A dynamic urban digital twin integrating longitudinal thermal imagery for microclimate studies

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ABSTRACT

Recently, the concept of a digital twin for the built environment has received significant attention due to its potential benefits to urban planners, engineers, and designers. The development of tools that aid in integrating real-world physical systems with digital capabilities is essential for advancing digital twin technology. In this work, we present one such digital twin tool that integrates the longitudinal thermal envelope data of buildings on the campus of the National University of Singapore with a virtual 3D model. Thermal images of the buildings were captured using a neighborhood-scale infrared observatory for a few months. The temperature profile of one of the buildings was extracted and mapped on the virtual 3D model. The digital twin model is developed in the *deck.gl* platform. This is one of the few studies on developing a dynamic digital twin incorporating temporally and spatially varying urban-scale 2D temperature envelope data with the virtual 3D model. The digital twin platform can study the microclimate and help urban planners identify the building elements contributing to the urban heat island (UHI) effect at the neighborhood scale.

KEYWORDS

Digital twin, Thermal imaging, Infrared observatory

1 INTRODUCTION

In recent years, Internet-of-Things (IoT) sensors have been extensively used for built environment applications such as monitoring

the construction process, indoor and outdoor environment, energy usage, HVAC performance, and many more [1, 21]. With the increase in computational power and the generation of more sensor data, it is essential to integrate and analyze the data on a platform that can help in performance prediction and decision-making. A digital twin is aimed at achieving the same. It essentially consists of a digital model that closely represents the physical world and is updated based on the sensor data [13, 31, 48]. Further, the information flow can be bidirectional; the physical system is modified based on the inferences from the virtual replica and simulations.

A digital twin is a relatively new concept in construction, architecture, and the built environment. Typically, the built environment requires integrating IoT sensor data with modeling such as building information model (BIM), leading to real-time predictions [15, 38]. At the local scale, the digital twin concept has been demonstrated for applications such as improving building energy efficiency [50], achieving occupant thermal comfort [11], monitoring HVAC performance and fault detection [23], and energy usage [2, 25]. However, there has been limited development of urban scale digital twin because of dispersed data ownership, security, privacy concerns, and barriers to bridging multiple sectors, as well as challenges with data collection and data interoperability[31, 39]. Nevertheless, its need for planning and management of the urban infrastructure for climate change and estimation of urban-scale energy demand has been identified and demonstrated in recent studies [24, 40, 44].

1.1 Digital twin integration with BIM and thermal imaging

This work aims to demonstrate an urban-scale digital twin that can be used for conducting microclimate studies. The two main components of a digital twin are a virtual model closely representing the physical system and the sensors measuring various parameters of the physical system. Building information models (BIM) are detailed building models that consist of geometry and information such as building elements, spatial relationships, materials, and costs, allowing the integration and collaboration between stakeholders and parties involved in the construction industry [6]. With the uptake of BIM and detailed building models and information availability, studies have used BIM models to create digital twins for asset management and sustainability studies [10, 26, 35]. There have also

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been many efforts to integrate BIM geometry and information into Geographic Information Systems (GIS) for geospatial studies and analyses [8, 18, 27, 46, 51]. These activities include efforts to convert BIM models and building data into GIS formats [5, 14] to facilitate spatial operations such as shadow analysis and indoor analysis [55].

Improvements in connectivity have enabled real-time information transfer from the IoT sensors measuring various parameters of the physical system. The sensor data can be geolocated data points, images, time series, etc. An infrared camera is a sensor that captures the long-wave radiation emitted by an object, which is then converted to temperature values [37]. One of the main advantages of the infrared camera is that it can be used even in low illumination. Its use for the built environment has been demonstrated through studies on building energy performance [22], estimation of U-value [17], evaluation of urban heat island effect [37] and operational pattern of HVAC system [4, 42].

