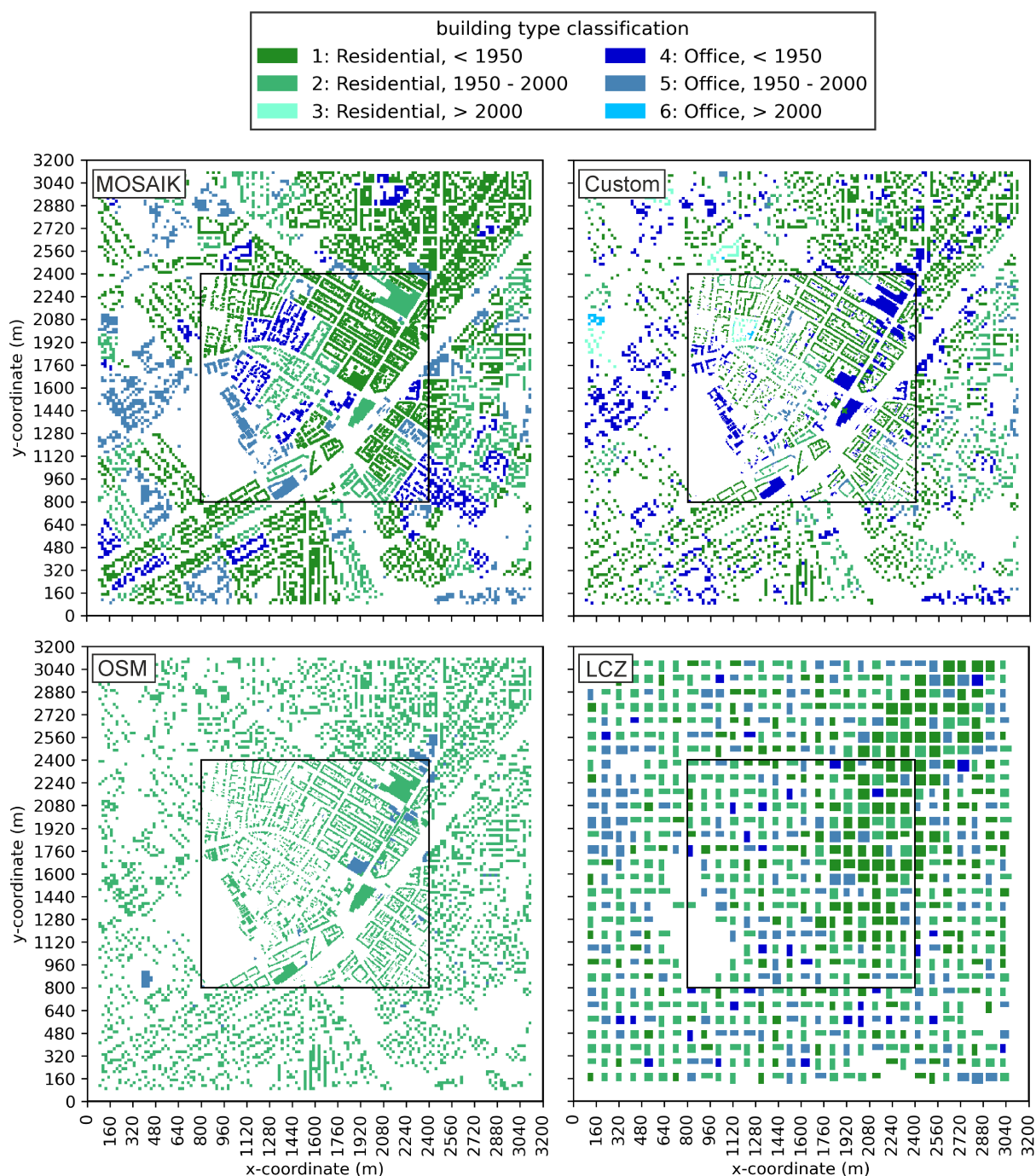
Figure 14. Comparison of building type for the different static drivers.
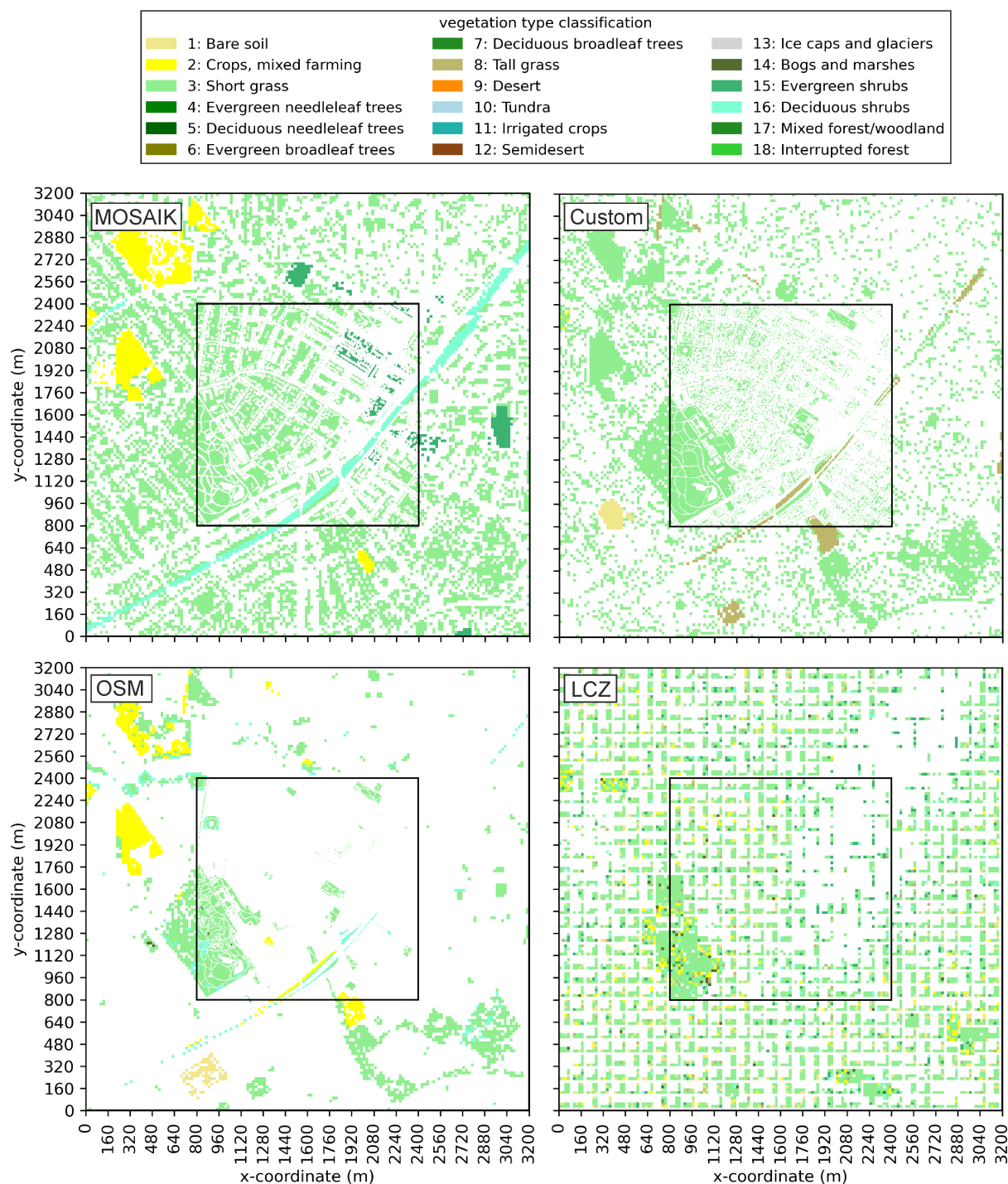
Figure 15. Comparison of vegetation type for the different static drivers.
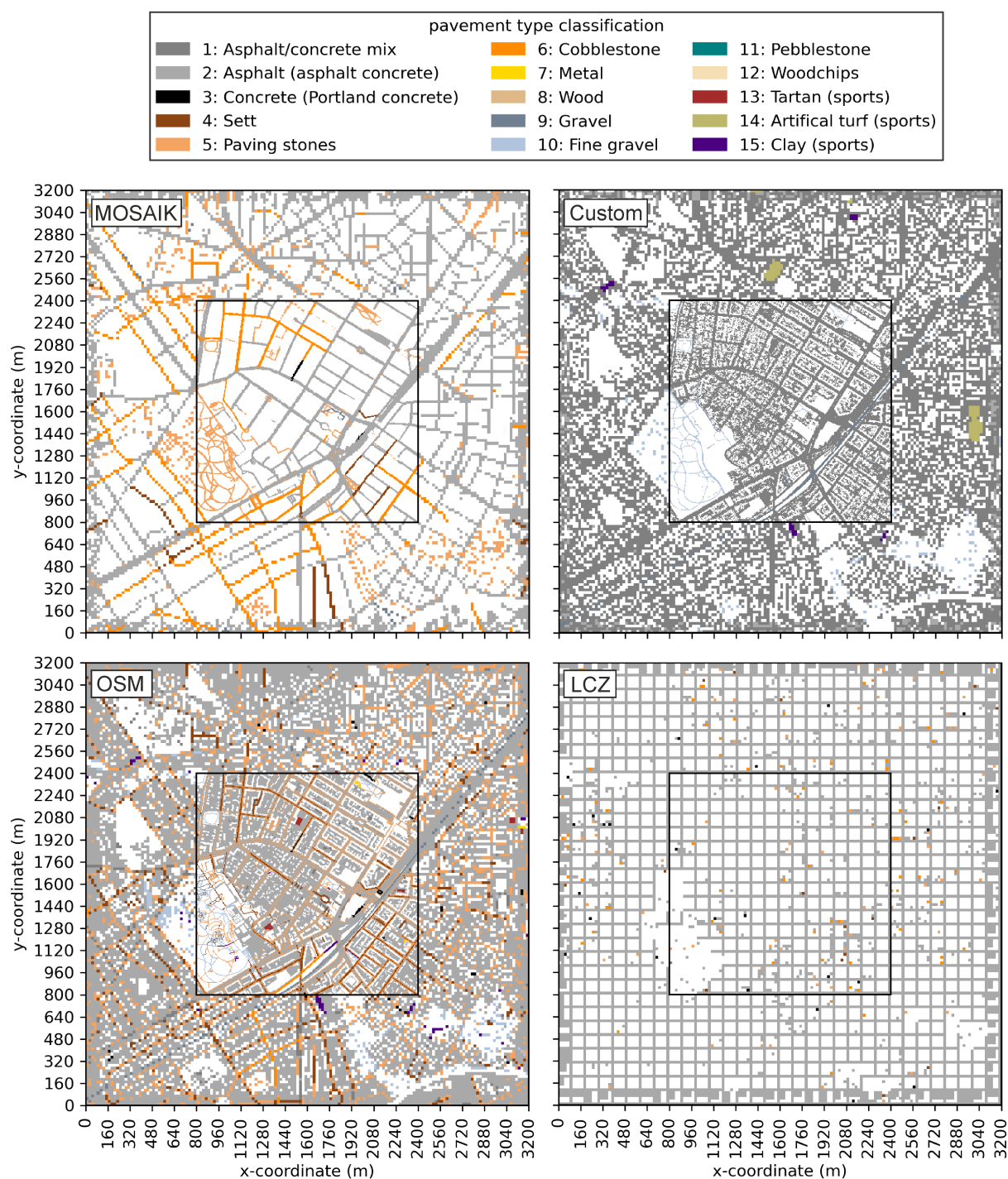
Figure 16. Comparison of pavement type for the different static drivers.

