

Article

Automated Microclimate Model Generation from Remote Sensing Data

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Abstract

The ongoing climate crisis has highlighted the need for sustainability and resilience in the development and maintenance of urban areas regarding climate comfort. Weather simulation tools can aid researchers in understanding the effects that weather has on the microclimate in urban areas. While simulations are handled autonomously by computers once set up, the creation of the requisite input urban models is still a highly manual process. In this study, a novel method for the automated generation of urban models using land and cadastral remote sensing data is presented. By analyzing grass, trees, buildings, and roads algorithmically, data can be extracted and configured into spatial models compatible with microclimate simulation software such as ENVI-Met. Comparison to a baseline model shows that our method enables the creation of models fit for use for exploring microclimate scenarios in the urban environment, saving time by eliminating the need for manual processing.

Keywords: microclimate modelling; ENVI-Met; automation; volumetric modelling; remote sensing

1. Introduction

In the face of climate transition, the study of climate comfort in the urban domain plays a crucial role in building climate-sensitive urban spaces [1]. Both in academia and in the architecture and planning professions, there is today a great emphasis on individual comfort and urban retrofitting as strategies for adapting urban areas to a changing climate [2]. The morphology of urban spaces has an effect on weather on the local level, or microclimate. Stress from excess heat or cold can negatively affect at-risk groups [3], and poor indoor conditions have a negative effect on the occupants' health and performance [4]. Careful planning of buildings and vegetation, as well as their constituent materials, can shield people from the effects of weather and help reduce urban heat stress [5–7]. It is therefore important that researchers and practitioners develop an understanding of what impact both existing and proposed local morphologies have on the microclimate.

Databases and datasets for weather observations [8–10] enable access to city-scale weather data, but microclimate-level observations require local observations, which are often unpractical and cannot account for yet-to-be-realized urban spaces, nor future changes in weather patterns. Instead, current and future urban scenarios can be explored by creating microclimate condition scenarios using microclimate simulation software, such as OpenFOAM [11], TUF-3D [12], MUKLIMO_3 [13], UMEP [14], or ENVI-Met [15], the latter of which is the simulation software used in this study. With a long history in the research



Academic Editors: Soheil Sabri and
Thomas W. Sanchez

Received: 31 December 2025

Revised: 6 February 2026

Accepted: 10 February 2026

Published: 14 February 2026

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community, ENVI-Met has been validated against real-world measurements in numerous studies [16–19].

However, microclimate simulations require specific input datasets to be set up, such as macro-scale weather conditions, location and temporal data, and spatial data pertaining to the urban environment, which needs to be carefully modelled. Time and location data are straightforward to set up, and for defining weather conditions at simulation boundaries, either basic constants are often used, or historical observations such as the Typical Meteorological Year, or TMY, weather data [10]. Site model construction requires a more involved setup. Modeling the physical environment encompasses much more than the act of constructing models, and modelers need to understand phenomena in the real world, know what phenomena to select for, and how they should be translated into a model representation [20]. Digital models of urban spaces for microclimate simulation can be created manually through a number of means, such as with the site creation tools Monde and Spaces bundled in the ENVI-Met suite. However, the modelling of urban environments can be rather time-consuming, particularly if the creation of site models is done by hand-modelling features measured on-site.

Plugins are available for other modeling software, such as the GIS application QGIS [21] and Grasshopper, a programming language and accompanying suite for the CAD program Rhino3D [22]. Modeler involvement varies greatly with the different modeling strategies, as does the amount of prepared data. For instance, microclimate simulation tools like Dragonfly [23], part of the Ladybug Tools suite [24], or Morpho [25], both offer tight integration of Rhino3D and Grasshopper with both OpenFOAM and ENVI-Met, enabling researchers and practitioners to define custom scenarios and iterate over CAD designs, such as in a study by De Luca et al. [26], who used the Ladybug Tools suite to develop a workflow for assessing the impact of building clustering variations on both indoor and urban microclimate.

Similarly, Pacifici and Nieto-Tolosa [20] conducted a comparative study between ENVI-Met and a Grasshopper setup utilizing Dragonfly, Honeybird, and Ladybug. They found that the grasshopper definitions ran faster than ENVI-Met for the same area, but ENVI-Met requires less work out of the box. By contrast, Grasshopper is more open-ended, enabling, but requires customizations that widen the areas of application. The authors concluded that ENVI-Met is more suitable for simulations on a more detailed scale, while the simpler simulations of the Grasshopper setup allowed for faster simulations of larger areas. However, as this approach interfaces through a visual programming language and a CAD environment, the approach requires researchers and practitioners to be familiar with both 3D CAD modelling and visual programming. Automating the generation of site models, meaning that the models are constructed by a computer program once desired features are specified, can therefore be beneficial, as researchers and practitioners do not require domain-specific hand-modelling knowledge, nor need to invest time in site model construction. This can especially be beneficial in rapid prototyping and exploration scenarios, where several models are iterated over before the construction of a more highly detailed final model [27].

3D computer representations of urban spaces have numerous applications and have therefore long been a topic of interest for researchers, and numerous studies have presented solutions for site model generation [28]. For instance, Župan, Vinković, Nikçi, and Pinjatela [29] presented a semi-autonomous method for creating 3D building meshes in urban settings using readily available digital elevation model and Digital Terrain Model, or DTM, data.

Comparatively few methods of site model generation are intended for the purposes of microclimate analysis. Heldens et al. [30] remarked that the lack of direct interfaces between remote sensing products and microclimate models was mainly due to the latter being aimed at ideal representations of real-world scenarios. Type, accessibility, and quality of data differ across the world and domains of endeavor. While projects such as OpenStreetMap [31] enable widespread access to publicly sourced geodata, sources often lack data crucial for microclimate site models, such as detailed height and vegetation data. For instance, LiDAR (Light Detection and Ranging) data is usually of high quality and can yield detailed models, but may not always be available, and methods that utilize it as a data source cannot therefore be deployed where this data source is lacking.

Models also require various amounts of pre-processing work. Depending on factors such as input datasets, implementation details, or end-use, methods can require either no pre-processing [32] or preprocessing steps such as the establishment of a dataset of prior examples separate from the input data for the model, a corpus, to assist classification [33]. As access to different types of data sources, scales, and areas of applications for the resultant site models can differ greatly, proposed methods show great diversity in input and output shape, and method makeup. For instance, the well-established WUDAPT framework is a series of tools for meso-scale urban analysis [33]. The project covers multiple scales, providing from L0 scale, a more typological view, down to L2, with coverage complete with footprints, envelopes, and building heights, although available coverage of the latter is sparse. In their main L0 scale, they engage local experts to classify sample areas, which are then used as a corpus for extrapolation over the whole area of interest via Random Forest. The resulting dataset is then combined with a set of parameters describing the characteristics of an area, yielding models suitable for urban analysis [33]. Gill et al. [32] presented a method for the generation of ENVI-Met site models via preexisting 3D visualization models. Moreover, they also presented a method for visualizing the results of the studies on the base 3D geometry. Heldens et al. [30] implemented an automated approach for the creation of ENVI-Met models using hyperspectral 4 m/pixel land data together with a stereo camera-derived 1 m/pixel digital elevation model data. Katal et al. [34] utilized a mixture of data sources: OpenStreetMap, Google Earth, and deep learning-generated footprint data for North America from Microsoft, to semi-automatically construct urban site models for microclimate analysis in CityFFD. Notably, the authors combined this approach with a dataset of likely building properties to extend their model towards building energy analysis.

In this paper, we aim to contribute to this inventory of approaches by presenting a method, to our knowledge not accounted for by existing methods, for the automated generation of digital site models based on a hybrid approach utilizing multispectral and height orthophoto raster data in conjunction with cadastral building footprint data. In Section 2, we introduce a method for the automated generation of site models suitable for microclimate simulation from land and cadastral data, more specifically, images in RGB and infrared, height images, and building footprint vector data. In Section 2.3, a case study site is presented, and site models are created both using our tools and through conventional means with the ENVI-Met Spaces software. Together with TMY weather data for winter and summer conditions, four scenarios are set up and run through ENVI-Met, producing four simulation results. Both the geometry of the site models and the results of the simulations are analyzed in Section 3. A comparison between the state of the art of microclimate model generation and our proposed method is presented below:

Table 1. Qualitative assessment of studies performed in ENVI-Met.

Study	Elnabawi, Hamza, and Dudek [19]	Krüger et al. [18]	Liu et al. [17]	Ayyad and Sharples [16]	Ours
Year	2013	2011	2024	2019	—
Site	Al Muizz, Cairo, Egypt	Curitiba, Brazil	Dongguan, Guandong, China	Al Ahliyya Amman Univ., Jordan	Porsön, Luleå, Sweden
Urban Makeup	Closed Street	Open Street	Courtyard	Campus	Open, Urban
Cell Size	1 m × 1 m × 3 m	6 m × 6 m × 3 m	1 m	1 m; 2 m (similar perf.); 3 m (too coarse)	2 m
Area Size	30 m × 140 m × 30 m; 30 m × 88 m × 30 m	1380 m × 360 m × 90 m	240 m × 200 m × 40 m; 140 m × 140 m × 40 m	60 m × 60 m, height > 18 m	732 m × 598 m × 46 m
Telescoping	20% after 25 m	—	—	No	20% after 26 m
Temperature	Good, undershot	—	Good	Good, undershot	Good
Wind	—	Good under 2 m/s, overestimated over 2 m/s	Good	Low variance in simulated wind, high variance in real-world measurements	Good, some variance between models
Humidity	Good, overshot	—	Good	Low correlation	—
Solar	—	Possibly Overestimated	—	—	Good, undershot
Weather Boundary Input	Weather Station on-site	Remote Weather Station, adjusted for cityscape	Remote Weather Station; RH, Irradiance Calculated	EPW, Remote Weather station, adjusted for urban cityscape	TMY EPW, Remote Weather Station

Assessments of ENVI-Met models are generally performed against on-site measurements. Depending on available data and purposes for the studies, different studies generally prioritize different metrics and aspects of both microclimate models and their resulting output. In comparison to studies assessing ENVI-Met (Table 1), we simulated a relatively large area, but with a typical cell size. Ayyad & Sharples [16] found that models with cell size sides of 1 m, respectively 2 m, performed similarly with regard to temperature, while models with cell size sides of 3 m lost resolution and performed erratically. Conversely, Krüger et al. [18], who mainly utilized ENVI-Met for wind assessment, found that cell sizes below 6 m × 6 m × 3 m did not improve accuracy. All studies got their boundary conditions from remote weather stations, but since the other studies were comparing against on-site data, only our study used typical mean year data. Temperatures generally followed on-site measurements in the studies, with our two models only showcasing minor differences. In the studies, wind speed was generally well simulated by ENVI-Met, with some caveats: Kruger et al. [18] found that the simulation overestimated wind speeds over 2 m/s, while Ayyad & Sharples [16] noted that ENVI-Met did not capture real-world variance in wind patterns but was closer to averaged measurements. Our models performed similarly, but with some variance throughout the models. Few studies assessed humidity, with mixed results. Elnabawi et al. [19] and Liu et al. [17] found that ENVI-Met generally performed well, while Ayyad & Sharples [16] did not find much correlation between ENVI-Met and observed values.

In comparison to earlier studies concerned with the generation of site models for microclimate studies, our method required relatively little preparation, especially in comparison to our base case, manual construction in ENVI-Met Spaces (Table 2).

