Derivation of High-resolution Local Thermal Conditions from Satellite-based Data

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Abstract
The present study proposes a statistical approach for obtaining spatially detailed near-surface thermal information regarding the urban domain. This is accomplished by defining a workflow, which considers location-specific attributes of the built environment and which can be applied by utilizing publicly accessible data via remote sensing and GIS sources. To this end, we employ a large set of ground-based and remotely sensed observations from the years 2000 to 2015 to realize these objectives. The results reveal a relationship with an adjusted R² of 0.92 for day-time and 0.98 for night-time conditions. Air temperature estimates utilizing the proposed approach yield RMSEs of 2.26 K and 1.40 K for day-time and night-time inquiries respectively.

Key Innovations
- Consideration of building-related characteristics for deriving near-surface thermal conditions

Practical Implications
Utilization of MODIS data in thermal assessments of the urban settings can be a practical alternative to the terrestrial meteorological data, when supplied with adequate location and observation-based information, i.e. built environment attributes and solar geometry (see, for instance, Benali et al., 2012; Schneider dos Santos, 2020).

Introduction
This contribution presents a statistical approach to attain high-resolution near-surface thermal information within urban areas using remote sensing and GIS data sources. It thus contributes to the efforts to address the challenges of simulation-based inquiries regarding urban thermal domain (“weather data”) (Crawley and Barnaby, 2019; Firat Ors et al., 2019).

In this context, a number of previous research efforts conducted in the city of Vienna (Austria) reported significant variations in the microclimatic observations, which could be linked in part with certain characteristics of the built environment (Mahdavi et al., 2013; Mahdavi, 2018; Vuckovic et al., 2015; Vuckovic et al., 2017). A further research effort (Firat Ors et al., 2019) addressed these issues by exploring remotely sensed thermal data as a potential indicator for location-specific thermal conditions. The study showed promising outcomes for day-time conditions in Vienna and a strong agreement (R² of 0.90) was observed between near-surface temperatures and the thermal data obtained from satellite acquisitions. Motivated by these outcomes, and in-line with the goals previously outlined by Firat Ors et al. (2019), the present study further investigates the potential of employing remotely sensed land surface temperature data for obtaining high-resolution thermal information in urban environments. For this purpose, it pursues the following workflow:

- Land surface temperature (LST) data acquired at four different intervals within a diurnal cycle was obtained and compared with near surface air temperature (Tₚ) measurements from seven stationary weather stations (WS).
- Built environment characteristics at WS locations were explored and quantified through the “local climate zone (LCZ)” classification scheme (Stewart and Oke, 2012).
- Calculated (geometrical) parameters of the built environment, obtained LST data and other complementary datasets obtained via remote sensing (i.e. black-sky albedo, solar zenith angle) were utilized to formulate a statistical procedure for deriving location-specific high-resolution thermal information over the study area, the city of Vienna.

Study area
City of Vienna, situated at North-East Austria, has more than 1.9 Million dwellers and covers an area of 414.9 km² (Figure 1) (Bauer et al., 2020; Firat Ors et al., 2019). The city’s climate displays both oceanic and continental characteristics (Vienna_Weather, 2021). The mean annual temperature and precipitation are around 10°C and 650 mm (Vienna_Climates, 2021). At the “Köppen-Geiger Climate Classification”, the climate observed in Vienna correspond to the CFB Class which indicates “warm temperate”, “fully humid” conditions with “warm summer” temperatures (Kottek et al., 2006; Firat Ors et al., 2019).

The elevation varies around 390 meters in Vienna (Bauer et al., 2020; Firat Ors et al., 2019). In West, the topography is delineated by greater altitudes of Vienna Woods (Vienna_Statistics, 2021), whereas the eastern parts are characterized by a relatively lower profile (MA 41, 2021). Vegetated areas and water bodies occupy 50% of the municipal area, while the remaining is covered by built areas (36%) and traffic zones (14%) (Bauer et al., 2020). The city is spatially divided into 23 districts with surface areas ranging from 1.1 km² to 102.3 km². Likewise, the amount of green and blue spaces also range between 1.9% and 70.7% within the districts (Bauer et al., 2020).
Microclimatic characteristics

Near-surface air temperature

To explore microclimatic conditions with regard to the spatial and building-related properties, seven locations were selected in the study area following Firat Ors et al. (2019). Availability of terrestrial meteorological datasets and certain variations in the spatial organization of these locations guided the selection process.