Table 4. Comparison of Static Drivers showing the statistics mean, standard deviation, minimum and maximum for continuous variables terrain height, building height, tree height and tree LAI.

Variable		MOSAIK		Custom		OSM		LCZ	
		parent	nest	parent	nest	parent	nest	parent	nest
Terrain height / m	*mean*	14.0	14.5	14.0	14.6	25.3	26.6	25.3	26.6
	std	5.4	6.1	5.4	6.1	6.9	7.3	6.9	7.3
	min	0.0	3.5	0.0	3.6	0.0	7.0	0.0	7.0
	max	37.0	37.2	37.1	37.4	52.0	52.0	52.0	52.0
Building height / m	*mean*	14.4	15.0	14.6	15.3	11.9	12.1	12.1	13.4
	std	6.4	7.4	6.1	7.3	5.9	5.9	7.9	9.2
	min	2.5	2.5	2.5	2.5	2.5	2.5	3.0	3.0
	max	118.7	118.7	114.6	115.8	107.3	61.9	109.4	109.4
Tree height / m	*mean*	10.2	10.6	11.4	11.8	12.0	12.0	15.0	15.7
	std	4.8	5.0	3.7	3.8	0.0	0.0	6.1	5.9
	min	2.5	2.5	2.5	2.6	12.0	12.0	3.0	3.0
	max	31.0	33.0	28.3	41.4	12.0	12.0	31.8	30.7
Tree LAI / $m^2 m^{-2}$	*mean*	0.7	0.7	0.4	0.4	0.4	0.1	0.1	0.1
	std	0.9	1.0	0.8	0.8	0.7	0.4	0.5	0.6
	min	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	max	4.7	4.9	4.2	6.2	1.8	1.8	4.8	4.6

In contrast, OSM shows no variation in tree LAI; due to the absence of values for both tree LAI and tree height, constant
540 default values are assumed for both.

Building types across the datasets show notable variations. Predominantly, buildings are classified as types 1, 2, 4, and 5 (Residential and Office before 2000), with types 3 and 6 (Residential and Office after 2000) being rare. The Custom data, sourced directly from the municipality, emphasizes type 1 (Residential before 1950) and type 4 (Office before 1950), while types 2 and 5 are less common. In contrast, the MOSAIK data, also based on municipal sources but further post-processed,
545 shows a significantly higher occurrence of type 5 compared to Custom, nearly matching type 4. Occasionally, buildings classified as office in MOSAIK are categorized as residential in Custom, and vice versa. OSM data predominantly features residential buildings, while LCZ data closely resembles MOSAIK data, as its type probabilities were derived from it. Overall, building type classifications exhibit significant variability across the different approaches.

