

Sensitivity of urban heat islands to various methodological schemes

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Abstract

Existing research has employed various methods to quantify urban heat island (UHI) effects, but the ideal method for individual cities remains unclear. This study investigated how different methods influence UHI understanding in Addis Ababa, a tropical city facing UHI challenges. Three methods were compared: dynamic urbanization, natural and built-up fractions, and urban center vs. surrounding rural areas. Satellite data and spatial analyses revealed maximum daytime UHIs of 4°C and 3.1°C in summer and autumn, respectively. Examining the mean temperature differences between urban and rural areas across methods yielded diverse results. This suggests that while the 'dynamic urbanization' method is statistically favorable in this specific case, averaging results from multiple methods produced a more robust and generalizable approach to understanding UHIs in different urban contexts. Ultimately, this study highlights the importance of context-specific method selection for accurately understanding the complex interplay between urban and rural environments.

keywords: urban heat islands; methods; urban climate; dynamic urbanization; land cover; natural and urban fractions

1 Introduction

World urban population is estimated to rise from the current 55% to 68% by 2050, out of which the nearly 90% increase will come from Asia and Africa (UN (2022)). This urbanization requires careful planning to accommodate people and to adapt to the consequences of urban climate under a changing environment. The urban environments are found to be warmer than rural areas (Oke (1982); Ferguson and Woodbury (2007); Oleson et al. (2011); Clinton and Gong (2013); Garuma et al. (2018); Kim and Brown (2021)) known as the urban heat island effect. Complemented with global warming, it puts the urban water and energy under a high constraint (McCarthy et al. (2010)). That is the combined overheating from the urban heat islands and global warming induced heat waves have adverse effects on human health and the urban biosphere.

The urban heat island (UHI) impacts more than just temperature. It alters precipitation patterns (Dixon and Mote (2003); Li et al. (2020)), fuels flash floods through intense thunderstorms (Qiu (2012); Ntelekos et al. (2007)), and even affects regional plant growth (Shochat

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et al. (2006)). To mitigate these effects, understanding UHI and its sensitivity to different measurement methods is crucial. While urban layout and materials significantly influence UHI intensity (Liu et al. (2021); Steeneveld et al. (2011); Liao et al. (2021); Liu et al. (2020b); Yin et al. (2018); Touchaei and Wang (2015); Stone Jr and Rodgers (2001); Santos et al. (2021)), no prior studies have compared various UHI calculation methods for sensitivity analysis. Existing research on UHI often compares urban and rural weather data (Wang et al. (1990); Roth (2012); Oke (2010); Garuma (2022)). This can be done in three ways: comparing urban centers to surrounding rural areas (Fig. S1), analyzing natural vs. built-up areas within the same grid (Fig. S2), or tracking UHI changes over time (Fig. S3).

This first method compares urban and rural grids directly (Fig. S1 (a)) (e.g., Garuma et al. (2018); Myrup (1969)). It chooses nearby grids to isolate the impact of the city from broader climate changes. Mean temperatures are then compared between the central urban grid and surrounding rural grids in different directions (Fig. S1 (b)). This is often applied in specific rectangular or circular areas within the city and surrounding countryside.

The second method compares urban and rural fractions within a single grid (Fig. S2). Often used in weather models (e.g., Li and Bou-Zeid (2014); Kusaka et al. (2012); Oleson et al. (2008)), it involves two simulations: one with an "urban canopy model" (Fig. S2 (b)) and another without (Fig. S2 (a)). Alternatively, real-world data such as earth observation information or ground measurements can be filtered based on urban and rural fractions (e.g., buildings vs. vegetation) (e.g., Tran et al. (2006); Singh et al. (2022); Zhou et al. (2010)). This requires land cover data and statistical techniques to identify urban and rural grids.

The third method, less common but crucial, tracks UHI changes over time (e.g., Ogashawara and Bastos (2012); Dutta et al. (2021); Liu et al. (2019)). It incorporates urban development into climate models, simulating how weather changes with city growth. This helps understand current UHI impacts and predict future effects, especially for land-use transitions (rural to urban or vice versa). While requiring detailed data on building properties and land-use changes, this method offers valuable insights for urban planning and adaptation, remembering to account for separate effects of global warming.