At the local scale, integration of thermal image with 3D models have been demonstrated for thermal comfort analysis [47], building inspection [3], and building energy performance [43]. Whereas at the urban scale, there have been limited studies on incorporating urban-scale thermal imaging with 3D models [45, 57]. This can be due to the lack of longitudinally and spatially rich urban-scale thermal image data sets [29] of the built environment that can potentially be used for studying the urban space over a long period of time. Also, most of the digital twin models described in the literature integrate homogeneous sensor data, and very few include heterogeneous sensor data. However, for microclimate analysis, there are several advantages to using multiple sensor types and combining heterogeneous data to accurately represent the physical system. This work addresses several research gaps by developing a dynamic digital twin model that integrates urban-scale longitudinal thermal imagery and outdoor weather station data with a 3D model. Such a model would facilitate urban planners and designers to conduct studies on microclimate, thermal velocimetry, urban scale building energy efficiency, outdoor thermal comfort, and identification of contributors and mitigators of the UHI effect.

The IRIS dataset [33] is one of the few thermal image datasets that are both longitudinally and spatially rich while capturing various features of the urban built environment. The dataset is a collection of two-dimensional images in radiometric format. To incorporate the two-dimensional radiometric temperature data of the building envelope into a digital twin, we need to map out the exact location on the virtual model. Further, the variation in the temperature profile of the building envelope changes with time due to the changes in solar radiation and weather conditions. This work introduces a pipeline for combining radiometric data, outdoor weather sensor data, and the 3D model for the digital twin platform, which can be of wide use to the built environment community.

The paper is organized as follows. In Section 2, the methods used for developing the digital twin model incorporating the thermal profile of the building and weather station data for microclimate analysis are described in detail. In Section 3, the results from the study are demonstrated. In Section 4 and Section 5, the discussion and conclusion are presented.

Table 1: FLIR A300 Thermal camera specifications.

Resolution	16 bit, 320x240 pixels
Thermal sensitivity	50 mK @ 30^oC
Sensor	Uncooled Microbolometer FPA
Spectral range	7.5 to 13 μ m
Field of view (FOV)	25° (H) and 18.8^o (V)
Accuracy	$\pm 2^o$ or 2% of reading
Power supply	110/220 V AC
Weight	0.7 kg
Size	170 mm x 70 mm x 70 mm

2 METHODOLOGY

A neighborhood-scale infrared observatory similar to [16] was deployed on the campus of National University of Singapore to collect longitudinally and spatially rich thermal images. Figure 1 shows the location of the IR observatory and the four buildings in focus. The thermal camera, a FLIR A300 IR, was housed inside a casing to protect it against harsh weather conditions. The protective casing was mounted on the pan-tilt unit, which can rotate along the horizontal and vertical planes. The pan-tilt is programmed to stop at the four instances along the horizontal plane to zero in on the buildings in focus. Building A is tall and glazed, Building B and C are reinforced concrete structures, and Building D is designed to net zero energy standards, providing a diverse mix for this research. The thermal camera specifications and the camera Plank's constants are listed in Table 1 and 2, respectively. Readers may refer to [33] for details regarding installation and operation.

The thermal images of the four views captured were stored in the radiometric format. Subsequently, the region of interest, such as the building, was segmented using the LabelMe annotation tool [52]. The temperature of the segmented region was extracted using FlirExtractor Python package [28] from the radiometric data using the following equation:

$$T_{obj} = \frac{B}{ln(\frac{R_1}{R_2(U_{tot}+O)} + f)} \qquad (1)$$

where U_{tot} is the signal response to the long wave infrared radiation incident on the camera detector, B, R_1, R_2, O and F are the camera calibration constants.

The extracted temperature of the region is stored as comma-separated values files. This paper uses the building in View 1 as an example to demonstrate the dynamic digital twin. The building is one of the tallest buildings on the National University of Singapore (NUS) campus. The building has glazed and steel panel fenestration. The facade is exposed to intense solar radiation between 10 a.m. to 3 p.m. In addition to the thermal image data, the outdoor temperature, wind speed, and solar radiation were also collected from the weather station installed at the same location as that of the IR observatory [56]. The methodology for extracting the three-dimensional model and visualization of the longitudinal sensor data on the virtual model is described in detail in the subsequent section.