Vegetation types across the datasets show distinct differences. The highest vegetation amount is in the MOSAIK case,
550 followed by LCZ and Custom, with OSM data having the sparsest vegetation. The dominant type across all cases is type 3 (short grass). The LCZ case also includes significant amounts of type 1 (bare soil) and type 2 (crops), while MOSAIK only

Table 5. Comparison of Static Drivers showing the percentage distribution of observed types for the categorical variables building type, vegetation type and pavement type.

Variable		MOSAIK parent	MOSAIK nest	Custom parent	Custom nest	OSM parent	OSM nest	LCZ parent	LCZ nest
Building type / %	*no-data*	69.2	63.0	80.9	77.1	80.5	76.1	71.6	66.2
	1	17.3	19.7	10.5	12.2	0.0	0.0	8.7	13.1
	2	6.0	8.5	2.8	2.6	18.8	22.5	11.9	12.6
	3	0.0	0.0	0.3	0.2	0.0	0.0	0.0	0.0
	4	3.0	4.7	4.8	7.2	0.	0.	1.1	1.5
	5	4.5	4.3	0.6	0.8	0.7	1.5	6.6	6.6
	6	0.0	0.0	0.1	0.1	0.0	0.0	0.0	0.0
Vegetation type / %	*no-data*	61.9	64.2	73.9	74.2	89.3	89.6	69.7	70.6
	1	0.0	0.0	0.3	0.0	0.3	0.0	2.6	1.8
	2	2.6	0.0	0.0	0.0	2.0	0.6	1.1	1.2
	3	32.3	31.9	24.7	24.8	7.4	8.5	22.8	21.8
	8	0.0	0.0	1.1	1.1	0.0	0.0	0.5	0.6
	14	0.0	0.0	0.0	0.0	0.0	0.0	0.2	0.3
	15	1.3	1.8	0.0	0.0	0.0	0.0	2.1	2.6
	16	1.8	2.2	0.0	0.0	1.0	1.3	1.1	1.2
Pavement type / %	*no-data*	69.6	73.4	45.8	49.2	30.8	34.8	58.7	63.2
	1	0.0	0.0	49.7	48.2	1.2	1.1	0.0	0.0
	2	21.8	16.9	2.6	0.2	52.0	46.4	40.6	36.0
	3	0.0	0.1	0.0	0.0	0.1	0.2	0.1	0.1
	4	0.6	0.6	0.0	0.0	3.2	3.8	0.1	0.1
	5	4.3	5.0	0.0	0.0	10.5	11.0	0.3	0.3
	6	3.6	3.9	0.0	0.0	0.2	0.3	0.3	0.3
	7	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0
	9	0.1	0.1	0.4	0.7	0.3	0.5	0.0	0.0
	10	0.0	0.0	1.0	1.7	1.3	1.4	0.0	0.0
	13	0.0	0.0	0.0	0.0	0.1	0.2	0.0	0.0
	14	0.0	0.0	0.4	0.0	0.0	0.0	0.0	0.0
	15	0.0	0.0	0.1	0.0	0.2	0.2	0.0	0.0

includes type 2 (crops) in the parent domain. The type distribution for LCZ was derived from MOSAIK data for the entire city boundary of Berlin, explaining the distribution differences. In the OSM case, a small amount of type 1 (bare soil) and a significant amount of type 2 (crops) are found in the parent domain. Both Custom and LCZ contain some type 8 (tall grass). A

555 similar amount of type 15 (evergreen shrubs) is found in both MOSAIK and LCZ, while type 16 (deciduous shrubs) is present in MOSAIK, OSM, and LCZ but absent in Custom. Overall, the amount and distribution of vegetation vary significantly among the four cases.

Pavement type shows significant variability across the datasets. MOSAIK has sparse pavement coverage (26.6 – 30.4 %), while Custom (50.8 – 54.2 %) and OSM (65.2 – 69.2 %) likely overestimate pavement. LCZ falls in between (36.8 – 41.3 %)

560 but remains higher than MOSAIK. The dominant pavement types differ: type 2 is prevalent in MOSAIK, OSM, and LCZ, while type 1 is dominant in Custom. MOSAIK includes significant amounts of types 5 and 6 (paving stones and cobblestone), OSM shows types 4 and 5 (sett and paving stones), and both Custom and OSM contain some type 10 (fine gravel). Only OSM includes type 7 (metal), which caused issues during the PALM-4U wall/soil spin-up due to high heat conductivity, resolved by using a smaller time step. Other types are sparse. Overall, the amount and type of pavement vary significantly among the cases.

565 We found that the MOSAIK case tends to overestimate building footprints and vegetation, while the OSM and Custom cases generally underestimate vegetation. The overestimation in MOSAIK likely results from the "all-touched" rasterization technique, which rasters all grid tiles touched by a vector polygon. Additionally, MOSAIK data may have been post-processed to prioritize vegetation over pavement. In contrast, the Custom and OSM cases raster only those grid tiles whose centers are covered by a vector polygon, resulting in more realistic building footprints. However, a downside of the Custom and

570 OSM cases is that the vegetation appears too sparse, and LAI data is missing, necessitating the use of default values. The overestimation of pavement in these cases occurs because, with sparse vegetation, pavement becomes the default surface type when no other type is defined. While MOSAIK data has been post-processed and prioritized, the other data sources are relatively raw. During processing in SanDyPALM, consistency checks and corrections were uniformly applied across all datasets, although customized strategies might have benefited different datasets.

575 This analysis illustrates that the choice of data source significantly influences outputs, with each processing strategy presenting its own advantages and disadvantages. Overall, the key differences between the test cases highlight variations in urban morphology, vegetation coverage, and data completeness, all of which may impact the outcomes of PALM-4U simulations.

3.2 Comparison of PALM-4U results to measurements

The next step in our investigation involved simulating the same test case using the four generated static drivers, while keeping

580 the dynamic driver consistent. This allowed for a comparison of the PALM-4U results, along with the WRF results, against measurements from the TUB monitoring tower located within the inner nested domain and the DWD weather station, which is covered only by the parent domain.

3.2.1 Tower measurements

For our investigation, we selected a limited number of measurement heights from the tower. For example, measurements at
585 2 m and 5 m are not expected to differ significantly, particularly in numerical models where values are interpolated from sparse
data points near the surface. Air temperature T was evaluated at heights of 5 m and 40 m above ground, relative humidity
ϕ_{rel} at 5 m, and horizontal wind speed U_{h} at 10 m and 40 m. The comparison of WRF and PALM-4U results with the tower
measurements is presented in Figure 17, and the metrics for all models compared to the tower data are compiled in Table 6.

Table 6. Metrics for comparing WRF and the PALM-4U results with measurements from the TUB Tower "Rothenburgstraße" (located in
nested domain).