Another rare approach compares pre-existing and post-construction climates (e.g., Beijing's Olympic expansion (Sun and Chen (2017); Liu et al. (2020a); Meng et al. (2018)). This leverages new city development, hypothetical pre-city scenarios, or disaster reconstruction (Renard et al. (2019)). It's also useful for studying urban redevelopment impacts or even individual building projects, revealing localized weather and climate changes.

Another approach uses scenarios to predict future UHI impacts based on changes in urban fractions like building coverage, roads, vegetation, and even solar panels. This helps compare past, present, and future trends or model different development scenarios (low, medium, high) or specific urban climate zones (Stewart and Oke (2012)). Analyzing these fractional changes reveals how different land use changes interact with local weather and climate.

Human activities also influence UHI, and anthropogenic heat and moisture emissions are also used to understand the impacts of human settlements (Shahmohamadi et al. (2011); Kato and Yamaguchi (2005); Ichinose et al. (1999)). Methods like comparing weekdays and weekends separate human-caused heat from solar effects (Kim and Baik (2005); Earl et al. (2016); Wang et al. (2022); Ngarambe et al. (2021); Nwaerema and Jiya (2021)). Similarly, comparing early mornings with later daytime conditions isolates the built environment's impact (Giannaros et al. (2013); Lehoczky et al. (2017)). These methods require detailed data on energy use, population, and other urban heat sources, but offer valuable insights into the combined effects of urban infrastructure and human activity on local weather and climate.

Despite a plethora of studies applying various methods to calculate urban climate, a crucial piece is missing: a comparative analysis of their outputs. This research fills this void by evaluating three prevalent methods used by urban climate researchers. These are: (1) comparing the urban

85 center to surrounding rural areas (Fig. S1 (b)), 2) analyzing the fractions of natural and built-up
 86 land cover (Fig. S2 (b)), and 3) exploring the temporal dynamics of urban land cover changes
 87 (Fig. S3 (a) and (b)). Accordingly, this paper examines the spatio-temporal characteristics
 88 of Tropical Surface Urban Heat Islands (TSUHIs) (Garuma (2023)) in a specific East African
 89 city. It employs three widely used methodologies, aiming to: (1) analyze and characterize the
 90 city's TSUHIs through diverse methodological approaches; (2) evaluate the performance and
 91 accuracy of each method against observational data; and (3) identify the optimal method for
 92 effectively determining the spatio-temporal patterns of TSUHIs in this specific tropical city.
 93 The paper is organized as follows: it commences with materials and data analysis methods
 94 (Section 2), delves into detailed results and discussion (Section 3), and culminates with the
 95 study's overarching conclusions (Section 4).

96 2 Materials and methods

97 2.1 Study area

98 This study evaluates three UHI calculation methods in Addis Ababa, Ethiopia (35.5°E - 39°E,
 99 8.7°N - 9.2°N). The rapidly growing city (urban cover 0% to 95%) (Fig. 1) experienced real
 100 estate booms expanding westward and eastward (2005-2015) (Mohamed and Worku (2019)).
 101 This rapid change prompted the study to compare methods for effective urban climate analysis
 102 in such scenarios. Addis Ababa, the most populous Ethiopian city, houses the African Union
 103 and other organizations. Its complex topography ranges from 2,300m to 3,200m above sea level.
 104 It has moderate temperatures (10°C to 30°C) with a wet summer and dry winter. Spring brings
 105 the rainy season, while summer is the wettest for the highlands, followed by drier autumn and
 106 winter (Diro et al. (2011)).