Table 2. Comparison between microclimate simulation site model generation techniques. The columns describe the studies, datasets used, estimated amount of manual involvement required, intended scale of simulation for the site models, and the simulation software the method is intended for.

Study	Input Datasets	Manual Involvement	Scale	Engine
Ching et al. [33]	Coarse dataset: Landsat and expert observations, detailed: third parties	Low to High	Meso-scale	Custom
Gill et al. [32]	Vector geometry, land usage data, manual observations	Medium-High	Microscale	ENVI-Met

Table 2. *Cont.*

Study	Input Datasets	Manual Involvement	Scale	Engine
Katal et al. [34]	OpenStreetMap; Microsoft Footprint; Google Maps; thermal, energy perf. and usage archetypes	Medium	Macro- to Microscale	CityFFD
Heldens et al. [30]	Hyperspectral aerial data, DEM for buildings, Lookup Tables for Vegetation.	Low	Microscale	ENVI-Met
Ours, Automatically Generated Model	Building Footprint vector, RGBI Orthophoto, DEM	Low	Microscale	ENVI-Met
Ours, Manual Model	Orthophoto, on-line and on-site measurements	High	Microscale	ENVI-Met
Pacifici and Nieto-Tolosa [20]	n/a	High	Microscale	ENVI-Met, Ladybug suite
Kastner and Dogan [35]	n/a	High	Any	OpenFOAM
Di Nunzio [25]	n/a	High	Any	ENVI-Met
Galanos and Roudsari [23]	n/a	High	Any	OpenFOAM

Preparation amount between methods depends greatly on the underlying datasets, and is to some extent a question of demarcation, as different data sources have already been preprocessed to certain extents. In the method presented by Katal et al. [34], the share of manual work is relatively high, as they use a number of data sources, OSM maps, footprint data from Microsoft [36,37], and building heights from Google Earth. While several steps of the method are automated, e.g., the fetching of building height data is fetched via an API provided by Google Earth, and site models are constructed via refinement of input data, rather than hand-modelling, model generation is moderately complex, as several steps are done in a variety of software suites. In addition, the authors relied on datasets for building thermal and energy performance, and building use, estimated based on age and building typology. The modelling process is somewhat involved in the method presented by Gill et al. [32]. The base site model is constructed using 2D vector data, but as the underlying dataset is not detailed enough, the site model is then edited manually, adding properties such as correcting region types or adding vegetation. As the method use case is for situations requiring 3D vector models intended for visualization, in addition to microclimate simulation, the resulting model can be highly detailed. The final microclimate model is then automatically derived from this 3D vector model, with only a few metadata properties having to be additionally defined. The authors specify that the use case for their method is in situations where the modelled buildings are being visualized as well. The method presented by Heldens et al. [30] is relatively automated in comparison with other methods. The authors relied mainly on hyperspectral data to generate the models, able to model roof textures well with the high spectral data afforded by the hyperspectral dataset, with building heights being derived from DEM data and greenery approximated via lookup tables. WUDAPT by Ching et al. [33] is more of a framework for the construction, assessment, and distribution of maps rather than a method. Nevertheless, they have similar goals and offer digital site models for microclimate analysis. As part of their framework, they offer ready-made site models of different scales, although at the most detailed scale, comparable to the other studies, their coverage is limited to a few cities. On the coarsest level, the authors use a mixture of mainly Landsat and Google Earth data, and input from local experts to estimate dominant local typologies [38]. As such, the amount of work required for usage of the dataset depends upon whether the area has been covered previously or if new classification is required. At the time of writing, the higher

levels of the dataset are only available as third-party datasets [39] and thus require a larger amount of work for use.

As Morpho [25], Butterfly [23], and Eddy3D [35] are plugins, they need custom definitions to be able to output models. The ultimate target of most studies was ENVI-Met. Studies that opted for other targets mainly used tools in conjunction, such as both of the Ladybug-compatible computational fluid dynamics plugins, Butterfly and Eddy3D, which both utilize OpenFoam. WUDAPT presented their own solution [33], and Katal et al. utilized CityFFD [34,40].

One of the main differences between methods for the automated generation of micro-climate models is the variation in required input data, making the different approaches suitable for use in different scenarios and depending on what datasets end users have access to. Ching et al. [33] relied on satellite data to produce meso-scale models, suitable for large-scale studies. Our proposed method utilizes data from the same data source. This can be beneficial in situations where such high-quality datasets are available, but in situations where this is not the case, it can be beneficial to use a mix of commercial and freely available datasets, such as Katal et al. [34]. Gill et al. [32] relied on 3D model data for site model construction. This can be beneficial in certain scenarios, such as new development scenarios, where a new cityscape has been proposed but not yet built. Conversely, in situations where aerial surveys have been conducted but buildings not fully modelled, the technique would require a significant amount of work constructing the required 3D model. The method by Heldens et al. [30] used hyperspectral data, making their method suitable in cases where end users have access to hyperspectral datasets. The framework approaches [20,23,25,35] benefit from not being connected to a particular set of input data, although requiring end users to manually create the software method for adapting their chosen input data to the respective frameworks instead. Out of the methods compared, only our modelled ground elevation.

2. Materials and Methods

In this study, we propose a method for the creation of digital raster site models from readily available cadastral data and orthographic land data through a number of categorization steps. The method is implemented as a Python-based application, freely available under the MIT License.

The general flow of the method can be described as six steps, progressively building up a site model (Figure 1), and is described in greater detail in Sections 2.1 and 2.2. The input data consists of 3 distinct datasets: Building Outlines, in vector format; RGB + Infrared, orthophotos in raster format; and Height Data, Digital Elevation Model orthophotos in raster format (Figure 1a). The input datasets are refined by a series of algorithms: the Building Outlines are rasterized and used to separate buildings from non-buildings. Greenery information is extracted from the input through the use of the well-established Normalized Difference Vegetation Index, or NDVI, with the ratio between red and infrared light in orthophotos to separate greenery from non-permeable surfaces. Originally described by Rouse et al. [41], NDVI is today the most popular index used for the purposes of vegetation assessment [42]. On-ground/off-ground pixels are classified via Cloth Simulation Filter [43] classification, allowing for the separation of ground and non-ground objects such as buildings and trees. The operations result in 3 Boolean filters: Inside Building, Above NDVI Threshold, and Off-Ground (Figure 1b). Based on the classifications, pixels in the input are classified as either Roof, Vegetation, Soil, Asphalt, or Errors via Boolean logic (Figure 1c). The DTM is then reconstructed from the height data. Height values of pixels with Roof, Vegetation, or Error classifications are discarded and replaced with values linearly interpolated from the height values for Soil and Asphalt-classified pixels (Figure 1d).

The datasets are then optionally rotated, cropped, and scaled down. Metadata, such as city, location, and time zone, are added (Figure 1e). Finally, the datasets are combined and encoded into the 2.5D INX file format used by ENVI-Met (Figure 1f).

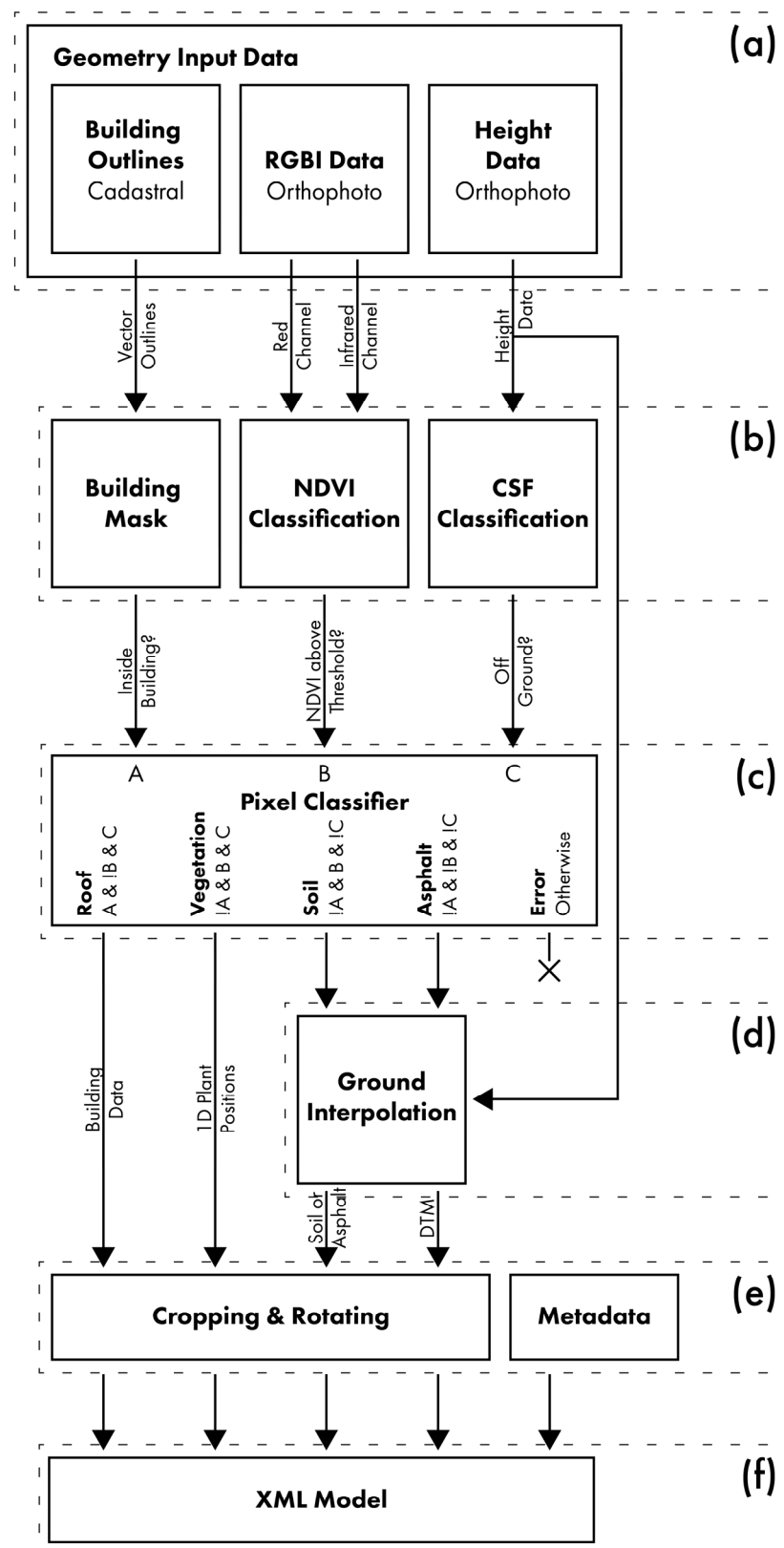


Figure 1. Description of method workflow. The input data (a) is refined and classified (b), the site classifications are constructed (c), missing ground interpolated (d), metadata added, and site model is scaled, cropped, and rotated (e), and written out into output file (f).