		WRF		MOSAIK		Custom		OSM		LCZ	
Quantity	**Unit**	*MBE*	*RMSE*	*MBE*	*RMSE*	*MBE*	*RMSE*	*MBE*	*RMSE*	*MBE*	*RMSE*
$T_{5\,\text{m}}$	°C	-0.02	1.72	-1.41	2.38	-0.79	1.86	0.16	1.59	-0.19	1.84
$T_{40\,\text{m}}$	°C	-0.94	1.53	-1.11	1.64	-1.08	1.62	-0.98	1.49	-0.88	1.51
$\phi_{\text{rel},\,5\,\text{m}}$	%	3.09	6.40	8.03	9.84	4.85	6.96	1.82	5.73	3.05	6.46
$U_{\text{h},\,10\,\text{m}}$	m s^{-1}	1.32	1.57	0.32	0.45	0.55	0.70	0.97	1.04	2.11	2.57
$U_{\text{h},\,40\,\text{m}}$	m s^{-1}	0.65	1.30	0.60	1.20	0.54	1.24	0.34	1.31	1.02	1.73

The general agreement between WRF and PALM-4U results and the measurements indicates that all relevant physical
590 processes are well resolved. However, some notable deviations exist. For temperature at 40 m, WRF and all PALM-4U results
are nearly identical, but all show lower daytime temperatures compared to tower measurements. At 10 m, the PALM-4U models
using MOSAIK and Custom data deviate increasingly from the WRF model, while the OSM and LCZ models remain close to
WRF. Unfortunately, this deviation is away from the measurements and is likely related to humidity.

The 5 m relative humidity shows increased nighttime values between sunset and sunrise, particularly for the PALM-4U
595 models using MOSAIK and Custom static drivers. The main difference is that these static drivers feature significantly more
vegetation than the others. The observed higher humidity may result from a combination of evapotranspiration from soil and
vegetation, reduced atmospheric mixing, and dew formation. Even after sunset, plants continue to release water vapor through
transpiration, while moisture retained by soil and vegetation during the day can evaporate as temperatures drop. Additionally,
surface cooling can create a stable atmospheric layer near the ground, reducing vertical mixing and allowing the air close to
600 the surface to retain more moisture. Dew formation and subsequent evaporation can also contribute to localized increases in
humidity.

These combined factors could explain the high humidity levels observed in vegetated areas during the evening and why these
effects are more pronounced with MOSAIK or Custom data, which feature greater vegetation coverage. However, it remains
unclear whether the amount of vegetation is overestimated in the input data or if the described effects are exaggerated in the
605 PALM-4U model.
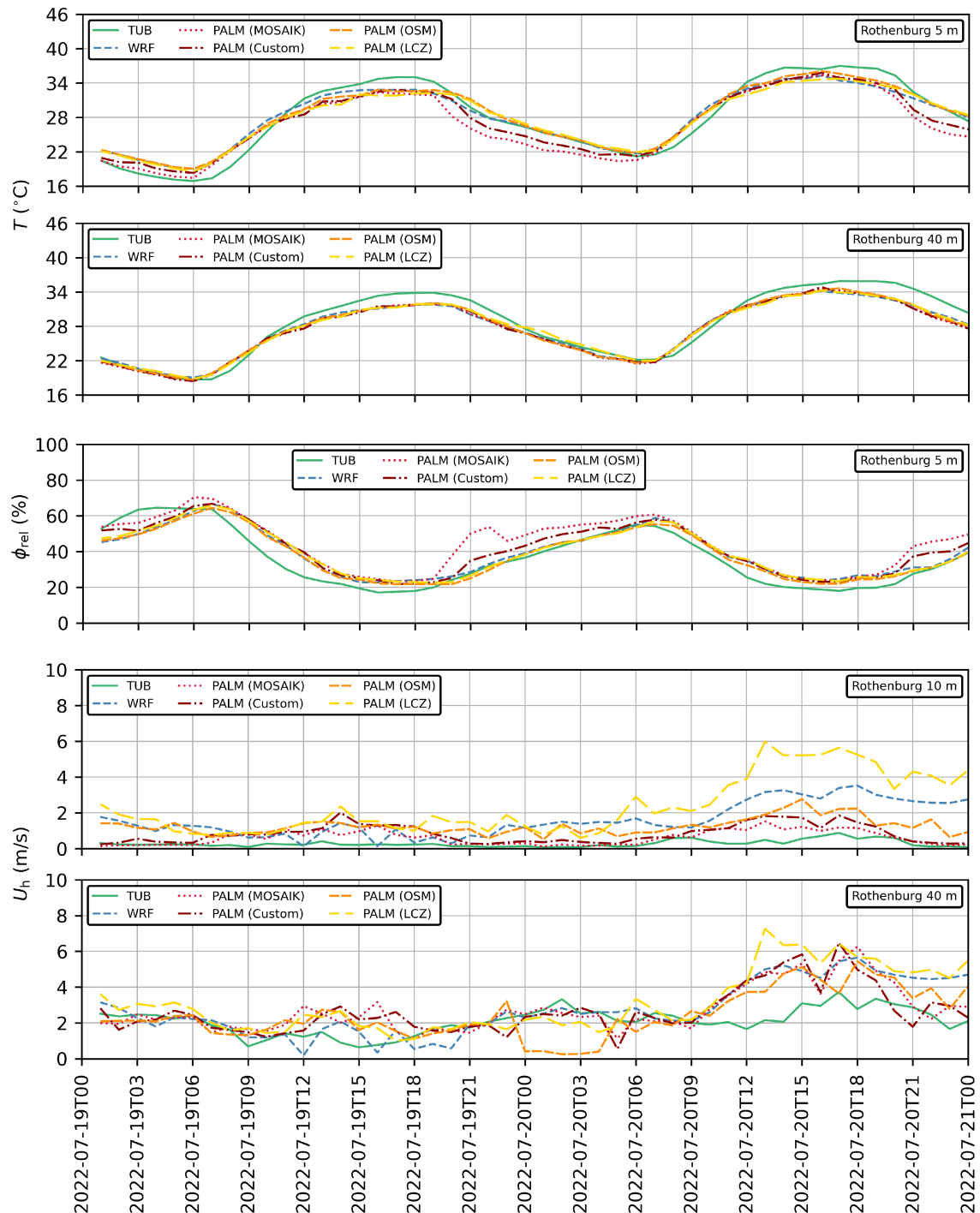
Figure 17. Comparison of WRF and PALM-4U results of temperature T, relative humidity ϕ_{rel} and horizontal wind speed U_h against measurements from the TUB tower at "Rothenburgstraße" (located in nested domain).

The measured wind speeds during this period are generally low. At 40 m, WRF slightly overestimates wind speed compared to tower measurements, while the PALM-4U models generally follow WRF, showing deviations toward both stronger and weaker wind speeds. At 10 m, the PALM-4U models tend to output lower wind speeds than WRF, aligning better with the measurements, except for the LCZ case, which records significantly higher wind speeds on the second day. The LCZ case is
610 unique, as the buildings are not accurately resolved, and the arrangement near the tower may differ significantly from the actual courtyard of the TUB tower.