$T_{\text{aw}}$ data was obtained from seven WS (Figure 1, Table 1). Four of these are situated in the municipal area of Vienna, whereas the remaining three are positioned in the surrounding regions of the city. The reported $T_{\text{aw}}$ is in hourly resolution and was provided by “Zentralanstalt für Meteorologie und Geodynamik (ZAMG)” (ZAMG, 2021).

Built environment characteristics

In order to describe and quantify the built environment properties that can potentially influence $T_{\text{aw}}$ observations of the selected WS, a “circle of influence” with 250m radius was defined around each (following Skarbit et al., 2017; Stewart and Oke, 2009). Selected parameters representing the 3D structure and spatial attributes of these “urban units of observations (U2Os)” (Mahdavi et al., 2013) were then calculated based on “local climate zone (LCZ)” classification system (Stewart and Oke, 2012).

These calculations were performed mainly in QGIS software (QGIS.org, 2021), utilizing or consulting geospatial data from various sources (Basemap.at, 2021; OGD Vienna, 2021; OGD NOE, 2021; City of Vienna, 2021; OpenStreetMap contributors, 2021; Google Earth, 2021) as well as by means of QGIS plug-ins (Conrad et al., 2015; Lindberg et al., 2018). Figures 2 and 3 illustrate the outcomes from this effort and represent the built environment characteristics at the WS locations.

Land surface temperature

As a potential alternative data-source for the microclimate assessments in the urban domain, LST data acquired by the MODIS sensors of Terra and Aqua satellites was also obtained (MODIS, 2021; Aqua, 2021; Terra, 2021). The LST data has 1 km spatial resolution (MOD11A1, 2021; MYD11A1, 2021). It can provide, via both Terra and Aqua satellites, observations at four different points in time within a diurnal cycle under ideal, cloud-free, circumstances (Table 2).

Obtained LST data is from the Version 6 of MOD11A1 (hereafter LST$_{\text{TERRA}}$) and MYD11A1 (hereafter LST$_{\text{AQUA}}$) products (Wan et al., 2015a; Wan et al., 2015b). The data provider for LST$_{\text{TERRA}}$ and LST$_{\text{AQUA}}$ datasets is the “Land Processes Distributed Active Archive Center (LP DAAC)” of NASA (LP DAAC, 2021; NASA, 2021). The data was accessed through the “Earth Engine Data Catalog” of the Google Earth Engine (GEE) and GEE was utilized for filtering and acquiring the LST data (Gorelick et al., 2017; GEE_Data, 2021; GEE_Terra, 2021; GEE_Aqua, 2021).

In order to gain insights regarding how variations of $T_{\text{aw}}$ observations relate to that of LSTs at different points in time during a diurnal cycle, both day-time and night-time datasets were acquired from the aforementioned LST products (LST$_{\text{TERRA-DAY}},$ LST$_{\text{TERRA-NIGHT}},$ LST$_{\text{AQUA-DAY}},$ LST$_{\text{AQUA-NIGHT}}$). Data filtering stages presented below were carried out separately for each dataset. The first criterion for data filtering was the time period of observations, which was decided based on available remote sensing and WS datasets (Table 2). The study area illustrated in Figure 1 was later defined in GEE as a “region of interest” (ROI). The ROI covers the municipal

Table 1: Details regarding the weather stations (partly based on ZAMG (2021), modified from Firat Ors et al. (2019))

<table>
<thead>
<tr>
<th>Station</th>
<th>ID</th>
<th>Location (lat., long.)</th>
<th>Elevation - Sensor h (m)</th>
<th>LCZ</th>
</tr>
</thead>
<tbody>
<tr>
<td>Donaufeld</td>
<td>DF</td>
<td>48.2573, 16.4313</td>
<td>160 – 2</td>
<td>6</td>
</tr>
<tr>
<td>Hohe Warte</td>
<td>HW</td>
<td>48.2486, 16.3564</td>
<td>198 – 1.9</td>
<td>6</td>
</tr>
<tr>
<td>Innere Stadt</td>
<td>IS</td>
<td>48.1984, 16.3664</td>
<td>177 – 9.3</td>
<td>2</td>
</tr>
<tr>
<td>Mariabrunn</td>
<td>MB</td>
<td>48.2069, 16.2294</td>
<td>225 – 2.1</td>
<td>9</td>
</tr>
<tr>
<td>Schwechat</td>
<td>SC</td>
<td>48.1174, 16.5815</td>
<td>183 – 2.2</td>
<td>DT</td>
</tr>
<tr>
<td>Seibersdorf</td>
<td>SD</td>
<td>47.9764, 16.505</td>
<td>185 – 2.1</td>
<td>9b</td>
</tr>
</tbody>
</table>
boundary of Vienna, as well as a minimum of 5 kms (5-6 whole LST pixels) from the WS locations thus constituting a good base to screen the sky conditions. LST datasets were filtered to include largely clear-sky observations within this area aiming to attain a better-quality dataset. This was ensured by excluding LST images if they had less than 90% valid pixels within the defined ROI. This threshold is decided based on the fact that LST\textsubscript{TERRA} and LST\textsubscript{AQUA} products do not include LST observations for pixels, which have a high likelihood of “cloud contamination” (MOD11A1, 2021; MYD11A1, 2021; Wan, 2013). Further data-filtering stages were performed individually for WS locations. This was done to include only