2.1. Site Model Generation

Microclimate simulation software such as ENVI-Met requires its input spatial model data to be meaningfully separated and structured, and input data therefore needs to be reworked to a suitable format. Our method works on 2D raster arrays of multispectral and height data, as well as vector data in the shape of outlines of the buildings in the area. The output of the model is an INX-file, describing the geometry of a simulated area. The input data and the output INX-file both consist mostly of 2D arrays of geometric data. However, while both describe data that is commonly found in the urban landscape, such as buildings, ground, and trees, the input datasets cannot be transformed into the output without processing. We therefore produce the final structured model by applying a series of steps to the input data. To separate the data, a classification mask is constructed. This mask is then applied to the dataset, yielding arrays containing the desired features. The mask is derived from the input data through a series of steps:

NDVI filter—In order to separate out greenery, NDVI values are calculated using the red and infrared channels of the orthophoto.

$$NDVI = \frac{NIR - Red}{NIR + Red}$$

The index spans from -1 to 1 . As leaves' chlorophyll absorb red light while their mesophyll scatters infrared light, a low NDVI value indicates an absence of vegetation while a high value indicates a high amount of greenery [44]. While NDVI suffers from saturation and is less sensitive to detecting differences between very dense vegetation [42], our model only detects differences between greenery and non-greenery. The NDVI values are calculated for every pixel in the input orthophoto. Pixels with NDVI values below a threshold value of 0 are treated as non-vegetation, and values equal to or above 0 are treated as greenery.

Building Outline filter—To be applicable for use as a filter, the vector outlines of individual buildings are rasterized, providing a raster denoting both pixel occupancy and an index of the buildings on the site. As both the raster and vector data are geographically indexed, the two datasets can be overlaid. A 2D array of the same size and location as the orthophotos is created, and for each building outline in the dataset, the pixels inside the outline are given a unique, ascending number that corresponds to the given building.

Cloth Simulation filter—The input height data is a digital surface model, or DSM. Rather than simply containing height values for the terrain in the area, the height data also contains objects such as trees and houses. To define the terrain in the model, the DSM needs to be converted into a DTM. To filter out ground and non-ground pixels, a Cloth Simulation Filter is applied. The method filters out the ground by turning the height model upside down and simulating a cloth being dropped down on the (now inverted) height data [43]. The filtering method was run for 500 iterations, without smooth slopes, a rigidity of 1 , at a cloth resolution of 0.75 , and with a classification threshold of 0.75 . The resulting filter denotes pixels in the model that are split between on-ground pixels and off-ground pixels (Figure 2).

The three input A, Building Outline; B, NDVI; and C, Cloth Simulation filters are combined using Boolean logic to create a classification mask denoting which pixels in the model belong to which respective category: houses (A & not B & C), trees (not A & B & C), permeable surfaces such as soil (not A & B not C), or non-permeable surfaces such as asphalt (not A & not B & not C) (Figure 1). An additional category, errors, denotes pixels that could not be properly classified. As the model used in simulation is fully 3D while the input data is 2D, some additional processing of the data is required. A continuous ground height map is constructed using the input height data and the classification mask.

Height values of pixels considered asphalt or grass are considered canonical and copied verbatim, while pixels considered trees, houses, or errors are considered obstructed and instead get height values linearly interpolated from surrounding values. For this study, the water source feature of ENVI-Met was not used, as ascertaining what pixels in the input images were water would be challenging.

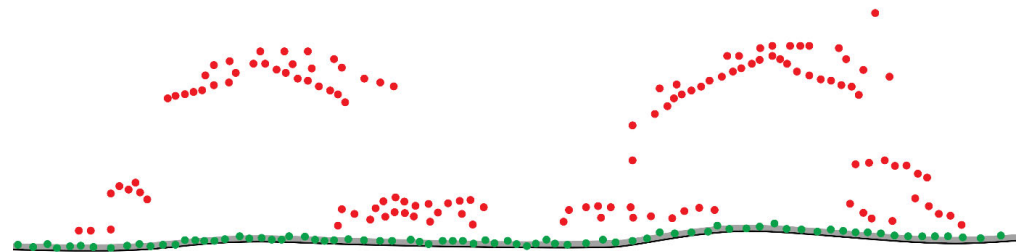


Figure 2. Illustrated section of the cloth simulation filter principle. The pixels within the boundary (green) of the simulated cloth (black) are considered ground (green), while the pixels further away are considered to be above ground (red). Based on data © Lantmäteriet.

2.2. ENVI-Met Integration

Due to the complexity of the simulation performed by ENVI-Met, there is often a need to have a much coarser resolution than the resolution of available orthophoto raster images. ENVI-Met uses Arakawa C-grids for its simulation, and typical simulation model resolutions span between 0.5 m and 5 m [15]. The relatively coarse resolution can cause issues with simulations if buildings are unaligned with the directions of the volumetric grid, creating a stairstep effect. To lessen the chance of errors, models are often rotated to align the grid with the majority of building facades [45]. The raster arrays are optionally rotated, cropped to final dimensions, and scaled down to the desired level of detail. The INX file format used by ENVI-Met is based on the Extensible Markup Language, or XML [46]. It describes all geometry present in a simulation, as well as some supplementary information, such as location and time zone, and technical settings for the model. The ENVI-Met authors recommend some distance to be given between the geometry in a model and model boundaries, as the simulation is less accurate at the boundaries. This is either done by the addition of grids at the edges of the model geometry, or it is handled by ENVI-Met at simulation time, by adding boundary cells with increasing distance between them [47]. In our model, the horizontal case is handled by the addition of empty cells at geometry boundaries, while in the vertical case, ENVI-Met's built-in telescoping feature is used. To ensure enough space for the model, the highest point in the model is found and multiplied by 3. Material properties, plants, soils, and coverings are not included in the INX file. Instead, ENVI-Met utilizes reference libraries. When such a description is required, a reference string points to the desired entry in the library. The respective fields of the model are then filled out: In the INX format, buildings can either be represented as 3D volumetric shapes or as simpler 2D arrays of columns that only define the top of the building and possible overhangs. Due to the nature of the input height data, only the height of the buildings can be ascertained. Buildings are therefore encoded in the "2.5D" representation and thus require four 2D arrays: (A) the height of the top of the buildings, (B) the height of any building overhangs, (C) individual buildings' indexes, and (D) whether building heights are measured from sea or ground level. Any column of cells in the volumetric grid that does not contain a building is represented by a value of 0 in arrays (A), (B), and (C).

The roof heights are rounded to the nearest integer and added to the array (A). Rather than encoding any real-world property such as block number or street address, the buildings' indices in (C) are given unique, ascending numbers used to differentiate the buildings from one another. As the existence of overhangs cannot be ascertained and the height of

the buildings denotes height above sea level in the input data, all entries in the arrays (B) and (D) are given the constant values throughout the arrays, 0 and 1, respectively. Similar to the case with buildings, plants are either described as “simple”, meaning 2D arrays where each cell describes a column of greenery, or “3D”, where discrete, instanced trees describe their whole canopy. As our model describes off-ground vegetation in a 2D array, the simple description format is more suitable. Pixels classified as off-ground greenery are denoted with a reference to a simple plant from the reference library, while pixels falling outside the classification are denoted by an empty string. Soils are described by a 2D array of soil reference strings. Our model distinguishes between greenery and non-permeable surfaces. The two types of ground material are mapped to soil and asphalt references from the library, respectively. As with roof heights, ground heights are rounded to the nearest integer and added to the model. ENVI-Met geometry models can include sources of particulate matter [48]. These sources are not considered by our model and are therefore represented by a 2D array of zeroes.

2.3. Case Study

To evaluate the performance of our method, we compared the simulation results of a manually constructed model with those of a model developed using our approach under two different weather scenarios. The area chosen for the case study is a section of Porsön, a suburb of the Swedish city of Luleå (Figure 3). With a latitude of 65.58° N, longitude of 22.15° E, Luleå is located in a subarctic climate, and the area is classified as belonging to the Dfc Köppen climate zone. In 2020, Luleå had 49,123 inhabitants [49]. The Porsön suburb has a medium-density suburban makeup and is of a Houses-in-Park [50] type of urban development, common in Sweden (Figure 3a). The central parts of the area are dominated by 8 5-story multi-tenant buildings and a small single-story commercial area, while the areas in the upper (North-Northwestern) and lower (South-Southeastern) parts of the area have 2-story multi-tenant buildings. Shallows are located to the right (Northeast), and a campus area of 2–3 story buildings is located to the left (Southwest) (Figure 3d,e).

2.3.1. Automated Site Model Generation

Using the described method, a site model of Porsön was generated. The spatial data for the project was provided through the Swedish Mapping, Cadastral and Land Registration Authority, or Lantmäteriet. Orthophoto data consisting of a series of multispectral aerial photographs was used as a base for the NDVI and height data calculations [51]. One RGB and Infrared image file provided the red and infrared bands required, with height data provided in a separate image file. The images were delivered in processed form, as 10,000 × 10,000-pixel orthophotos with a pixel density of 4 × 4 pixels/m², encoded in the Geotiff file format. Additionally, 2D vector building outline data was used for determining building placement. The vector data set used was the “Ytskikt med Byggnader” data layer shapefile, part of the “Fastighetskartan” cadastral data source provided by Lantmäteriet [52]. Both datasets used the Sweref 99 Transverse Mercator projection, EPSG:3006. The data was downloaded from an online portal, to which the data was delivered on 28 April 2021.

A 366 × 299 × 23 tile site model was generated by applying our developed method on the input data. The model rotation was set to 27.4° clockwise to align the majority of buildings in the model in the cardinal directions, and the cell size was set to 2 m in all directions. 2 m cell size has been found to perform similarly to 1 m cell size models with regards to temperature, whereas 3 m was found to lose resolution and perform erratically [16]. The “20 m Medium-density Tree” 1D vegetation type provided by ENVI-Met was deemed to be representative of the vegetation of the area and was placed at each pixel deemed vegetation by our method. Ground deemed permeable by the model was

designated as sandy loam, while non-permeable ground was designated as asphalt road, as this was the most typical ground covering in the area. Site model generation took 3 min and 40 s, running on Ubuntu 24.04 under WSL on a Windows 10 laptop with an Intel i9-11950H CPU and 64 GB of RAM clocked at 3200 MHz, using Python 3.13.