Additionally, the generally low measured wind speeds and the tendency for simulations to overestimate wind speed can be attributed to the courtyard's surroundings, which are lined with tall, dense trees. This creates significant wind shading, an effect not accounted for by the WRF model. The accuracy of the PALM-4U models in this location also heavily relies on the precise
615 locations and characteristics of the trees and buildings.

3.2.2 Station measurements

WRF and PALM-4U results were compared to measurements from the DWD station in Dahlem, which is only resolved in the parent domain of our PALM-4U setup. Air temperature T and relative humidity ϕ_{rel} were evaluated at a height of 2 m above ground, while horizontal wind speed U_{h} was evaluated at 36 m. These evaluation heights correspond to the measurement
620 heights of the station. The comparison of WRF and PALM-4U results with the station measurements is presented in Figure 18, and the metrics for all models compared to the station data are compiled in Table 7.

Table 7. Metrics for comparing WRF and PALM-4U results from the four test cases with measurements from the DWD station "Dahlem" (located in the parent domain).

Quantity	Unit	WRF		MOSAIK		Custom		OSM		LCZ	
		MBE	RMSE	MBE	RMSE	MBE	RMSE	MBE	RMSE	MBE	RMSE
$T_{2\,\mathrm{m}}$	°C	1.66	3.01	-1.08	2.35	-0.416	2.35	-0.861	2.35	-0.611	2.03
$\phi_{\mathrm{rel,\,2\,m}}$	%	-3.43	12.1	6.25	12.2	2.94	11.2	4.40	11.0	4.28	10.0
$U_{\mathrm{h,\,36\,m}}$	m s^{-1}	-0.857	1.40	0.285	1.26	0.328	1.34	0.109	1.36	-0.0517	1.42

For this station, the WRF model overestimates nighttime temperatures, likely due to an exaggerated urban heat island effect. The LCZ map used in WRF classifies the area around the station as "LCZ 6" (Open low-rise), which is appropriate for the entire 1 km WRF grid tile but does not accurately represent the densely vegetated botanical garden around this station. In contrast,
625 the PALM-4U models, which realistically resolve buildings and vegetation, are significantly closer to the measurements in this case.

Humidity is underestimated by WRF at night and overestimated during the day. The PALM-4U models generally predict higher humidity than WRF, with a moderate increase during the day and a more pronounced rise at night. At the end of the first night, PALM-4U results align more closely with measurements than WRF, but on the second and early third nights, they
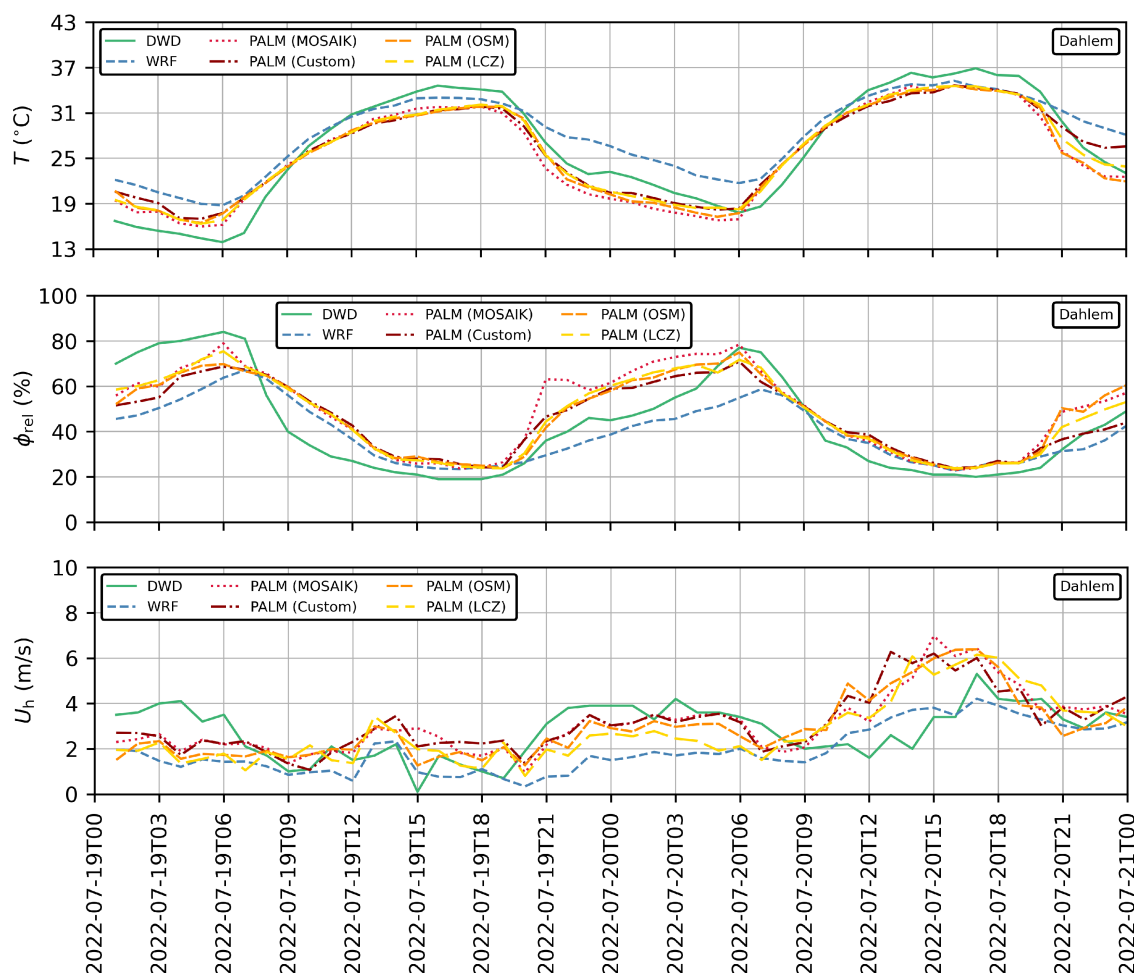
Figure 18. Comparison of WRF and PALM-4U results for temperature T, relative humidity ϕ_{rel}, and horizontal wind speed U_{h} against measurements from the DWD station "Dahlem" (located in the parent domain).

630   overestimate humidity compared to the measurements. Similar to the tower data, PALM-4U humidity shows significant spikes around sunset.

Wind speed at this location is comparable to that at the upper tower location, which has a similar height. While WRF overestimates wind speed at the tower, it underestimates it at the station. This discrepancy may arise because the tower is surrounded by large trees and buildings that create wind shading, whereas the station is situated in an open park with less

635   restricted wind flow. The WRF model, lacking detailed information about trees and buildings, resolves both locations similarly. In contrast, wind speeds from the PALM-4U models are closer to the measurements, with all PALM-4U models performing comparably well.

3.3 Comparison of PALM-4U results to each other

To compare the PALM-4U simulation results across the four test cases, we evaluated the potential temperature θ (Figure 19) and

640   the mixing ratio q (Figure 20) at the first vertical centered grid level, corresponding to a height above ground of $h_{\mathrm{AGL}} = 2.5\,\mathrm{m}$. The horizontal wind speed U_{h} (Figure 21) was evaluated at the second vertical centered grid level, corresponding to a height of $h_{\mathrm{AGL}} = 7.5\,\mathrm{m}$. All quantities were time-averaged over the entire simulation period, which spanned two days. A quantitative comparison of the statistics for the four different simulation test cases is presented in Table 8. For each quantity, the mean, standard deviation (std), minimum (min), and maximum (max) values were calculated over the entire two-day simulation

645   period and across all grid points (excluding no-data values).