Models from two different sources were combined to develop the digital twin. The first one is the detailed virtual three-dimensional model that represents the detailed urban form of the university
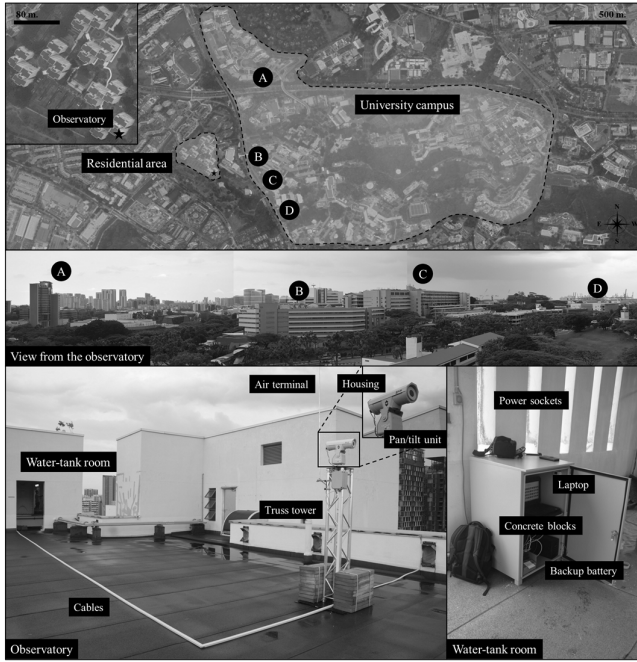
Figure 1: A map showing the location of the IR observatory (top), buildings that were imaged using the thermal camera (center), and the infrared observatory (bottom) [37]. Basemap courtesy of Google Maps.

Table 2: FLIR A300 Thermal camera default Plank's constants.

R_1	14911.1846
R_2	0.0108
f	1.0
O	-6303.0
B	1396.6

campus. The second one is the extruded footprint models based on OpenStreetMap (OSM) and OSM Buildings [36], which is widely used around the world to generate 3D models [7]. The virtual 3D model (shown in Figure 2) offers an accurate context for mapping the thermal image data as it provides finer details, such as the location of the windows and shading devices, but such marriage has not been established yet to the extent of our knowledge. To achieve that in our work, individual models of the building had to be extracted from larger meshes and adjusted to remove faces to avoid issues in visualization because of back-face culling. At the same time, the simplified extruded footprint models based on OSM buildings were added to complement the detailed models and provide additional contextual information. The model consists of each building as a separate object, in line with semantic 3D city modeling practices [30, 32, 41]. However, the elevations of the buildings had to be adjusted to better fit the terrain and for buildings with different heights, such as podiums. These changes were performed

in Blender, and the resulting 3D models were exported as .obj files [12].

To support the visualization of the thermal data, it is necessary to map the two-dimensional thermal image onto the three-dimensional geometry. The surfaces imaged using a thermal camera were selected for each building. The four bounding points of each surface were then identified in the thermal image. Subsequently, the 3D coordinates of the corresponding surfaces and points were obtained from the 3D model. These inputs were used to create the transformation matrices to map each pixel of the surface in the thermal image to the 3D model. This mapping was performed in Python, and the *pyproj* library was used to project the final points from meters to The World Geodetic System 1984 (WGS84) [49]. This results in a distribution of 3D points across the visible surfaces of the building, with each point associated with the surface temperature measured in the thermal image.

2.1 Digital twin development

The 3D model and thermal data underpin the digital twin. The digital twin integrates 3D city models, thermal image data, and weather station data to create an interactive platform that can be used to understand the microclimate and the changes in the temperature of the building envelope across time. The dynamic digital twin is implemented using the *deck.gl* framework [54], which allows the construction of complex visualizations by composing existing layers designed to view different data types. The 3D models of buildings and trees are loaded using *SimpleMeshLayer*, which renders 3D geometry and supports several standard formats. The thermal data is loaded as multiple *PointCloudLayers* that render a point cloud with 3D positions and colors. Although our resulting data set is not a point cloud, a dense set of 3D points across the surface of an object typically obtained through 3D scanning using LiDAR sensors [19, 34], it is fairly similar. *PointCloudLayer* allows us to visualize the points and their associated thermal information easily, by using a function to map temperature to a color scale, instead of recorded RGB values. One *PointCloudLayer* is created per timestamp. This setting allows the timestamp to toggle visibility so the user can view the corresponding data set.