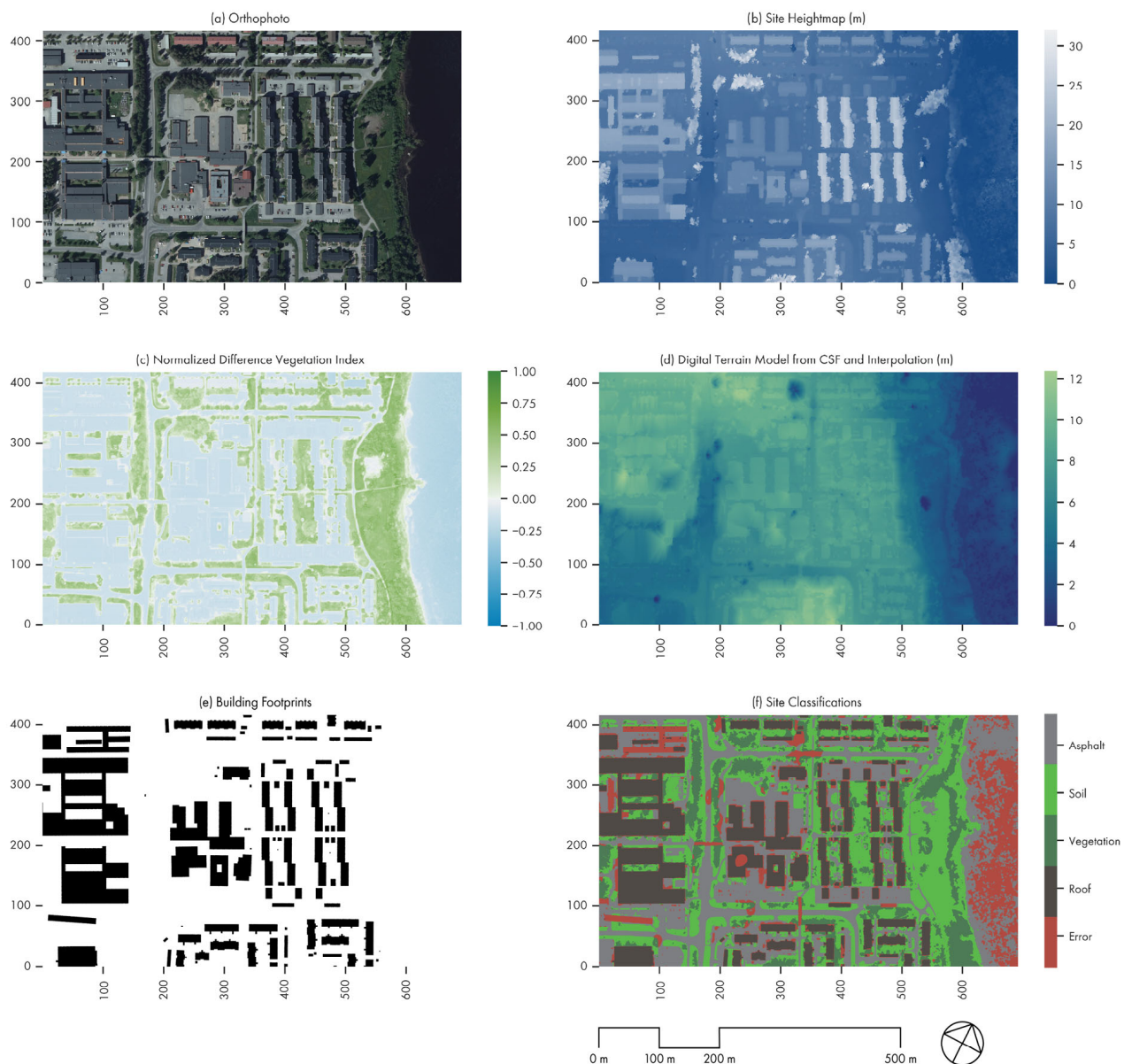


Figure 3. The chosen site, Porsön in Luleå, as (a) an orthophoto, and (b) Digital Site Model Heightmap, (c) Normalized Difference Vegetation Index, (d) DTM after applying the Cloth Simulation Filter and interpolating missing ground, (e) building footprints, and (f) the classification used as a basis for the generated model. Note that in comparison to other plots of the site, these plots are not padded. Based on data © Lantmäteriet.

2.3.2. Manual Site Model Construction

The manual model was constructed in ENVI-Met Spaces and derived from on-site and online measurements. Building heights were measured on-site with a laser rangefinder, with multiple measurements of the buildings taken and an average recorded. While commercial buildings were measured individually, representative measurements were taken of multifamily homes. Trees and greenery were photographed for use as reference. A site model of the same scale and size as the automatically generated model was developed in Spaces: The same orthophoto used for the automated approach was manually cropped,

rotated, and used as background for the model. Building positions were determined using the orthophoto and building heights were set based on the recorded readings. Ground elevation was sampled from the publicly available Min Karta online tool provided by Lantmäteriet [53], while soil coverings were read from the orthophoto. Heights were not sampled uniformly. Rather, areas that were found to have large changes in elevation were sampled more frequently. The same values as were used in the automated model were specified for deviation from north and coordinates for latitude and longitude. Finally, tree type, size, and position were determined from reference photographs, orthophoto, and on-site estimations. The trees in the model are a mix of 3D trees and 2D simple trees used for hedges. A comparison between the models can be found in Table 3.

Table 3. Settings and materials comparison.

	Automated Model	Manual Model
Width	366 tiles	366 tiles
Depth	229 tiles	229 tiles
Height	23 tiles	23 tiles
Tile Size	2 m × 2 m × 2 m	2 m × 2 m × 2 m
Telescoping Factor	20% after 26 m	20% after 26 m
Model Rotation	27.40° CW	27.40° CW
Coordinates	65.58° N, 22.15° E	65.58° N, 22.15° E
Timezone Longitude	CET/15.00° E	CET/15.00° E
Soil Types	Sandy Loam: 33,395 tiles Asphalt Road: 50,419 tiles	Sandy Loam: 62,325 tiles Asphalt Road: 20,219 tiles Gray Concrete Pavement: 879 tiles Dark Concrete Pavement: 131 tiles Granite Pavement: 260 tiles
Roof/Wall Types	Default Wall/Default Wall	Default Wall/Default Wall
2D Tree Types	20 m Medium-density Tree: 8527 tiles	50 cm Grass: 1010 tiles 1 m Dense Hedge: 812 tiles
3D Tree Types	—	15 m Cylindric: 449 trees 5 m Cylindric: 121 trees 15 m Conic: 92 trees 5 m Spherical: 35 trees 15 m Cylindric: 23 trees 5 m, Cylindric: 1 tree

2.3.3. Weather Data

Although ENVI-Met enables detailed simulation of weather conditions on an urban scale, it cannot simulate weather outside the bounds of the model. For the duration of the simulation, ENVI-Met either simulates boundary conditions that are in a simplified, constant format or more fine-grained. As with site data, inaccessibility of weather data can be a challenge [54]; however, efforts such as the Climate.OneBuilding.org repository enable access to city-scale weather data in a standardized way [8,9]. To allow for higher accuracy, observation-based TMY data were used for the simulations. TMY datasets are well-defined datasets of hourly observations of weather conditions typical for a given site [10]. To ensure the weather is representative of the conditions generally experienced on the site, a TMYx dataset provided by the OneBuilding repository was used. The datasets are compilations of typical weather compiled from historical weather observations, with each month in the dataset being based on the month from the year that had the most typical weather for that given month [8]. Observations from the nearby Luleå Airport, located at

65.54300° N, 22.11900° E, were used to ensure good proximity and coverage. To test the models in differing conditions, two days of the year were selected for simulation: the days of the summer and winter solstices. The typical year for June was in 2017, during which the summer solstice fell on the 21st. The highest temperature for the day was 13.1 °C at 17:00 in the afternoon, while the lowest temperature was 6.8 °C at 23:00. Humidity reached its highest at midnight, at 90%, while it was at its lowest 53% at 17:00. The typical year for December was 1975, in which the winter solstice fell on the 22nd. The highest temperature for that day was 0.6 °C at 01:00 in the morning, dropping to the day's coldest observed temperature of −5.3 °C at 23:00. Humidity was at its lowest at 04:00 in the morning, at 45%, but reached 61% two hours later at 06:00, the highest for the day. Weather data for the selected time ranges were converted to CSV format expected by ENVI-Met.

2.3.4. Simulation

Each site model was run through two simulations, once each with the summer and winter settings, respectively, totaling in 4 separate simulations. Full weather forcing was set up, using wind, air temperature, radiation, and relative humidity data from the weather dataset. For all cases, the in-simulation start time was set to 08:00, a total of 10 h being simulated for each model. The simulations ran in ENVI-Met version 5.7.1 on a Windows 10 desktop computer with an Intel i7 12700 CPU and 64 GB of RAM clocked at 4000 MHz. The simulation run time averaged around 49 h and 20 min. To facilitate evaluations of the data, ENVI-Met was configured to output data in NetCDF format [55], in addition to its own simulation format.

3. Results

3.1. Geometry Comparison

As the two site models were constructed independently, several discrepancies were to be expected between them. While the same value for rotation, cell size, and model dimensions were used in both models, and the models are constructed from the same orthophoto as base, the manual model was created by hand in ENVI-Met Spaces, and the models therefore differ slightly in their horizontal positioning. As the sides of the model are padded in both cases, this is unlikely to affect the simulations. To find a position where the two buildings align the most, various offsets between the buildings were tested, and the offset with the Mean Squared Error, or MSE, between the heights of pixels was the lowest and selected. Combinations of offset values between −20 and 19 were tested, finding that offsetting the automated model by 4 m, or 2 cells downwards in the vertical direction, and no offset in the horizontal direction produced the smallest MSE of 18.32 m², when compared to the roof heights of the manual model. By contrast, the MSE between the non-offset building height maps was 22.48 m².

Our developed method uses DEM sources for terrain construction. While the generated model is coarser than the input DEM, it is still significantly more detailed than a manually created model can be expected to be. When compared to our manually created site model, significantly more detail can be seen in the generated model (Figure 4). This is, however, somewhat mitigated by the fact that while the ground in the INX files is in meters, the simulation seldom uses as detailed cell sizes, requiring rounding. Due to errors in the input height data, our model contains several pits, visible as dark spots in the figure, as well.

The two site models largely concurred with regard to the classification of surface coverings (Figure 5). Some areas with non-permeable coverings were obscured by either tree crowns or roofs (in the case of carports) in the input orthophoto. This resulted in our model misclassifying the surfaces as permeable. As the manual construction was informed by on-

location observations, this could be avoided in the manual model, although with the caveat that this requires site visits, which might not always be feasible. Our method also misclassified certain areas, such as the erroneous pits and the periphery, as non-permeable.

Digital Terrain Model Comparison (m)

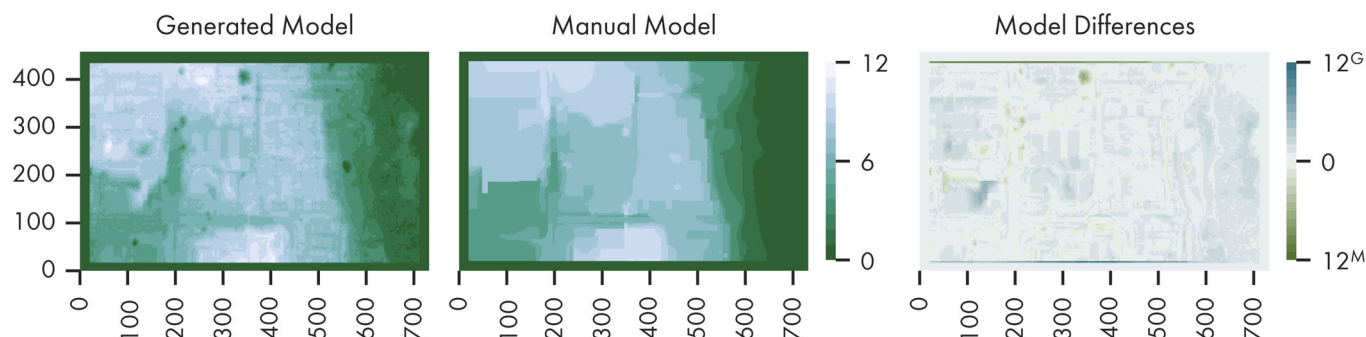


Figure 4. Heightmaps of both models, and their differences. The automatically generated model is situated to the left, and manually constructed model in the center. A map showing their differences is to the right, with blue representing higher values in the generated model (G), green in the manual (M). Due to the differing ways of construction, the automated model is more intricate than what can be reasonably expected from a manual model construction; however, due to errors in the input height data, several voids/areas where the ground is significantly lower/holes are present in the automated model. Based on data © Lantmäteriet.