- observations with “view zenith angles” in the range of -/+ 35 degrees over WS locations (following Hu et al., 2014 and Monaghan et al., 2014);
- observations with certain acquisitional quality: Pixels, which correspond to WS locations were screened and included if they provided the average error threshold of 0.02 for emissivity and 2 K for LST. For the “unpacked” descriptions of the “bit-encoded” quality information provided by LST\textsubscript{TERRA} and LST\textsubscript{AQUA} products, a small portion of the LST dataset was also obtained from AppEEARS (AppEEARS Team, 2020a; Wan et al., 2015a; Wan et al., 2015b; MOD11A1, 2021; MYD11A1, 2021). Based on the insights gained from this dataset, data filtering for the afore-mentioned quality criteria was conducted in GEE.

After this step, 4136 LST\textsubscript{TERRA-DAY}, 3172 LST\textsubscript{AQUA-DAY}, 2807 LST\textsubscript{TERRA-NIGHT} and 2420 LST\textsubscript{AQUA-NIGHT} observations were selected for further analyses. These observations belonged to the pixels at the selected seven WS points.

**Deriving near-surface air temperatures**

**LST – T\textsubscript{air}**

Aiming to derive T\textsubscript{air} with a good agreement, approaches with different degrees of complexity were evaluated within the scope of this study. In this context, first, the relationship between LST and T\textsubscript{air} datasets were explored. The aim was to gain insights regarding how these two types of thermal data responded to temporal (diurnal) and location-based variations.

For this purpose, a “dataset matching” was performed between the LST and T\textsubscript{air} datasets. This was done by interpolating the hourly T\textsubscript{air} data based on the acquisition times of the LST data. Due to some pre-existing data gaps in the T\textsubscript{air} dataset, 81 LST observations could not be matched with corresponding T\textsubscript{air} observations and thus removed from the LST dataset at this stage. Consequently, a total of 7255 day-time and 5199 night-time T\textsubscript{air-LST} pairs were matched and prepared for further analyses.

The comparison of LST and T\textsubscript{air} data was performed at several steps. At the first step, a linear regression analysis was performed separately for LST\textsubscript{DAY} and LST\textsubscript{NIGHT} datasets and the respective T\textsubscript{air} data (Table 3, Figures 4 and 5). The results show a strong relationship for both inquiries, with R\textsuperscript{2} values 0.903 and 0.967 for LST\textsubscript{DAY-T\textsubscript{air}} and LST\textsubscript{NIGHT-T\textsubscript{air}} datasets respectively.

In the following step, four LST datasets, namely LST\textsubscript{TERRA-DAY}, LST\textsubscript{TERRA-NIGHT}, LST\textsubscript{AQUA-DAY}, LST\textsubscript{AQUA-NIGHT} were individually compared with the respective T\textsubscript{air} observations (Table 3). The results from this inquiry yielded similar trends as the previous analyses. All investigated LST datasets showed strong relationships with the T\textsubscript{air} data, and the agreement was significantly stronger for night-time datasets with 0.976 and 0.963 R\textsuperscript{2} values for LST\textsubscript{TERRA-NIGHT} and LST\textsubscript{AQUA-NIGHT} respectively (Table 3).