3 RESULTS

3.1 Thermal image dataset and segmentation

Figure 3 shows the thermal image of the four views captured using the IR camera. The pixel brightness represents the temperature intensity in the region. Darker pixels correspond to regions cooler than the rest in a particular image. In this paper, we demonstrate the application of three-dimensional modeling of the building corresponding to View I. A similar procedure can also be adopted for the buildings in other views. For exporting the temperature of the building facade from the thermal image, first, the building is segmented using the LabelMe annotation tool. Figure 4 shows the building's thermal image and corresponding segmentation mask. The temperature values of the pixels in the masked region are then extracted using the FlirExtractor Python package from the radiometric data. The temperature values are stored in comma-separated files for ease of access.
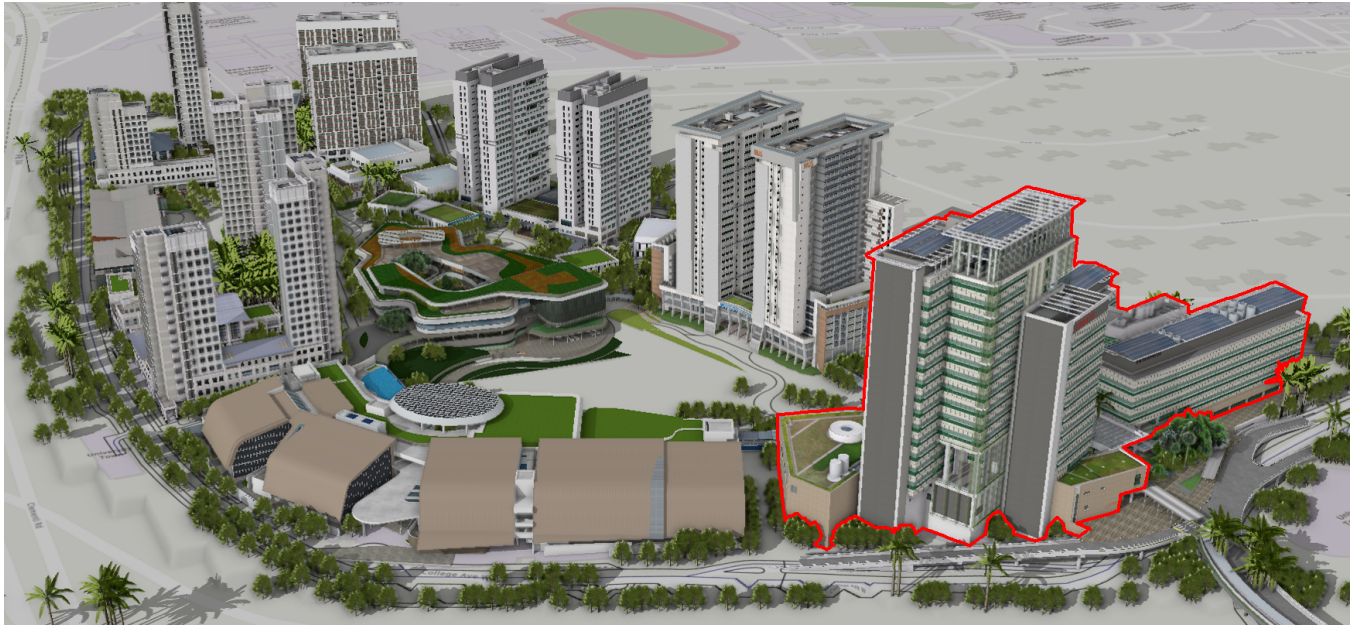
Figure 2: Virtual three-dimensional model of the educational campus. The building highlighted in red was one of the four buildings extracted for this study.
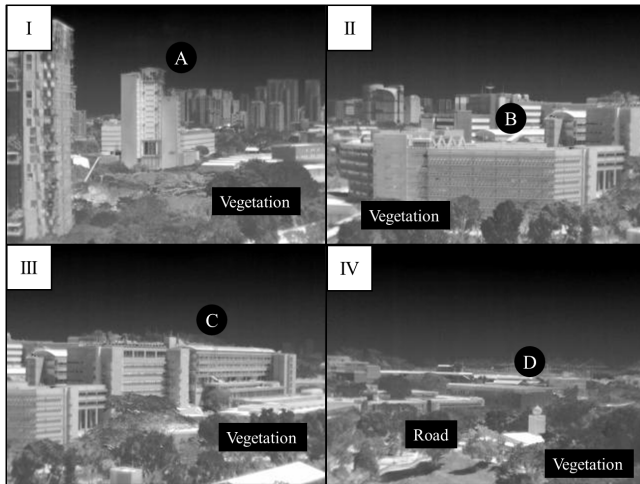

Figure 3: Thermal images of the buildings captured using the IR camera ([37]).