Surface Covering Comparison

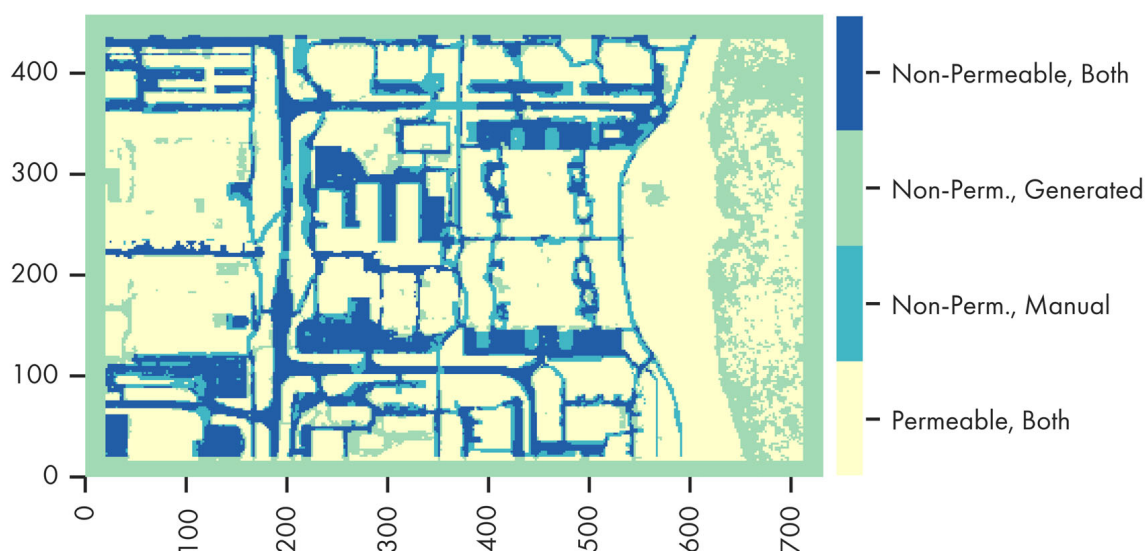


Figure 5. Surface covering comparison. Deep blue areas were marked non-permeable by both models. Green areas were determined non-permeable only by our method, while teal areas were marked as such only in the manual model. Yellow areas were marked as permeable in both models. Based on data © Lantmäteriet.

Building placement was fairly consistent between models (Figure 6). Building placement and size differed with nearly every building. Our method generally made buildings larger and more intricate, with more complex facades, taking balconies and similar items into account. Although this added to the detail of the model, the nature of the items was not discernible by the method, resulting in all additional surfaces being classified as solid building. Buildings were generally made equally as large in both models (Figure 7),

but some larger buildings differed significantly. This was mostly due to several of these buildings being built after the orthophoto scans had been taken, but before the cadastral data was gathered, resulting in our model having issues with classifying said buildings.

Building Footprint Mismatches

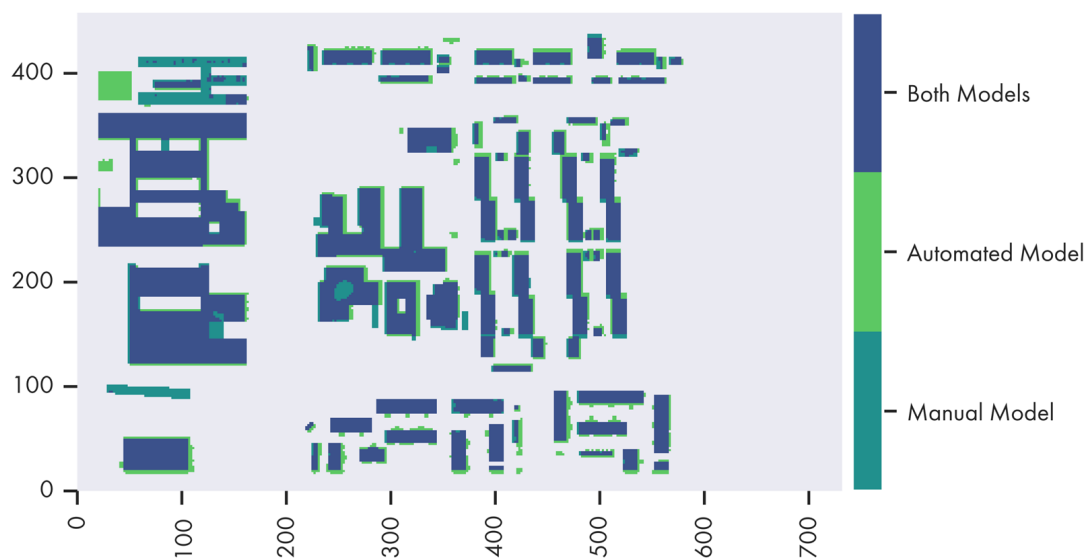


Figure 6. Overlap of building shape and placement between the automated and manual model. Blue indicates overlap between models, while green indicates that buildings are present only in the generated model, and teal the reverse. Based on data © Lantmäteriet.

Building Size Comparison

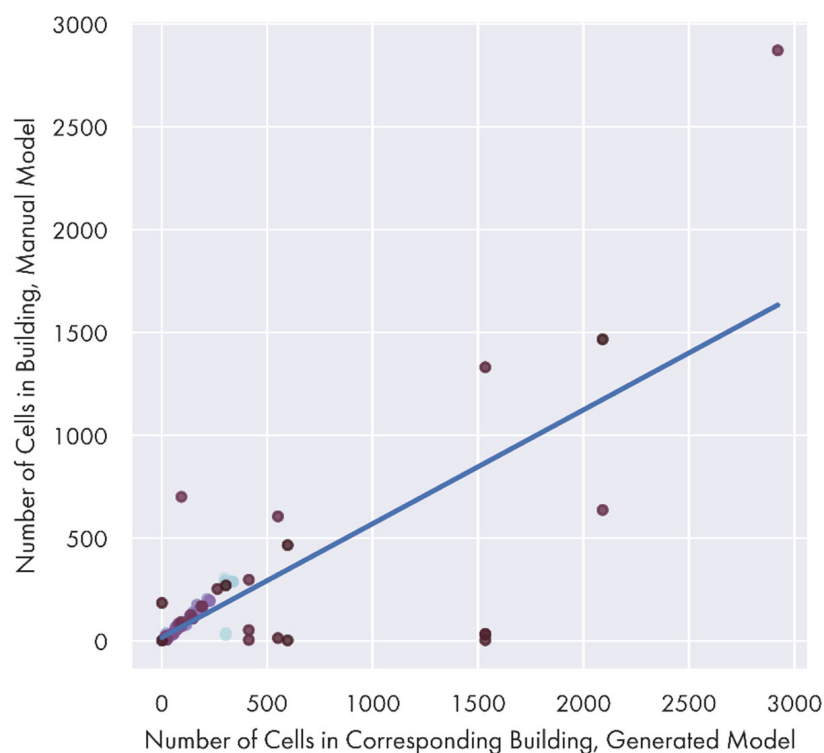


Figure 7. Building size comparison, showing building sizes plotted against the size of their equivalents. Based on data © Lantmäteriet.

Tree cover had little overlap between models (Figure 8). Our method placed a lot more trees when compared to the manual model, while the manual model clustered trees in areas separate from the generated model. While our method used the same tree index for each occurrence, several different types of trees, both 1D and 3D, were used for the manual model.

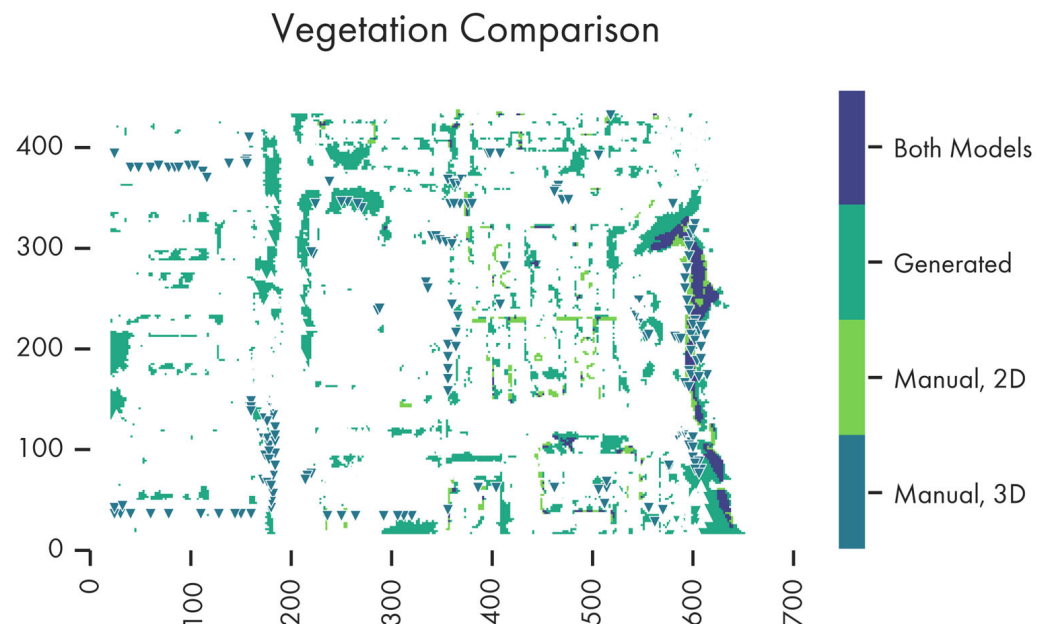


Figure 8. Differences in greenery between the models. The green hue represents trees in the automatically generated model, light green 2D trees in the manually constructed model, and dark blue their intersection. Blue triangles represent 3D trees in the manually constructed model, where trees pointing down are of the 5 m types, and trees pointing up are of the 15 m types. Based on data © Lantmäteriet.

3.2. Simulation Comparison

In addition to the comparison of spatial properties of the generated and manually created site models themselves, the simulations of both models were compared to each other. As with the geometry analysis, the simulation result datasets were offset to ease comparison. The four simulations were analyzed by taking 2D slices in the height dimension. The slices were not taken uniformly at a set level due to the terrain. Typically, ENVI-Met site models do not account for terrain differences. While this seldom reflects sites accurately, it simplifies site modeling and analysis. As both the automatically generated and manually constructed models model terrain, figures representing 2D slices of the volumetric space follow the terrain instead of presenting the slice of the model at a set distance from sea level. Cells above the terrain were selected, representing a span of 2 m height-wise, with their center at 1 m above ground. This was done to allow the graphs to represent conditions above ground uniformly, although the representation introduces some discontinuities into the graphs, visible as fringing in Figures 9 and 10. Similarly, cells within 12 m of the model boundaries were filtered out in Table 4 and the analysis below.

In the winter scenario (Table 4, Figure 9), individual potential air temperature cells differed 0.27 °C at most, with the generated model reaching the lowest individual cell temperature for the slice, at −1.74 °C at its lowest, with the cell in the manual model being −1.70 °C. The highest temperature was reached in the manual model at −1.29 °C, the respective cell in the generated model being −1.56 °C. The automatically generated model showed a little more varied temperatures and was somewhat warmer in the core of the site model. Greater variance could be seen in the wind speed. The cells differed by 8.31 m s^{−1} at most, with the highest wind speed measured in the manual model at 9.14 m s^{−1}, with

the automatically generated model having a wind speed of 1.0 m s^{-1} . The direct shortwave radiation only reached a negligible 1 W m^{-2} , only reaching the measured area at the lower left edges of the models, which, due to the low sun angle, can be assumed not be present at the actual site, as the site has buildings blocking the sun outside the modelling area. The site received no direct shortwave radiation at 09:00, nor at 15:00, as sunup was at 09:55, and sundown at 13:03 CET (Table 4, Figure 9).