Table 8. PALM-4U results statistics for the four different test cases.

Quantity	Unit	Statistic	MOSAIK parent	nest	Custom parent	nest	OSM parent	nest	LCZ parent	nest
$\theta_{2.5\,\mathrm{m}}$	°C	mean	25.6	25.6	26.3	26.3	26.7	27.0	26.7	26.6
		std	5.9	5.6	5.5	5.3	5.4	5.2	5.3	5.2
		min	13.8	14.1	14.5	14.6	14.6	14.9	14.1	14.4
		max	37.5	37.6	37.1	37.7	37.0	38.3	37.1	38.0
$q_{2.5\,\mathrm{m}}$	$\mathrm{g\,kg^{-1}}$	mean	9.4	9.4	9.0	9.0	8.9	8.8	9.0	9.0
		std	1.4	1.4	1.2	1.2	1.2	1.2	1.2	1.2
		min	5.2	6.4	6.0	4.4	4.8	6.4	0.0	6.6
		max	29.1	26.0	17.1	25.0	19.0	13.4	19.8	16.9
$U_{\mathrm{h}\,7.5\,\mathrm{m}}$	$\mathrm{m\,s^{-1}}$	mean	0.7	0.5	0.8	0.7	1.0	0.9	1.1	1.1
		std	0.7	0.5	0.7	0.6	0.8	0.8	0.9	0.8
		min	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
		max	6.1	5.7	6.1	6.8	6.9	6.7	7.0	7.4

One issue we encountered, particularly when applying the LCZ method to the parent grid at a coarse resolution of $20\,\mathrm{m}$, is the gap-filling of terrain and building grid boxes performed by PALM-4U. While this gap-filling is an important preprocessing step for the PALM-4U model, it prevents us from using the exact building shapes we designed. We observed that narrow street canyons became blocked, rectangular footprints were altered into arbitrary shapes, and small courtyards formed within

650   building areas. The source of this problem is that street canyons that are only one grid box wide are considered too narrow by the PALM-4U model. Conversely, we cannot use additional grid boxes at coarse resolutions, as this would result in excessively wide street canyons. Our intention in creating the LCZ4PALM method was to design regularly shaped buildings at coarse resolutions and to prevent the usual clustering of dense building areas into one continuous mass. However, running the model at such coarse resolutions remains challenging, and we must accept that, in the simulation, the buildings and street canyons do