3.2 Three-dimensional model and thermal data

As mentioned in Section 2, the 3D building model is extracted, and each surface in the thermal image is mapped to the corresponding surface in the 3D model and geolocated. The surfaces and points used for Building A in View I (Figure 3) are shown in Figure 5. The white dots in the thermal image and the 3D model are the reference points of the surfaces selected for mapping. The two steel surfaces and one glass facade are mapped for the example building chosen. This process is repeated for each surface and timestamp and exported as JSON files.
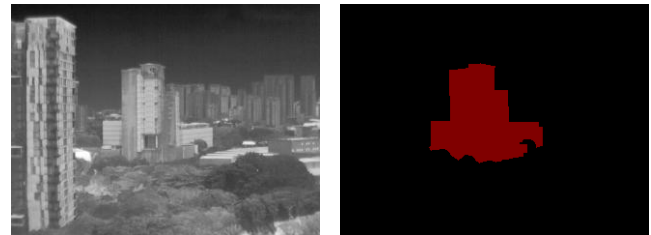
**(a) Thermal image**   **(b) Segmentation mask**

Figure 4: (a) Thermal image of the building and (b) segmented image. The region highlighted in red delineates the building of interest.

3.3 Digital twin and thermal visualization

In modern urban planning, engineering, and architectural design, the concept of a digital twin has emerged as a powerful tool with transformative potential. In this section, the integration of a dynamic digital twin within the context of a vertical surface temperature profile visualization is discussed in detail. Building upon the foundation of the digital twin concept, this work explores the synergy between remote sensing and digital twin visualization facilitated by the *deck.gl* framework.

Deck.gl is a versatile WebGL-based visualization framework that simplifies the rendering and interactive exploration of extensive data sets within dynamic digital twin environments [53]. By intertwining temporally and spatially varying thermal data with a virtual 3D model, here we showcase the development, implementation, and benefits of a digital twin tool that not only enhances our understanding of the building's thermal facade behavior but

(a) Thermal image

(b) 3D Model

(c) Projected points
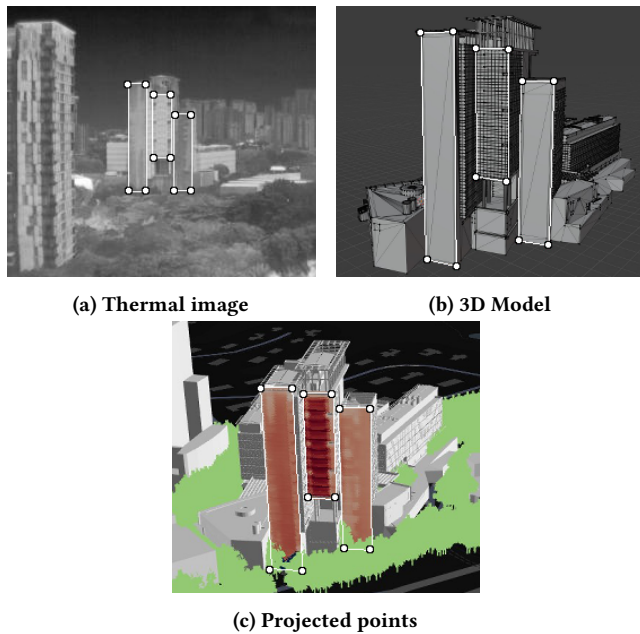
Figure 5: Selected surfaces and points, from (a) thermal image of the building and (b) 3D model, and (c) the final resulting surfaces and points from the mapping process.