Simulation comparison for Dec 22 at 12:00

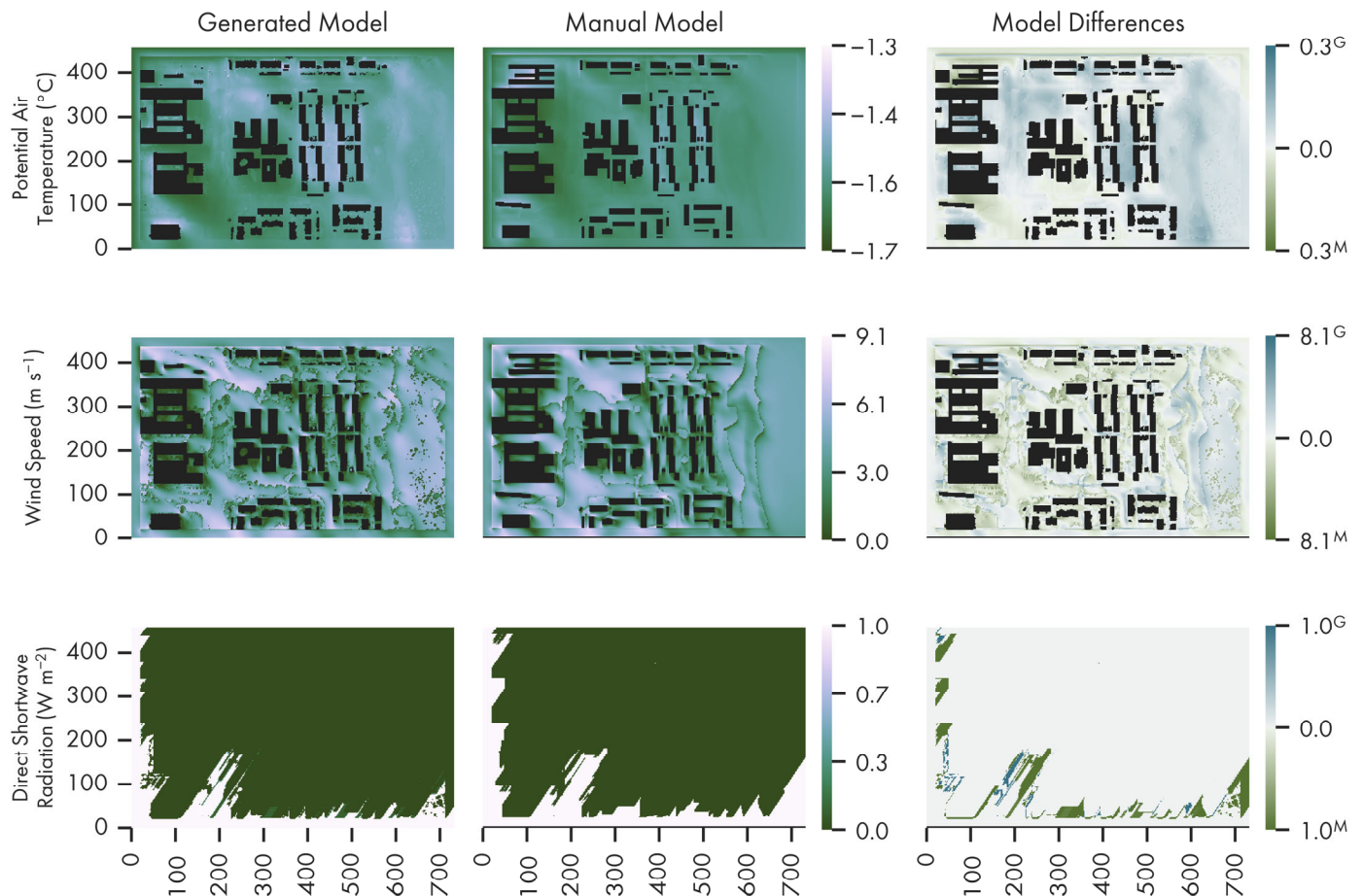


Figure 9. Comparison between the automatically generated model and manually created model for the winter scenario, values are taken from cells centered 1 m above the DEM surface. The first two columns show respective model values, while the third shows their differences, with blue representing higher values in the generated model (G), green in the manual (M). The stairstep effect seen in the data is caused by readings at different levels due to differences in elevation. Based on data © Lantmäteriet.

In the summer scenario (Table 4, Figure 10), the largest difference between cells was $1.02 \text{ }^{\circ}\text{C}$, with the lowest value in both models being $11.97 \text{ }^{\circ}\text{C}$, in different cells. In the manual model, the equivalent cell in the generated model had a temperature of $12.19 \text{ }^{\circ}\text{C}$, and in the generated model, the manual model had a temperature of $12.29 \text{ }^{\circ}\text{C}$. The generated model reached the highest temperature at $13.82 \text{ }^{\circ}\text{C}$, with $12.80 \text{ }^{\circ}\text{C}$ in the manual model. The manual model reached $13.51 \text{ }^{\circ}\text{C}$, with $13.01 \text{ }^{\circ}\text{C}$ in the corresponding generated model cell. While the maximum overall wind speed for each model differed little, with speeds in the generated model simulations reaching 4.00 m s^{-1} and 4.09 m s^{-1} in the manual model, the largest difference in cell-wise wind speed was 3.47 m s^{-1} . Both models reached a maximum direct shortwave radiation intensity of 188.25 W m^{-2} (Table 4, Figure 10).

Simulation comparison for Jun 21 at 12:00

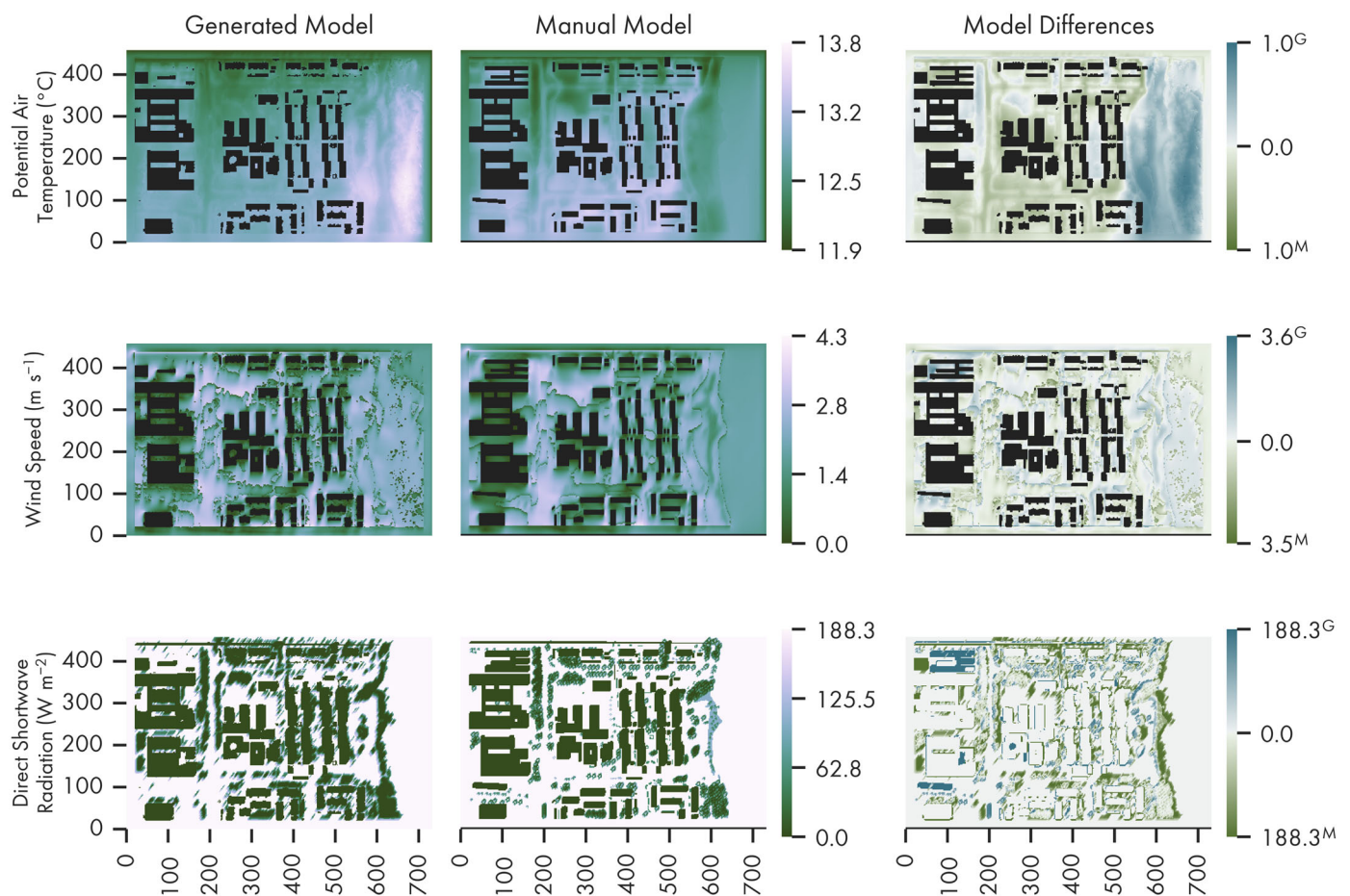


Figure 10. Comparison between the automatically generated model and manually created model for the summer scenario, values are taken from cells centered 1 m above the DEM surface. The first two columns show respective model values, while the third shows their differences, with blue representing higher values in the generated model (G), green in the manual (M). The stairstep effect seen in the data is caused by readings at different levels due to differences in elevation. Based on data © Lantmäteriet.

The cells of the spatial models were compared to each other based on position. The data was subsampled to 10% of the original values and plotted (Figures 11–13). The spatial models performed similarly to each other in both simulation scenarios. Temperatures fell throughout the simulated period in the winter scenario, whereas they rose in the summer. Cell temperatures held similar values between the generated model and manual model simulations, showing less spread between models and between cells at colder temperatures. The wind simulations differed more between models, but the cells correlated well. The majority of direct shortwave radiation either received 100% of the incoming radiation or none of it. The minority of cells receiving radiation in an amount between either extreme did not do so uniformly between models, likely due to the different strategies for placement of trees (Figure 10).

Whether or not the compared cells were inside a building in one or both site models had little effect on their performance, showing no discernible pattern, with the exception of surface temperature, as cells beneath buildings had their temperature set to 20 °C by ENVI-Met (Figure 13). Cell surface temperatures outside buildings were much more varied between models in comparison to potential air temperatures, likely due to the variances in geometry having a larger effect on the readings.