<table>
<thead>
<tr>
<th>LST Data</th>
<th>GEE Datasets</th>
<th>Filtered Dates</th>
<th>Datasets</th>
<th>Acquisition Time (CET)</th>
</tr>
</thead>
<tbody>
<tr>
<td>LST\textsubscript{TERRA}</td>
<td>MOD11A1.006 Terra Land Surface Temperature and Emissivity Daily Global 1km</td>
<td>05.03.2000 - 01.09.2015</td>
<td>LST\textsubscript{TERRA-DAY}</td>
<td>~ 10:30 – 11:30</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>LST\textsubscript{TERRA-NIGHT}</td>
<td>~ 21:30 – 22:30</td>
</tr>
<tr>
<td>LST\textsubscript{AQUA}</td>
<td>MYD11A1.006 Aqua Land Surface Temperature and Emissivity Daily Global 1km</td>
<td>04.07.2002 - 01.09.2015</td>
<td>LST\textsubscript{AQUA-DAY}</td>
<td>~ 12:30 – 13:30</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>LST\textsubscript{AQUA-NIGHT}</td>
<td>~ 01:30 – 02:30</td>
</tr>
</tbody>
</table>

![Figure 2: Mean building height and SVF at WS locations.](image2.png)

![Figure 3: Surface fractions at WS locations.](image3.png)
Influence of building-related attributes

As stated earlier, obtained relationships presented in Table 3 show a good agreement between the two investigated indicators of the urban thermal domain. Within the scope of this present contribution, alternative strategies were further explored with the aim of improving the established relationships for LST and $T_{air}$ datasets. The assumption was that certain parameters can influence the relationship between these two variables, and may thus facilitate more accurate estimations of $T_{air}$ (see, for instance, Zakšek and Schroedter-Homscheidt, 2009; Benali et al., 2012; Schneider dos Santos, 2020).

For this purpose, first the previously calculated built environment parameters (Figures 2-3) were assigned to the respective LST and $T_{air}$ observations in order to obtain a new dataset representing the (geometrical) variations in the built environment and the corresponding microclimatic conditions. Moreover, as presented earlier, the comparisons from the previous efforts (Figures 4-5, Table 3) indicated that the relationship between LST and $T_{air}$ data was significantly stronger at night-time conditions. Motivated by this fact, the contribution of solar radiation in the established relationships was also decided to be considered. This was accomplished by including “black sky albedo (broadband shortwave) (BSA)” and “solar zenith angle (SZA)” data (following Schneider dos Santos, 2020) to the day-time datasets. Utilized BSA and SZA data stems from MODIS observations and was obtained from AppEEARS (Vermote and Wolfe, 2015a; Vermote and Wolfe, 2015b; Schaaf and Wang, 2015; AppEEARS Team, 2020b). Note that, due to missing observations in the BSA data, the number of available observations for the study decreased from 4104 to 3767 for LST$\_TERRA$-day datasets and from 3151 to 2947 for LST$\_AQUA$-day datasets. This resulted in a slight change in the linear regression outputs for the datasets including day-time observations. For instance, for the LST$\_TERRA$-$T_{air}$ dataset, the $R^2$ was noted as 0.896 (instead of 0.903) and the “standard error for the regression” (SE) was now reported as 2.57 K.

In this context, a multiple regression analysis was carried out in two phases with different dependent variables. In the first step, the temperature difference ($\Delta T$) between corresponding LST and $T_{air}$ observations ($\Delta T=LST-T_{air}$) was considered as the dependent variable, and in the second step, LST was considered among the independent variables as well, and $T_{air}$ was solely taken as the dependent variable. This workflow was intended to lead to a better understanding regarding the role of the investigated parameters towards deriving location-based high-resolution thermal information in the urban domain. The multiple regression analysis was carried out separately for day-time and night-time data, in the light of the considerations presented earlier on the introduction of additional data to the day-time dataset.

All in all, “building surface fraction” (BSF), “pervious surface fraction” (PSF), (area-weighted) “mean building height” (MBH), “sky view factor” (SVF) were the

Table 3: Comparison of LST and $T_{air}$ data.