Figure 6: Combining multiple *PointCloudLayers* and *SimpleMeshLayer* in *deck.gl* platform.

also serves as a pivotal resource of information for designers and researchers on seeking urban heat island effects mitigation and optimizing microclimatic conditions. Four hot and clear days were selected out of the operation period of the infrared observatory based on total daily solar radiation and the availability of complete thermal data. The comma-separated files for the selected days, extracted as described in Section 3.1, were aggregated to calculate the hourly average for each pixel and mapped according to the process in Section 3.2.

After mapping the thermal images to the 3D models, both the models and resulting JSON files are loaded in *deck.gl*. The 3D model is loaded as obj files using *SimpleMeshLayer*, and the thermal data is loaded as multiple *PointCloudLayers* as shown in Figure 6. To toggle visibility, each *PointCloudLayer* is configured to be visible if its date and time match the selected ones. This allows users to toggle between thermal data for each time period via buttons and a 24-step slider in the pop-up control panel. Alongside the thermal data, weather station data, including air temperature, relative humidity, solar radiation, wind speed, and wind direction, were also aggregated hourly and displayed.

Figure 7 shows the resulting fusion of dynamic digital twin technology with the vertical surface temperature of Building A from View I, as viewed in the *deck.gl* Digital Twin. This dashboard can be viewed at the following link: *https://limyyj.github.io/BEAM_thermalcamera/*. The visualization also presents a comprehensive information dashboard. This dashboard amalgamates mapped thermal imagery, weather station data, and sun path trajectories across different days, offering a holistic view of building performance. By distilling intricate data into a unified interface, stakeholders
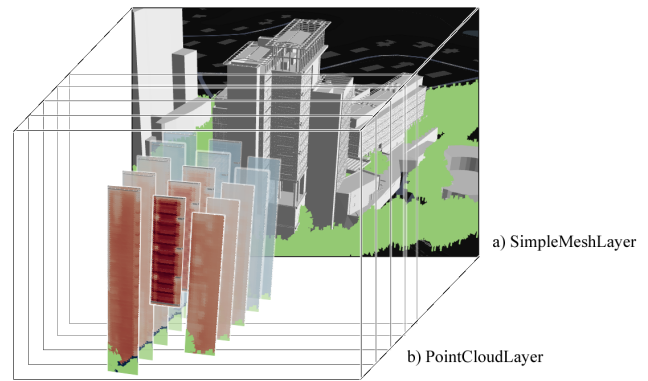
can decipher patterns, extract correlations, and optimize microclimate dynamics and energy efficiency. Figure 8 shows the changes in thermal data for the three selected building surfaces between 2 - 3 p.m. across the four selected days. The shadow cast by the sun and the corresponding air temperature and wind speed from a nearby weather station at that time are also shown. Here, darker red indicates a higher surface temperature.

4 DISCUSSION

A digital twin is one of the essential components of Industry 4.0. Especially with the increased use of IoT sensors to monitor the built environment, it is necessary to design a framework for combining the sensor data with the digital model to accurately represent the physical world. Further, the sensor data can be 1D, 2D, or 3D, and combining the heterogeneous data and visualizing it on the digital platform requires the development of a framework that largely depends on the type of application. This advancement constitutes one of the very first studies bridging this research gap. Here, the urban scale thermal images and weather station data are integrated with the 3D model for digital twin applications in the built environment, such as the UHI effect. Such a study is important as it is essential to make urban areas liveable and comfortable for residents and mitigate future climate change effects.