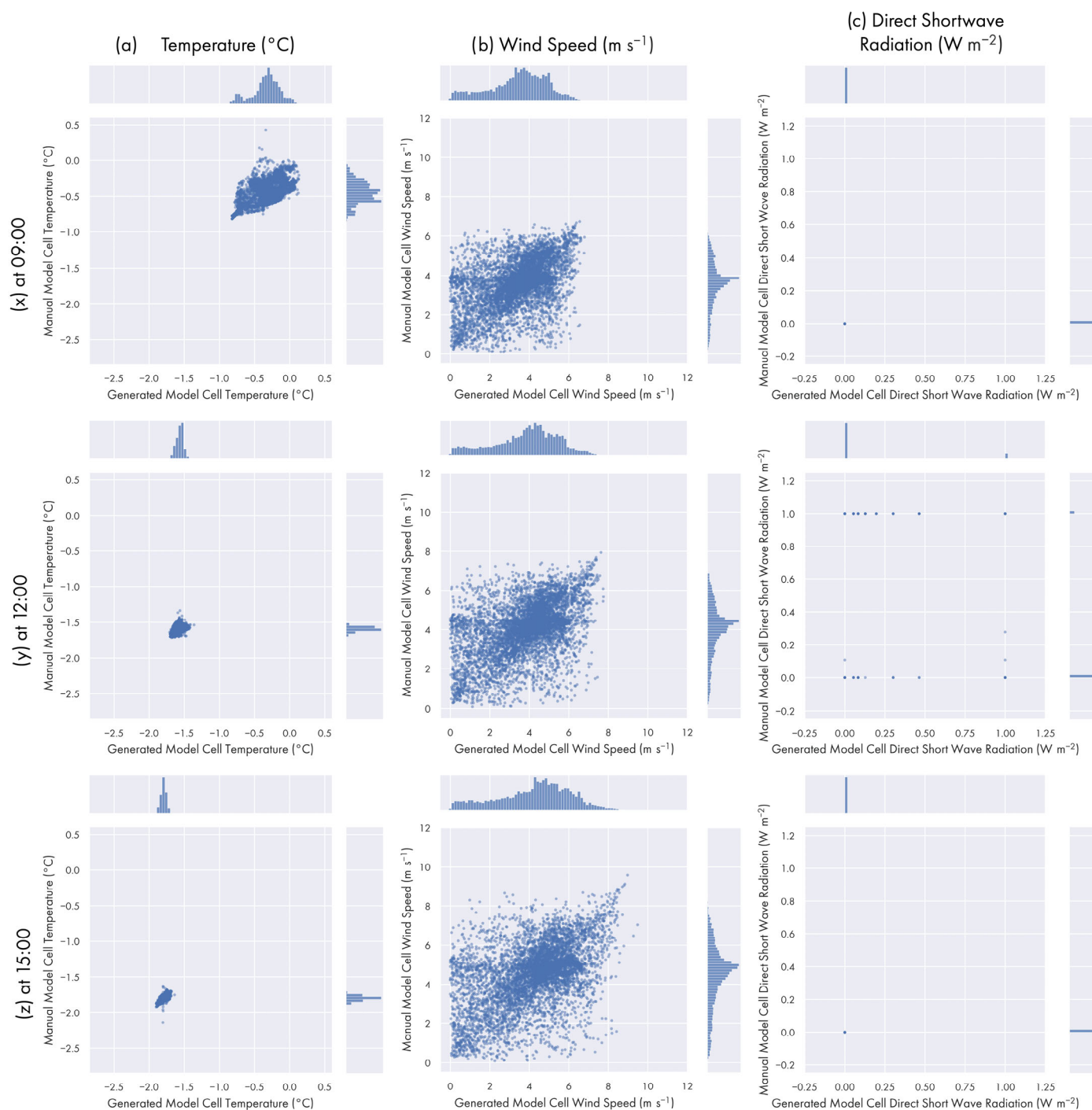


Figure 11. Column-wise: comparison of (a) Temperature, (b) Wind Speed, and (c) Direct Shortwave Radiation, between cells located 1 m above ground. Row-wise: measurements at (x) 09:00, (y) 12:00, and (z) 15:00, on 22 December. Each subgraph plots differences between models, measured for each cell. Horizontal axes plot generated model values, while the vertical axes show manual model values. The auxiliary plots graph density, using 90 bins per axis. Based on data © Lantmäteriet.

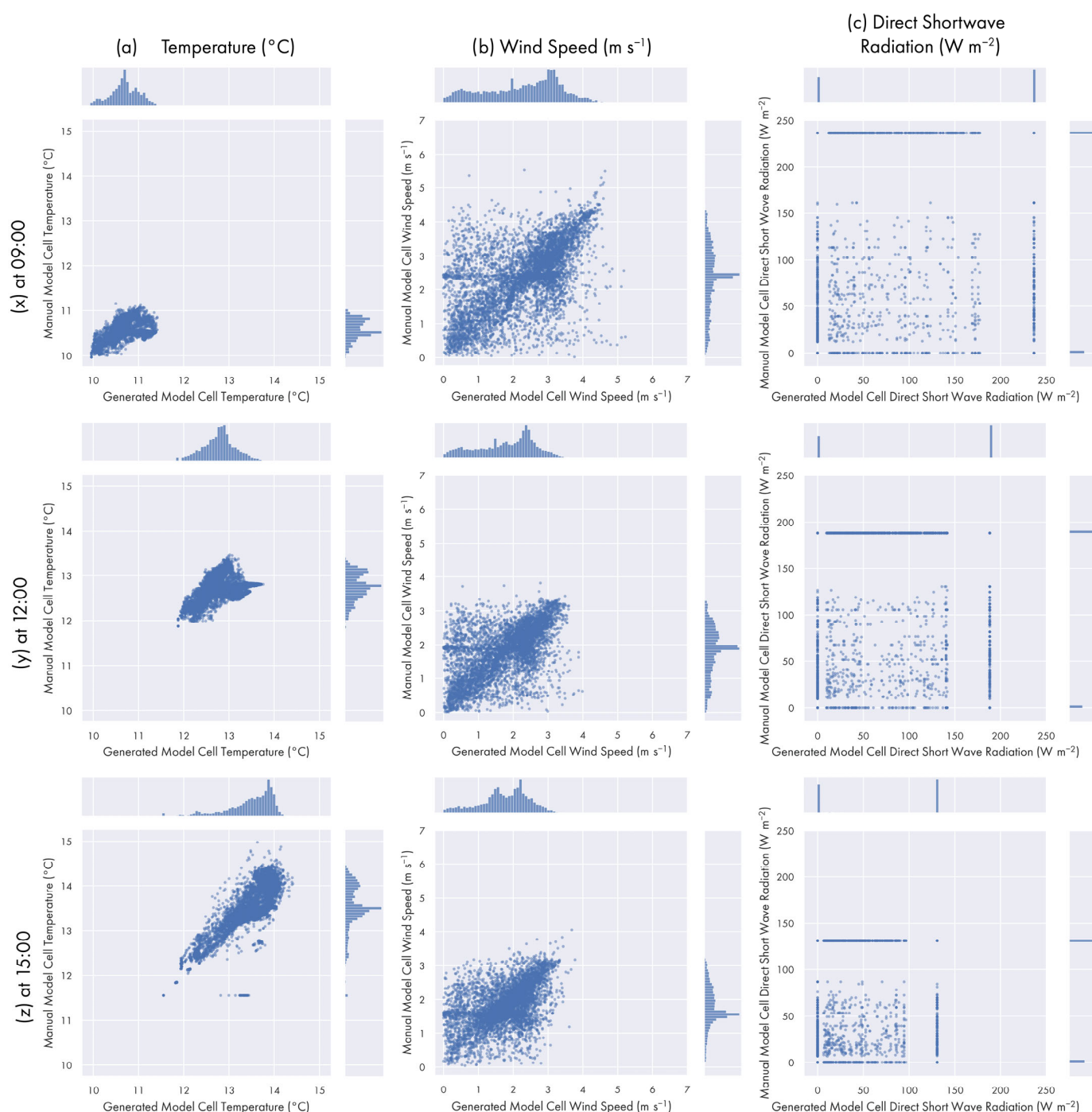


Figure 12. Column-wise: comparison of (a) Temperature, (b) Wind Speed, and (c) Direct Short Wave Radiation, between cells located 1 m above ground. Row-wise: measurements at (x) 09:00, (y) 12:00, and (z) 15:00, on 21 June. Each subgraph plots differences between models, measured for each cell. Horizontal axes plot generated model values, while the vertical axes show manual model values. The auxiliary plots graph density, using 90 bins per axis. Based on data © Lantmäteriet.

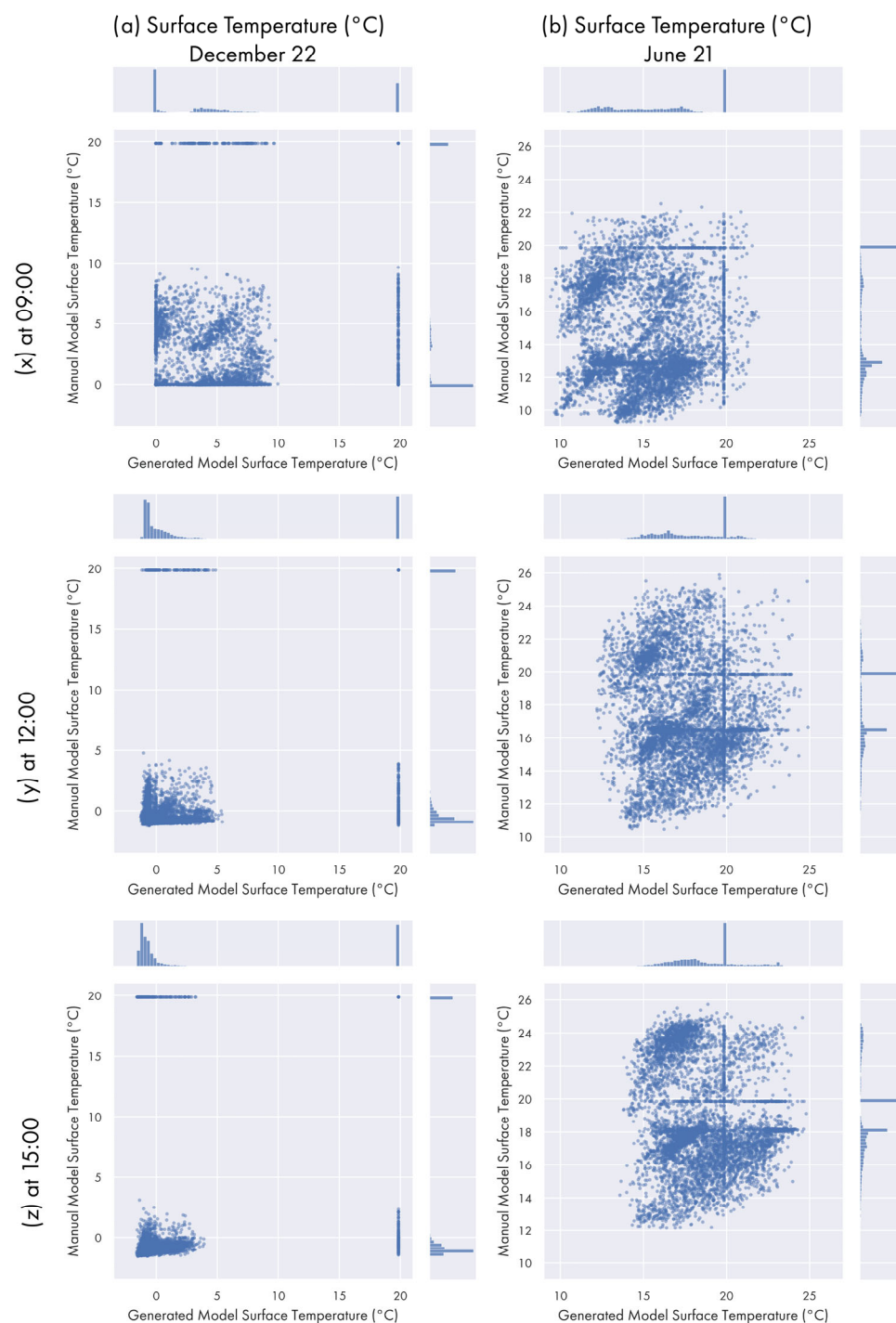


Figure 13. Column-wise: comparison of Surface Temperature on (a) 22 December, and (b) 21 June, between cells located 1 m above ground. Row-wise: measurements at (x) 09:00, (y) 12:00, and (z) 15:00. Each subgraph plots surface temperature differences between models, measured for each cell. Horizontal axes plot generated model values, while the vertical axes show manual model values. The auxiliary plots graph density, using 90 bins per axis. The surface temperature is set to 20 °C by ENVI-Met at the locations of the buildings, forming lines in the plots. Based on data © Lantmäteriet.