655   not take the shapes we intended.
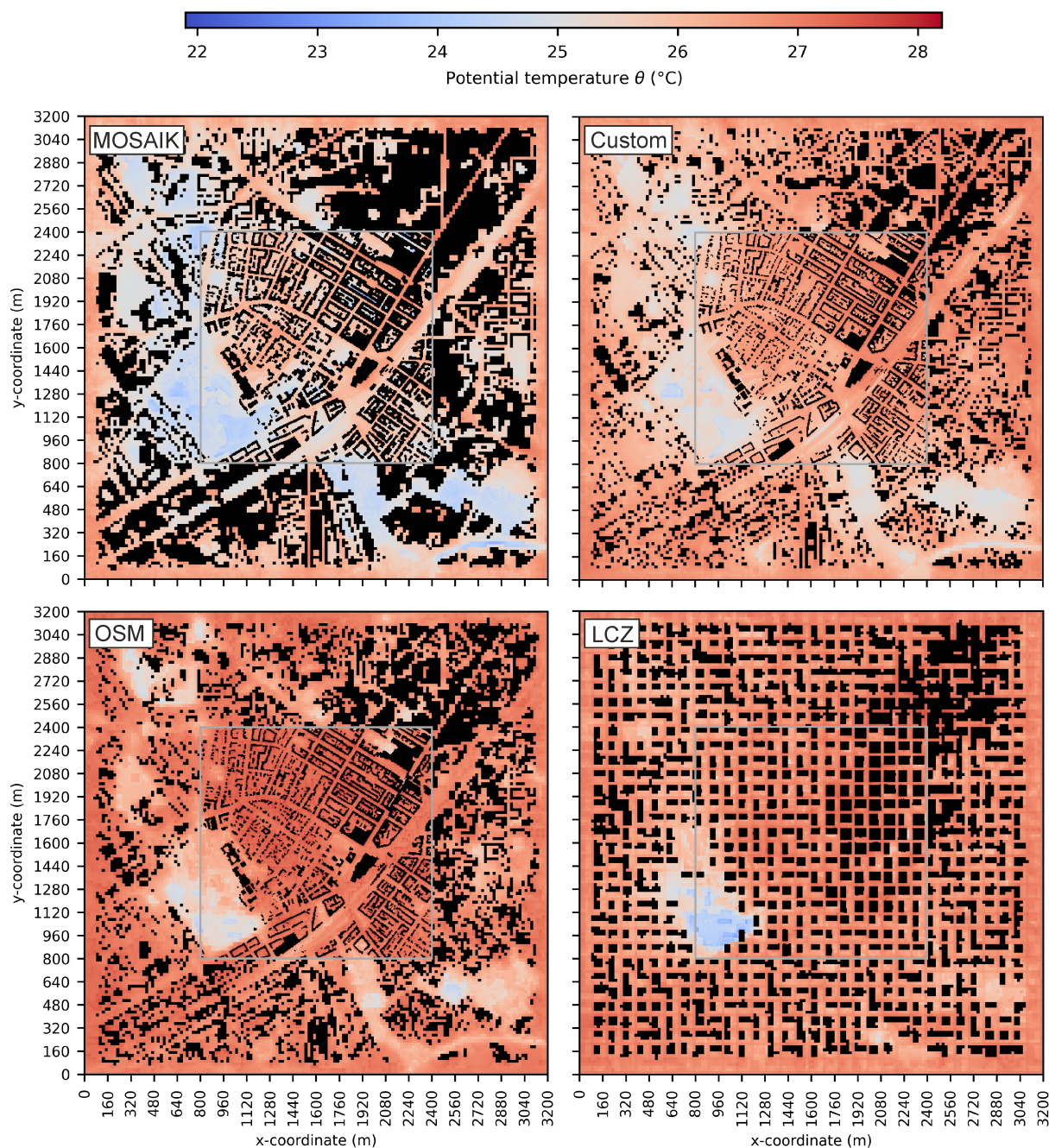
Figure 19. Comparison of time-averaged potential temperature θ evaluated at $h_{\mathrm{AGL}} = 2.5\,\mathrm{m}$.
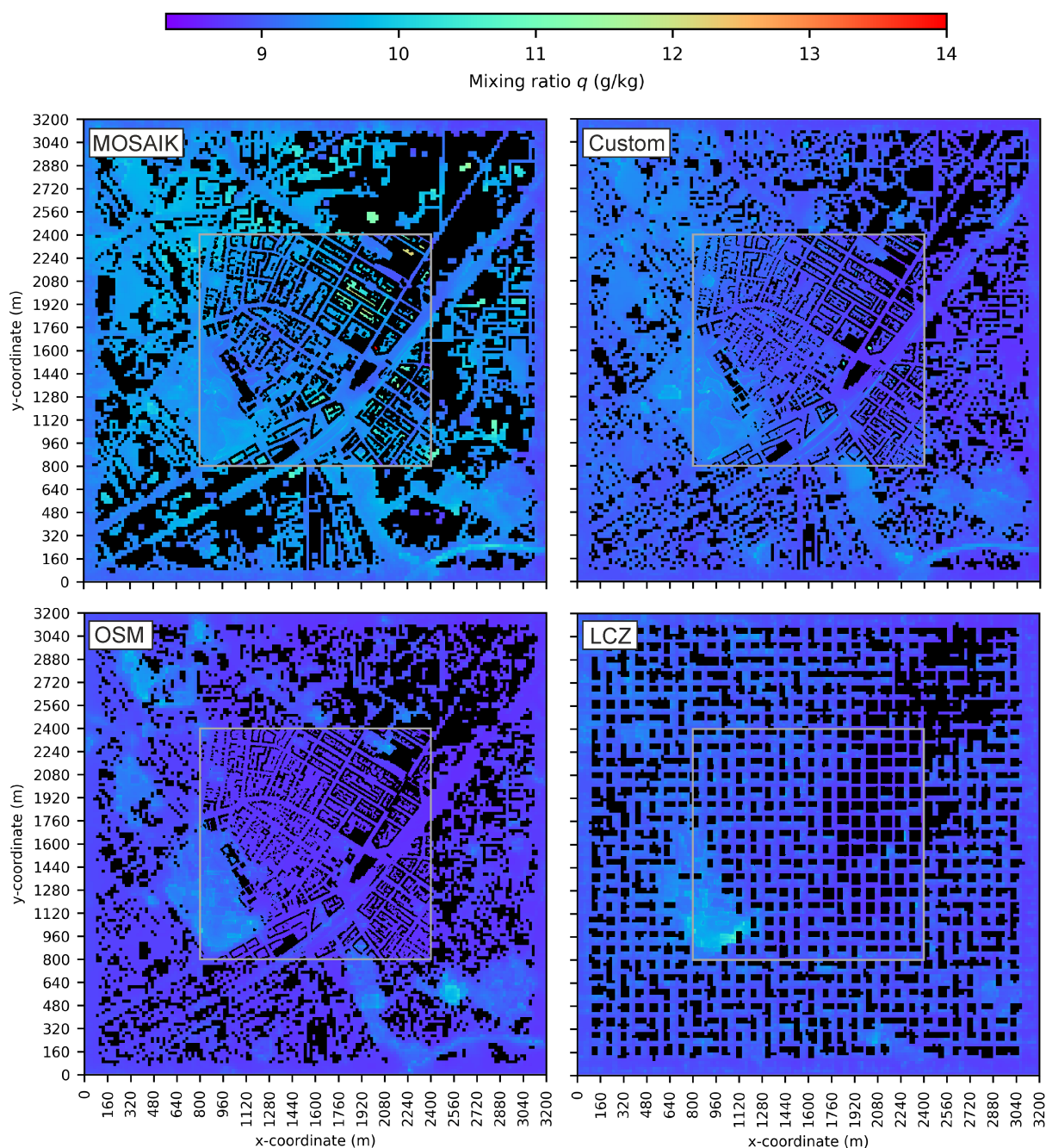
Figure 20. Comparison of time-averaged mixing ratio q evaluated at $h_{\mathrm{AGL}} = 2.5\,\mathrm{m}$.
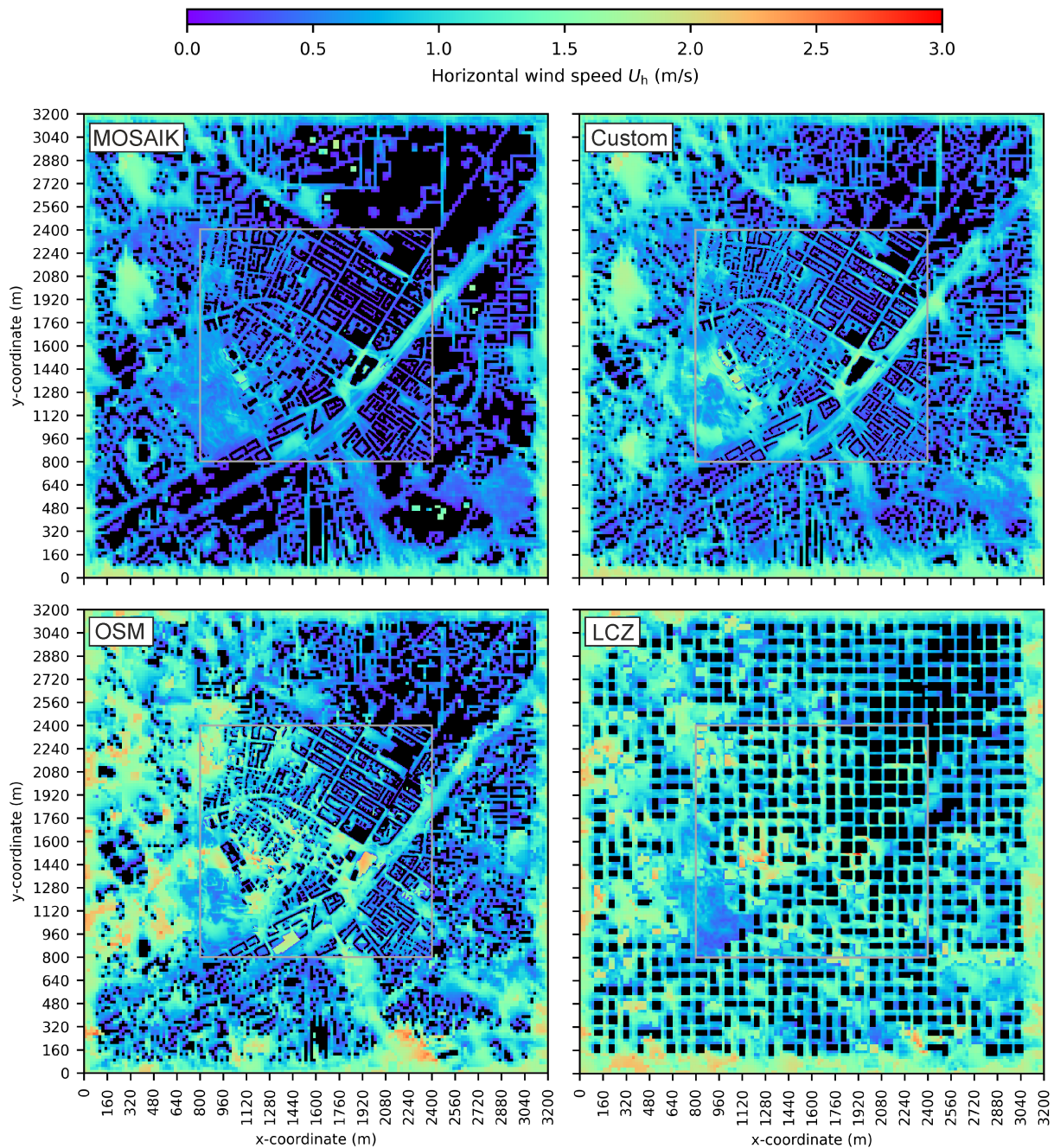
Figure 21. Comparison of time-averaged horizontal wind speed U_h evaluated at $h_\mathrm{AGL} = 7.5\,\mathrm{m}$.