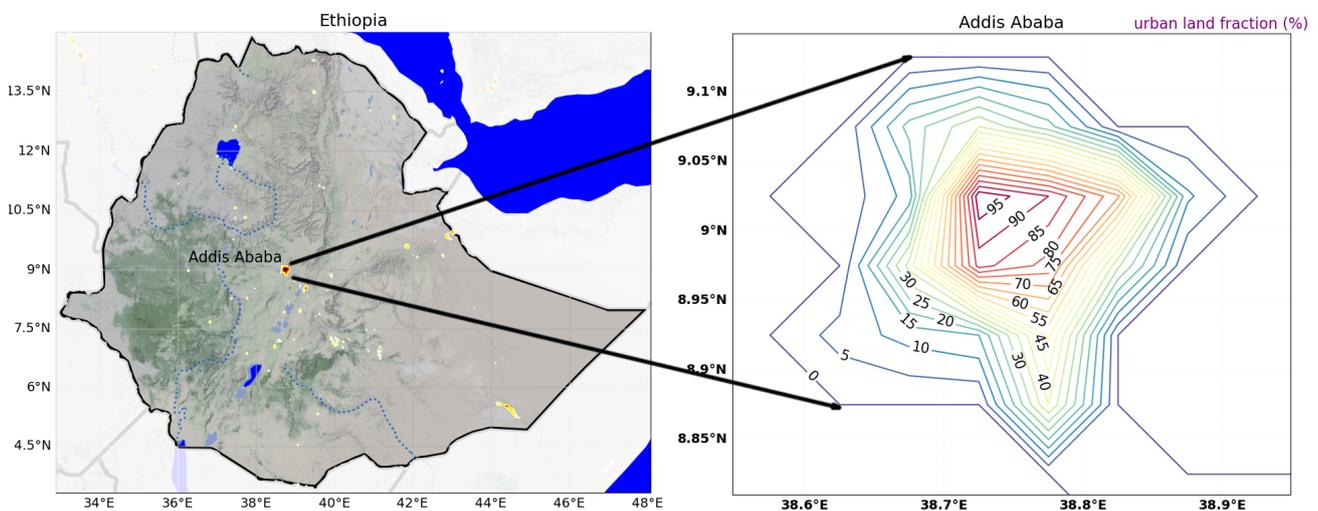


Figure 1: This map reveals the varying levels of urban development around and within Addis Ababa. Contour lines with increasing color intensity depict a gradient in urban density, with blue representing 0% at the city's periphery and deep red signifying 95% in the central areas.

107 2.2 Data sources

108 This study utilized daily and monthly land surface temperature and land cover data from
 109 the MODIS sensor (0.05° resolution) for the period 2000-2020 (Wan et al. (2015)). MODIS

110 land cover data helped identify urban and rural fractions within each grid cell (Fiedl and Sulla-
 111 Menashe (2015)). To ensure accuracy, MODIS land surface temperature data was bias-corrected
 112 and validated against measurements from meteorological stations in Addis Ababa, including
 113 Bole International Airport and the Ethiopian Meteorological Institute’s main office. The tem-
 114 perature data from the meteorological stations was obtained from the National Meteorological
 115 Agency (http://www.ethiomet.gov.et/data_access/information) and the Berkley Earth
 116 Database (<https://data.berkeleyearth.org/locations/8.84N-38.11E>).

117 **2.3 Bias correction**

118 MODIS land surface temperature data contained a bias compared to ground stations. To
 119 address this, the satellite data was bias-corrected using station observations from the nearest
 120 grid point. Station data was first filtered for outliers using the median filter outliers method
 121 (Lim (1990)) and then used to calculate a correction factor based on the average temperature
 122 difference between MODIS and station data. That is,

$$T_{BC}(t) = T_M(t) + (\overline{T_O} - \overline{T_M}) \quad (1)$$

123 where the T_{BC} , T_M and T_O are the bias corrected (BC) land surface temperature (LST), the
 124 MODIS LST and station observation temperatures respectively.

125 This correction was applied to the MODIS data, resulting in a bias-corrected version (T_{BC}).
 126 The effectiveness of the correction was assessed by comparing the spatial pattern of the bias-
 127 corrected MODIS data with the station observations. Pattern similarity correlation between
 128 the observation LST (T_O) and the bias-corrected MODIS LST (T_M) is

$$R = \frac{\frac{1}{N} \sum_{n=1}^N (T_M - \overline{T_M})(T_O - \overline{T_O})}{\sigma_{T_M} \sigma_{T_O}}, \quad (2)$$

129 where $\overline{T_M}$ and $\overline{T_O}$ are the mean values and σ_{T_M} and σ_{T_O} are their respective standard deviations.
 130 The correlation coefficient reaches a maximum value of 1 when the two data sets have the same
 131 centered pattern, otherwise the R values are less than 1. A high correlation coefficient indicated
 132 successful correction.

133 **2.4 Tropical surface urban heat islands**

134 This study compares three established methods for examining urban climate: 1) natural vs.
 135 built-up fractions, 2) urban centers vs. surrounding rural areas, and 3) dynamic changes over
 136 time.