Table 4. Weather extremes observed in respective microclimate simulations.

			Potential Air Temperature (°C)		Wind Speed (m s ^{−1})		Direct Shortwave Radiation (W m ^{−2})	
			Min	Max	Min	Max	No Exposure	Full Exposure (Intensity)
22 December	09:00	Generated	0.16	−0.78	0.00	6.76	100%	—
		Manual	0.50	−0.75	0.03	7.79	100%	—
	12:00	Generated	−1.74	−1.34	0.00	7.88	93.29%	5.65% (1.00)
		Manual	−1.71	−1.29	0.03	9.14	90.80%	9.13% (1.00)
	15:00	Generated	−1.93	−1.62	0.00	9.28	100%	—
		Manual	−2.14	−1.45	0.02	10.88	100%	—
21 June	09:00	Generated	9.99	11.45	0.00	5.42	39.58%	43.00% (236.53)
		Manual	10.00	11.15	0.02	6.42	32.21%	53.99% (236.53)
	12:00	Generated	11.97	13.82	0.00	4.00	36.49%	44.38% (188.25)
		Manual	11.97	13.51	0.01	4.09	30.51%	55.10% (188.25)
	15:00	Generated	11.77	14.63	0.00	4.09	44.32%	38.61% (130.74)
		Manual	12.33	15.21	0.02	4.52	35.47%	52.08% (130.74)

4. Discussion

The site models generated by our method and manually generally concurred in their construction. Excluding the boundary areas and areas only modelled in one or the other model due to their relative shift, the models' 2D footprints overlapped to a great extent. Due to the different levels of detail between models, DTM heights varied slightly. 48.76% of tiles had the same height value in both models, while 42.49% and 7.16% had a difference of 1 or 2 m, respectively. 1.58% of tiles had an error of 3 m or more. 81.97% of cells in the otherwise excluded top and bottom 4 m of the site models' DTM differed 2 m or more due to the shift (Figure 4). A total of 47.08% of the terrain is non-permeable in the generated model, 28.51 in the manual model, with 19.62% of the area being marked as non-permeable by both models. More thorough marking of terrain and incorrect marking of water contributed to a higher amount of terrain being marked as non-permeable by our method (Figure 5). In the automatically generated model, the building footprint covers 23.00% of tiles, and in the manually created model, 21.72%. The building footprints are 75.88% aligned, with 3.71% of tiles only considered building tiles in the automatically generated model, and 2.43% the opposite. In general, the automatically generated model modelled buildings larger, while the manually modelled model included details not found in the generated model, such as the loading bay, found in the centre of the area (Figure 6). Several structures were only found in one or the other model, such as the two larger buildings to the left in the manually constructed model, not present in the height input data. The automated model has a vegetation cover of 10.17%, while the manual model had a significantly lower 2.17%, with only 1.11% of the total having overlapping vegetation, as the manual model additionally relied on 3D trees (Figure 8).

The simulations generally showed little difference in terms of temperature (Figures 9 and 10). A few trends could be observed in the winter scenario. The center of the generated model was slightly warmer, while the periphery was slightly warmer in open areas toward the south-southeast. In the summer scenario, temperatures fluctuated somewhat more, although the difference in the highest and lowest temperatures reached was within a degree in both cases (Table 4). Temperatures in the center and lower parts (south) of the manually constructed model were slightly warmer, and the periphery, especially to the right (East-

Northeast) in the model, was somewhat warmer. The wind simulations differed to a greater extent in both scenarios, likely due to the more fragmented nature of the ground in the automatically generated model, as this made the ground less continuous. The manually constructed model consistently achieved higher wind speeds. Due to the low angle of the sun during the winter, the winter scenario mostly differed in the down-left edges of the site, although this effect is lessened in reality, as the areas would have been obscured more by geometry and vegetation off-site (Figure 11). In the summer scenario, shadow patterns from trees were less heavy and more varied in the manually constructed model, and the percentage of exposed cells was consistently higher in the manually constructed models in both scenarios, indicating that our presented method may overestimate the amount of vegetation, and thus provide shading, on the site. This affected relatively few cells, however, as the majority of cells were either fully exposed or fully shaded (Figure 12). In terms of geometry, manually modelling features allows model makers to make assumptions not afforded to our method, such as making paths continuous, assessing vegetation qualities based on maps and local observations, assessing building shapes partially obscured by vegetation, or making qualitative judgements about errors. However, apart from the aforementioned issues, no definitive trends in either geometry or simulation performance could be ascertained.

By global standards, the area studied has a rather extreme climate, with especially low temperatures in wintertime. In their assessment of ENVI-Met accuracy, Liu et al. [17] found simulations to perform better in summer than in winter with regard to both air temperature and wind speed. They also noted that around 90% of ENVI-Met evaluations were performed in hot summer microclimates. Additionally, a majority of microclimate studies are done in warmer climates. For instance, in their literature study of thermal comfort in educational buildings, Zomorodian, Tahsildoost, & Hafezi [4] found that only 4% of field studies focused on sites in group D Köppen climates, with no field studies focusing on polar or alpine climates. More diverse test sites in more popular Köppen climate groups have the potential to further refine the presented method, and more generally, the underserved sub-arctic and arctic regions would benefit from being included in more microclimate studies. Our presented study compares site models, but future research could focus on comparison with onsite measurements, both regarding our presented method, as well as microclimate simulations in arctic conditions in general.

Furthermore, we did not consider water sources in this study. Water sources can have a cooling effect on the microclimate of areas, as they have a higher specific heat capacity compared to land [56]. Freshwater sources in the study area are iced over in the winter, further complicating water body modelling. It would be beneficial for future research to consider the integration of hydrological data to further refine the performance of generated site models, especially in relation to the complexities of modeling freezing or frozen water bodies.

Methods for modelling aspects of the world, such as site models and simulation software, are tools that are always affected by their development and use [57]. While we presented a method that compares well with the state of the art, assumptions made in, e.g., the simulation software, can bias both methods. As such, validation against real-world measurements is of importance. This study utilized TMY data, historical real-world observations, representative of the weather for the location. While this assists in generalization, ensuring that simulation results are more typical for the area, the historical nature of the dataset precludes making on-site microclimate observations. Future research would benefit from testing the performance of the presented method against real-world local observations and on-site microclimate measurements.

The method presented in this paper is relatively straightforward, which enables the construction of urban site models with relative ease, but does not cover every use case. Depending on the application, future work could focus on several aspects. For instance, Heldens et al. [30] emphasized the role of albedo in their model and presented an intricate method for determining surface properties. For more detailed site model analyses, emphasizing albedo would likely benefit from more complex material determination algorithms but would necessitate larger repositories and site analyses to ensure proper material assignment. Furthermore, Ayyad & Sharples [16] found that ENVI-Met was not very responsive to albedo when measuring temperature.

We also used a simple combination of NDVI values and height data to estimate vegetation positioning. Future methods could benefit from more closely modelling tree canopies, although significant work would likely be required to achieve accurate results. Liu et al. [46] found that there was no holistic technique to model vegetation in ENVI-Met 4, citing the simplified rotary tree crown models as a limitation for simulating the real world and stressing the need for leaf area density and height measurements for trees. Since the publication of the study, ENVI-Met has introduced Lindenmayer system, or L-system, tree canopy models [58], which, while more accurately modeling vegetation, would require identifying both discrete positioning and tree species from input data to be usable in site models. L-systems are a formal grammar for modelling branching structures, primarily plants [59]. First introduced by Lindenmayer in 1968 [60], L-systems, and later derivatives, allow for the generation of complex shapes using iterative rewriting of shapes. Compared to our 2D method presented in this paper, L-system trees offer the potential to model more complex tree canopies in 3D, and future research would benefit from the integration of more complex tree canopy models, such as L-system-based trees for vegetation generation. Modeling of discrete trees, however, would incur a complexity cost, as our presented method calculates vegetation for each input pixel in a context-free manner, whereas modeling more complex tree canopies would require segmenting out and classifying individual trees from the orthophoto data. Numerous methods for tree segmentation and classification have been proposed, using methods such as Random Forest and Support Vector Machines [61–63], although advanced methods introduce their own complexities, such as relying on hyperspectral data, the requirement of a pre-training corpus to identify trees, or additional runtime cost.

5. Conclusions

Digital site models are crucial datasets for a wide set of methods that enable understanding of the built environment, especially for modelling urban sites' microclimate. Due to the disparate sources of data and the differing requirements and goals of applications, site models are often bespoke and modelled by hand. However, manual modelling can become a time-consuming obstacle, limiting the applicability of software and techniques that rely on it, wherefore the automation of site model generation can be of great utility within both academia and industry.

In this paper, we presented a novel method for the generation of volumetric site models based on widely available multispectral and height orthophoto raster data in conjunction with cadastral building footprint data, offering high automation and minimal preparation. The performance of our method was compared to a manually created baseline site model in a site study and was found to perform well, both in comparison to typical manual modelling techniques and to state-of-the-art methods for automated site model generation.

Our method presents an alternative for rapid automated site model generation with minimal preparation, enabling researchers and practitioners to more quickly assess mi-

croclimate conditions in disparate locations without the need for time-consuming model construction. It has the potential to provide utility for researchers and practitioners for the evaluation of the microclimate of existing sites or as a basis for site models evaluating new construction scenarios. Furthermore, our method can provide a basis for applications requiring typologically differentiated volumetric urban site models, such as simulation environments, platforms for environmental planning, or interactive digital environments for participatory design.

Author Contributions: Conceptualization, M.S., K.L. and A.R.; methodology, M.S. and K.L.; software, M.S.; validation, M.S. and K.L.; formal analysis, M.S.; investigation, M.S.; resources, M.S. and K.L.; data curation, M.S.; writing—original draft preparation, M.S.; writing—review and editing, M.S.; visualization, M.S.; supervision, K.L. and A.R.; project administration, A.R.; funding acquisition, A.R. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by Svenska Forskningsrådet Formas [grant number 2018–01267] and the Energimyndigheten [grant number 46355–1].

Data Availability Statement: This study contains land and cadastral building data, which is not licensed for further sharing: GSD-Fastighetskartan Vektor, © Lantmäteriet; GSD-Orthophoto, © Lantmäteriet. The software method presented in this paper is available online under the MIT license:

- Software name: shapegen
- Developer: Max Spett
- Contact: max.spett@ltu.se
- Date first available: 23 May 2025
- Software required: dependencies available via pip requirements file, see documentation.
- Programming Language: Python
- Source code repository: <https://github.com/mxparc/shapegen> (accessed on 23 May 2025)
- Documentation: Detailed documentation, including install and usage instructions are available at: <https://github.com/mxparc/shapegen> (accessed on 23 May 2025)
- Data required is available through the original cloud platforms; see data availability statement.

Acknowledgments: This article was proofread and checked for clarity by Frida Thuresson and Camilla Schlyter.

Conflicts of Interest: The authors declare that they have no known competing personal or financial interests that could influence the work presented in the paper.

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