Regarding temperature, humidity, and wind speed, we observed notable differences among the test cases.

Examining mean temperatures in the nested domain, we find 25.6 °C for MOSAIK, 26.3 °C for Custom, 27.0 °C for OSM, and 26.6 °C for LCZ. There is a clear increase in temperature from MOSAIK to Custom to OSM, with LCZ falling between Custom and OSM. The parent domain shows a similar trend. The minimum temperatures are lowest in MOSAIK, followed by

660 LCZ, Custom, and OSM. Maximum temperatures exhibit more variability between the parent and nested domains.

Humidity shows the largest divergence among the test cases and between the nested and parent domains. The mean humidity is particularly high in the MOSAIK case at $9.4\,\mathrm{g\,kg^{-1}}$, compared to the other cases, which range from $8.8\,\mathrm{g\,kg^{-1}}$ to $9.0\,\mathrm{g\,kg^{-1}}$. This is likely due to the higher vegetation density in the input data. MOSAIK also produces extreme maximum humidity values of up to $29.1\,\mathrm{g\,kg^{-1}}$, which seem unrealistic. Conversely, the LCZ case exhibits extremely low values, down to $0.0\,\mathrm{g\,kg^{-1}}$.

665 However, such physically unrealistic values were observed only in rare instances in space and time. Their occurrence was limited to only one or two output time steps at sunrise or sundown and only a few grid boxes in narrow street canyons or courtyards, particularly in conjunction with an abundance or absence of vegetation nearby. For example, the low humidity in the LCZ case occurred only in one output time step and in a single grid box that has a paved surface beneath and is surrounded by tall buildings. Although it is advisable to avoid narrow street canyons or courtyards, preventing them in practical workflows

670 is challenging, especially at relatively coarse resolutions.

Wind speed is generally lowest in the MOSAIK case, followed by Custom, OSM, and LCZ. This trend may again be attributed to vegetation density, which is highest in MOSAIK and lower in OSM and LCZ. Additionally, the OSM and LCZ cases partially or fully utilize approximate building heights derived from coarse global datasets, and their terrain elevation data is less accurate compared to the more precise representations in MOSAIK and Custom.

675 Interestingly, the OSM and LCZ test cases, despite being automatically generated and using approximations, yield results comparable to the heavily preprocessed MOSAIK and Custom cases. In the LCZ case, while the local distribution is less realistic due to unresolved buildings and streets, areas like the botanical garden in the lower-left of the nested domain are well represented. Despite geographic precision shortcomings, the overall results of the LCZ case compare surprisingly well to the other cases.

680 The main question remains: which dataset most accurately represents the selected district, and how can we further improve data quality? Each test case has its advantages and disadvantages. The MOSAIK case utilized extensive data and underwent significant preprocessing, yet it overestimates building footprints and underpredicts temperature, suggesting an excessive amount of vegetation or that PALM-4U overestimates vegetation impact. The Custom case, designed by an expert, benefits from more accurate building footprints and less vegetation cover, leading to reduced temperature underprediction near the surface. The

685 OSM case, fully automatically processed, features similar building footprints to the Custom case but significantly less vegetation, resulting in the highest overall temperatures. Wind speeds are also higher than in the MOSAIK and Custom cases, likely due to differences in vegetation, building heights, and terrain elevation. Finally, the LCZ case, also automatically processed, shows relatively high temperatures and the highest wind speeds, with variations in building heights, footprints, and distribution impacting both temperature and wind speed results. Similar to the OSM case, differences in terrain elevation and vegetation

690 density also play a role.

Overall, this research indicates that the outcomes of realistic urban microclimate simulations depend strongly on input data. Different data sources for the same test case can yield varying results, yet the outputs do not diverge excessively. Although the test cases were selected for diversity, the overall features of the microclimate simulations are similar, with no extreme outliers in the comparison statistics, except for the described instabilities regarding humidity in certain locations.

4   Conclusions

In this study, we presented SanDyPALM, an innovative toolkit designed to streamline the creation of static and dynamic input data for the PALM-4U model, thereby enhancing realistic microclimate simulations.

We introduced two novel methods, OSM2PALM and LCZ4PALM, which facilitate the generation of static drivers from widely available geospatial data sources. These methods enhance the accessibility and applicability of urban climate modeling, allowing for parametric studies and the creation of models on coarse grids where real building shapes cannot be resolved.

By comparing four static drivers derived from different sources—MOSAIK, Custom, OSM, and LCZ—we observed substantial variations in the representation of building footprints, vegetation, and pavement. The MOSAIK dataset, while rich in detail, tended to overestimate building footprints and vegetation, whereas the Custom, OSM, and LCZ datasets underestimated vegetation coverage.

The results of our simulations were validated against measurements from a weather monitoring tower and a weather station, revealing that all models captured the essential physical processes. However, notable discrepancies were observed, particularly in temperature and humidity. The PALM-4U models using MOSAIK and Custom data exhibited elevated nighttime humidity levels, likely due to their greater vegetation density. In contrast, the OSM and LCZ models, despite being based on approximations, produced results closer to measurements due to their lower vegetation density. This raises the question of whether the observed deviations stem from the amount of vegetation or the modeling approach used in PALM-4U.

In very rare cases, unrealistic humidity values were observed inside narrow street canyons or courtyards for a limited number of output time steps. This issue could be addressed by adjusting urban morphology or refining the humidity model in PALM-4U. Another challenge is that the urban morphology is altered by PALM-4U preprocessing to fill narrow street canyons and terrain, which modifies building shapes and closes off a substantial number of street canyons. Without changes to the PALM-4U model itself, it may be advisable to apply further terrain smoothing, enforce wider street canyons, or increase the grid resolution of the parent domain.

The results indicated that while expert-driven approaches, such as the MOSAIK and Custom datasets, provide detailed and accurate representations of urban environments, automated methods like OSM2PALM and LCZ4PALM can yield comparable results, offering a viable alternative when expert resources are limited.

Future research should focus on refining these automated tools and exploring additional data sources to further enhance the reliability of urban microclimate simulations.

Code and data availability. The code for SanDyPALM v1.0 (Vogel et al., 2025) is publicly available at https://doi.org/10.5281/zenodo.14772519. The code will be further maintained in the code repository https://gitlab.cc-asp.fraunhofer.de/upm/sandy-palm. The necessary input data is either included (if not openly available) or instructions are provided on how to download the data (if openly available). An exception is the "MOSAIK" dataset, which could not be included and is not openly available.

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