<table>
<thead>
<tr>
<th>Dataset Pairs</th>
<th>Observations</th>
<th>Obtained relationships</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>LST$_DAY$ - $T_{air}$</td>
<td>7255</td>
<td>$T_{air} = 0.7755 \text{ LST}_{DAY} - 0.1768$</td>
<td>0.903</td>
</tr>
<tr>
<td>LST$_NIGHT$ - $T_{air}$</td>
<td>5199</td>
<td>$T_{air} = 0.976 \text{ LST}_{NIGHT} + 1.9316$</td>
<td>0.967</td>
</tr>
<tr>
<td>LST$_TERRA$-DAY - $T_{air}$</td>
<td>4104</td>
<td>$T_{air} = 0.7763 \text{ LST}_{TERRA}$-DAY - 0.2487</td>
<td>0.904</td>
</tr>
<tr>
<td>LST$_AQUA$-DAY - $T_{air}$</td>
<td>3151</td>
<td>$T_{air} = 0.7727 \text{ LST}_{AQUA}$-DAY - 0.0356</td>
<td>0.899</td>
</tr>
<tr>
<td>LST$_TERRA$-NIGHT - $T_{air}$</td>
<td>2797</td>
<td>$T_{air} = 0.9877 \text{ LST}_{TERRA}$-NIGHT + 2.2809</td>
<td>0.976</td>
</tr>
<tr>
<td>LST$_AQUA$-NIGHT - $T_{air}$</td>
<td>2402</td>
<td>$T_{air} = 0.9539 \text{ LST}_{AQUA}$-NIGHT + 1.5707</td>
<td>0.963</td>
</tr>
</tbody>
</table>

Figure 4: Relationship between LST$\_DAY$ - $T_{air}$.

Figure 5: Relationship between LST$\_NIGHT$ - $T_{air}$.

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independent variables selected to represent the built environment characteristics of the investigated areas and were included to both day-time and night-time datasets. BSA and SZA data sets were additionally included to the day-time dataset, as stated before. The multiple regression analyses were conducted utilizing Analysis ToolPak (2021).

For the day-time dataset (6714 number of observations from both Terra and Aqua satellites), the regression results showed an (adjusted) R² of 0.534 with 2.31 K SE, when the dependent variable was taken as AT. When LST was added among the independent variables, the results indicated an adjusted R² of 0.920 and a slightly lower SE of 2.26 K, with T_air as the dependent variable. As included in Table 4, P-value results suggest that all investigated parameters had an influence on the dependent variables. This and the changes in R² (from 0.896 to 0.920) and SE (2.57K to 2.26K) values with the introduction of investigated variables confirm that considering these variables improve the estimation of high-resolution thermal information for the selected locations for day-time conditions. Further details of the regression outputs for day-time inquiries can be found in Table 4.

When the aforementioned variables representing the built environment were utilized in the regression models for night-time analyses, adjusted R² outputs were 0.239 and 0.975, and SE estimates were 1.41 K and 1.40 K, respectively for the dependent variables ∆T and T_air. But the P-value results for both models were higher than the commonly applied threshold of 0.05 for PSF and MBH outcomes, indicating these variables did not have a significant impact on the dependent variables. Therefore, the analyses were conducted once more by extracting these two variables, for obtaining the model coefficients in a simpler approach to be evaluated in future inquiries (Table 6). In parallel with the outcomes from day-time analyses, both night-time models showed an improvement with the introduction of additional variables (R² values from 0.967 to 0.975 and SE outcomes from 1.60 K to 1.40 K). Based on these results, obtained coefficients were utilized to calculate air temperature values (T_air) to gain insights regarding the models’ performance. These coefficients were taken from the models, which consider T_air as the dependent variable. For the night-time inquiry, the model which included three independent variables (BSF, SVF, LST – Table 6) was used. By utilizing the same datasets as the regression inquiries, T_air was calculated for both day-time and night-time data.

![Figure 6: Box-plot diagram for day-time (blue) and night-time data (grey).](image)

**Table 4: Regression outputs for day-time inquiries.**

<table>
<thead>
<tr>
<th>Dependent Variable: ΔT</th>
<th>Coefficients</th>
<th>SE (K)</th>
<th>P-value</th>
<th>Coefficients</th>
<th>SE (K)</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>3.1485</td>
<td>0.47</td>
<td>0.0000</td>
<td>1.5261</td>
<td>0.53</td>
<td>0.0041</td>
</tr>
<tr>
<td>LST</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>SZA</td>
<td>-0.1535</td>
<td>0.00</td>
<td>0.0000</td>
<td>0.0873</td>
<td>0.00</td>
<td>0.0000</td>
</tr>
<tr>
<td>BSA</td>
<td>-10.5203</td>
<td>1.08</td>
<td>0.0000</td>
<td>6.9545</td>
<td>1.08</td>
<td>0.0000</td>
</tr>
<tr>
<td>BSF</td>
<td>37.1705</td>
<td>1.61</td>
<td>0.0000</td>
<td>-33.2328</td>
<td>1.59</td>
<td>0.0000</td>
</tr>
<tr>
<td>PSF</td>
<td>10.7354</td>
<td>0.78</td>
<td>0.0000</td>
<td>-9.6276</td>
<td>0.77</td>
<td>0.0000</td>
</tr>
<tr>
<td>MBH</td>
<td>-0.2679</td>
<td>0.02</td>
<td>0.0000</td>
<td>0.2413</td>
<td>0.02</td>
<td>0.0000</td>
</tr>
<tr>
<td>SVF</td>
<td>1.2656</td>
<td>0.39</td>
<td>0.0010</td>
<td>-0.9469</td>
<td>0.38</td>
<td>0.0121</td>
</tr>
</tbody>
</table>