The study has a few limitations, which are discussed here. In this work, the pixels in the thermal image are manually mapped to the corresponding points in the 3D model. Although the thermal cameras used are stationary, and thus, each image needs to be projected only once, there is still a small amount of camera drift among images, which may result in mismatches of a few pixels. This inconsistency is significant for surfaces that are only around 15 pixels wide. This mismatch is handled by manual adjustment as this proof of concept study only considers a small sample of dates and locations. As this work scales in the future, manual adjustment will no longer be feasible, and we will consider using libraries such as OpenCV to correct such a drift [9]. It may also be worthwhile to look into object detection to aid in the initial mapping process as the number of locations increases.
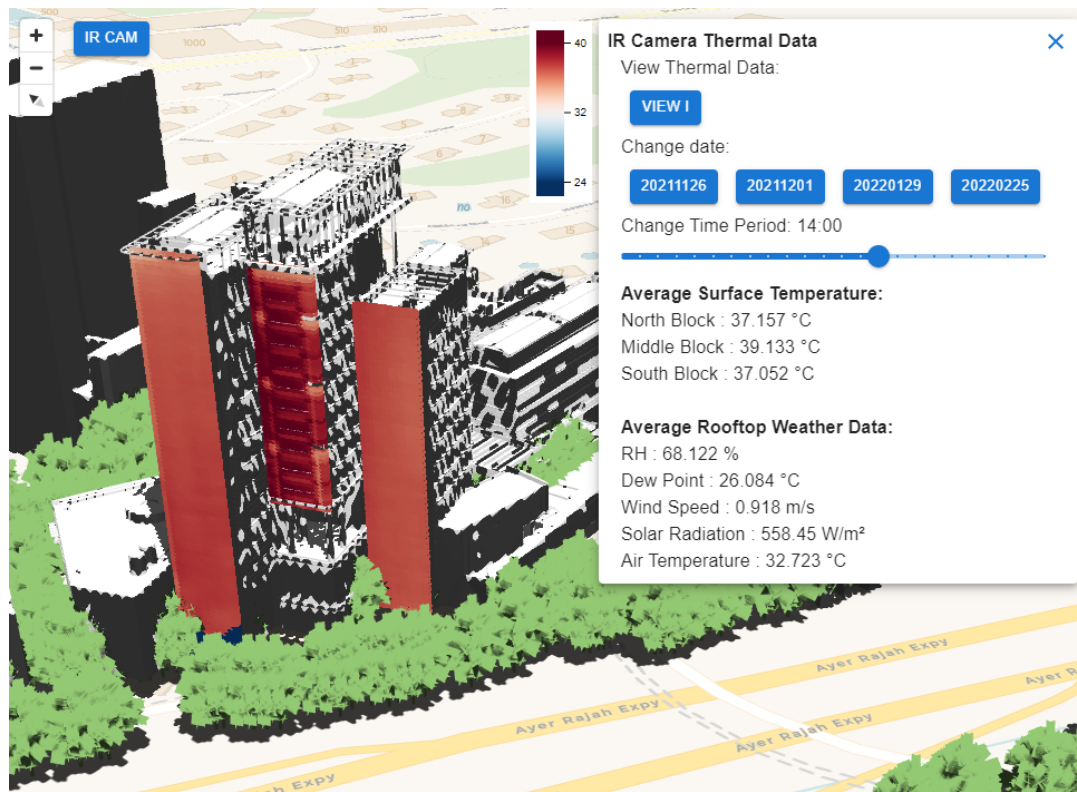
Figure 7: Digital twin dashboard of the building showing the thermal envelope of the building facade. The dashboard also shows the average surface temperature and the weather station data. The dashboard allows the user to toggle between different times of the day.

Another limitation is that only one face of the facade has been imaged. To conduct in-depth studies about the impact of the surrounding environment and weather conditions on buildings, information from all faces of the building is required. It would be beneficial to collect thermal images from multiple directions. The number of cameras required to build a complete 3D IR model will depend on the building's orientation and structure. Currently, the digital twin is uni-directional. It only displays information about the real world collected by the weather stations and thermal cameras. In discussions regarding urban digital twins, a bi-directional flow of information where the digital twin can also change the real world is considered an important feature [31, 38]. As such, the digital twin should be developed to include predictive analytics and help guide decision-making. In processing the thermal image data, intermediate formats such as unlabelled tabular *.npz* files and .json files are not standardized. Data interoperability is noted as a major challenge in various studies about digital twin challenges. It may be helpful to consider packaging the final result into a standardized format, such as CityGML [20] and its *dynamizer* module, or a well-documented API, to facilitate interoperability.

5 CONCLUSION

A dynamic digital twin model for incorporating thermal images and weather station data of buildings on an educational campus is presented. An urban-scale infrared observatory was operated over a few months to capture the thermal images of various building features such as buildings, vegetation, roads, and traffic. The thermal image is two-dimensional radiometric data, and its incorporation into the three-dimensional virtual model requires the development of a suitable framework. Here, we use a detailed virtual 3D model showing different features of the buildings alongside an extruded 3D building model that provides additional surrounding context as a base for viewing the thermal data. Each building surface in the thermal image is mapped and geolocated to the corresponding surface in the 3D model. The resulting data points are rendered on the 3D model as separate *PointCloudLayers* on the *deck.gl* platform. The developed digital twin platform allows visualization of the thermal image on the 3D model along with the weather station data. This work is one of the very few that combines the building's spatially and temporally varying 2D urban-scale thermal signature and weather station data with the 3D model for a dynamic digital twin.

This framework transcends data representation, becoming a transformative tool for microclimate studies and possibly energy modeling. Urban planners can strategically position green spaces, optimize shading solutions, and curate energy-efficient designs. The interactive capacity to toggle through time periods, weaving
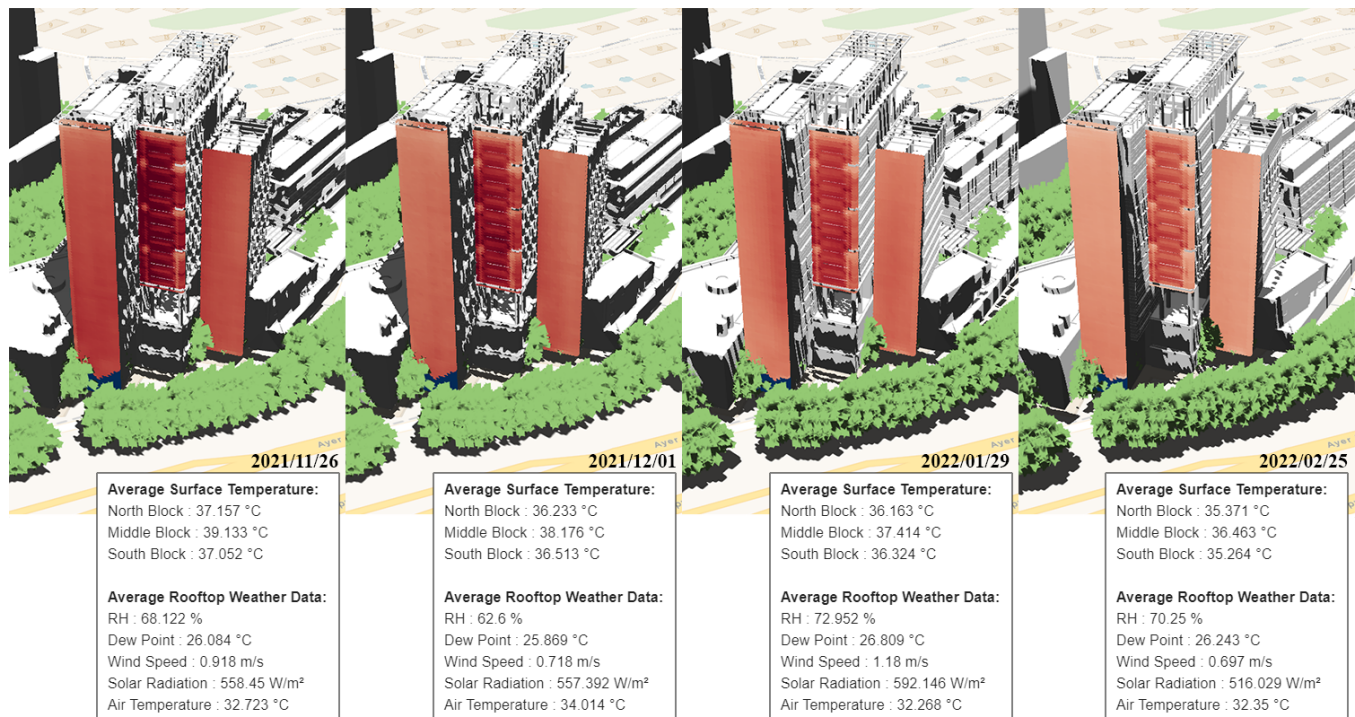
Figure 8: Figure showing the thermal envelope of the building on a clear day across four different months on the *deck.gl* platform.

weather, sun path, and thermal distribution empowers users to experiment, simulate, and innovate in unprecedented ways. In essence, this contribution represents a step forward in our approach to understanding and utilizing building performance data, contributing to the ongoing journey toward sustainable and adaptable urban environments.

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