**Table 5: Regression outputs for night-time inquiries.**

<table>
<thead>
<tr>
<th>Dependent Variable: ΔT</th>
<th>Coefficients</th>
<th>SE (K)</th>
<th>P-value</th>
<th>Coefficients</th>
<th>SE (K)</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>4.0639</td>
<td>0.31</td>
<td>0.0000</td>
<td>-3.9167</td>
<td>0.31</td>
<td>0.0000</td>
</tr>
<tr>
<td>LST</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>BSF</td>
<td>-8.9019</td>
<td>1.14</td>
<td>0.0000</td>
<td>9.2365</td>
<td>1.13</td>
<td>0.0000</td>
</tr>
<tr>
<td>PSF</td>
<td>-0.8969</td>
<td>0.56</td>
<td>0.1068</td>
<td>1.0209</td>
<td>0.55</td>
<td>0.0634</td>
</tr>
<tr>
<td>MBH</td>
<td>0.0155</td>
<td>0.02</td>
<td>0.3053</td>
<td>-0.0191</td>
<td>0.01</td>
<td>0.2022</td>
</tr>
<tr>
<td>SVF</td>
<td>-5.5225</td>
<td>0.27</td>
<td>0.0000</td>
<td>5.4440</td>
<td>0.27</td>
<td>0.0000</td>
</tr>
</tbody>
</table>
In order to better evaluate the model’s performance, a new dataset was constructed by subtracting $T_{air}$ observations from respective $T_{air,c}$ values. The box-plots from this dataset are presented in Figure 6 and details regarding further statistics can be found in Table 7.

### Conclusion

This paper examined an approach to deriving local thermal information with high spatial detail within urban settings by utilizing remotely sensed and GIS data sources. Regression analysis results indicated that, for day-time conditions, all considered parameters had an influence on the dependent variables and introducing the parameters improved the models’ performance ($R^2$=0.896 to $R^2$=0.920; SE=2.57K to 2.26K). For the night-time conditions, it was noted that the input parameters PSF and MBH did not have a significant influence on the model outputs. Although it is expected from the urban climate point of view that the influence of SVF on the nocturnal temperatures would be the greatest among investigated parameters, it would be more insightful to re-evaluate the influence of PSF and MBH parameters with a more detailed dataset in terms of built environment characteristics. Nevertheless, a model improvement was also observed for night-time conditions (from $R^2$=0.967 to $R^2$=0.975; SE=1.60K to 1.40K) when comparing the models with the outcomes of $LST_{NIGHT}$-$T_{air}$ dataset. Regression analysis further suggested that considering $LST$ among the independent variables slightly improves the model’s performance in both cases (from 2.31 K to 2.26 K SE for day-time, from 1.41 K to 1.40 K SE for night-time conditions).

Our next steps include the analyses of data in view of the relative differences between different locations at different times. This would allow to judge if the proposed approach is robust in view of temporal and local factors. Moreover, we intend to test the proposed approach in another geographic location to assess its applicability under different climatic and topographic conditions. In this context, it might be insightful to note here NASA POWER (2021), a global-level data source, through which many meteorological and climatic information for building science inquiries can be accessed, although with broader (i.e. 0.5° latitude x 0.5° longitude) spatial resolution (NASA POWER, 2021). Furthermore, as stated earlier, utilizing a dataset with more spatial detail would also provide more insights regarding the proposed models for future inquiries.

### Nomenclature

- $LST$ = land surface temperature
- $T_{air}$ = near-surface air temperature
- $T_{air,c}$ = calculated air temperature
- $WS$ = stationary weather station
- $BSF$ = building surface fraction
- $PSF$ = pervious surface fraction
- $MBH$ = area-weighted mean building height
- $SVF$ = sky view factor
- $BSA$ = black-sky albedo
- $SZA$ = solar zenith angle

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### References