137 **Method 1: Natural vs. built-up fractions**

138 This method uses land cover fractions (vegetation vs. urban) to identify urban and rural
 139 areas (Fig. S4). Urban fractions are higher in the city center, while vegetation dominates the
 140 outskirts. TSUHI is calculated as the difference in land surface temperature (LST) between
 141 grids with high urban and high vegetation fractions (LST urban - LST rural). Grids with $\geq 5\%$
 142 vegetation and $\leq 5\%$ urban area are considered rural, while the opposite defines urban grids.
 143 The day/night TSUHI ($TSUHI_{d/n}$) is then determined by the LST difference between these
 144 categories, i.e.,

$$TSUHI_{(d/n)} = LST_{(d/n;u)} - LST_{(d/n;r)} \quad (3)$$

145 where $LST_{d/n,u}$ and $LST_{d/n,r}$ are the urban and rural LST respectively during the day and
 146 night (d/n). For the observation analysis the skin surface temperature from two meteorological
 147 observation sites at the airport and center of the city are used.

148 **Method 2: Urban centers vs. surrounding rural areas**

149 This method defines urban areas as a central region with high urban land cover (Fig. S4 (d))
150 surrounded by rural areas with more vegetation (Fig. S4 (e)). Figure S4 (f) shows the urban
151 land cover (red shaded contours) overlaid within the urban domain and the surrounding rural
152 fractions shown with more vegetation fractions (green contours). The surface urban heat island
153 (SUHI) is calculated by comparing the average land surface temperature of the central urban
154 area with the surrounding rural areas, similar to equation 3. This method uses a larger rural
155 area than the previous method, leading to a higher average vegetation fraction (39% vs. 35%
156) (compare Figs. S4 (b) and (e)).

157 **Method 3: Dynamic urbanization**

158 This method tracks changes in urban land cover and vegetation over time to assess UHI impacts
159 (Fig. S4 (c)). It compares the differences between early and later periods of rapid urbanization
160 (2000-2010 vs. 2011-2020) using land cover (Fig. S4 (g)) and vegetation fractions (Fig. S4 (h)).
161 As shown in Fig. S4 (i), the western and eastern city areas underwent significant expansion
162 (red contours), highlighting the impact of recent development.
163 The surface urban heat island computed in this method is

$$TSUHI_{(d/n)} = LST_{(d/n;p2)} - LST_{(d/n;p1)} \quad (4)$$

164 where the (d/n) is the day or night values; $p1$ and $p2$ are the periods where there was low and
165 high urban developments respectively. The period $p2$ is a later period than $p1$. For this study,
166 $p1$ and $p2$ are the periods from 2000-2010 and 2011-2020 respectively.

167 **2.5 Performance of the methods compared to the mean**

168 The performance of each method in capturing UHI was assessed using standard deviation (SD),
169 root mean square deviation (RMSD), and correlation coefficient (CC) compared to observations
170 and a composite mean. Taylor diagrams (Taylor (2001)) and boxplots additionally evaluated
171 the overall skill of each method. These metrics helped determine which method produced results
172 closest to observations, indicating better performance for this specific city. This evaluation also
173 helps understand how sensitive the methods are to UHI calculations. The priority lies in SD
174 and RMSD, as high values indicate significant errors or outliers, even with a high CC.

175 **3 Results and discussion**

176 **3.1 Bias correction and validation**

177 Bias correction for MODIS data was performed using eqn. 1., leveraging observation data
178 from the closest meteorological station. The correlation between the corrected MODIS and
179 observation data was then calculated to evaluate the correction's impact on data suitability.
180 Bias correction significantly improved the agreement between MODIS data and station ob-
181 servations. Daytime and nighttime urban temperatures exhibited strong correlations, with
182 R-squared values of 0.94 and 0.99, respectively (Figs. 2 (a) and (b)). Compared to nighttime
183 data, daytime LST displayed a wider scatter around the mean and higher variability. Notably,
184 the mean LST for both day and night achieved an R-squared value of 0.97 (Fig. 2 (c)). These
185 findings demonstrate the high accuracy of the bias-corrected MODIS data for our research pur-
186 poses. This implies that the data is well-suited to investigate the methodological sensitivities
187 of urban heat island characteristics in this specific tropical city.

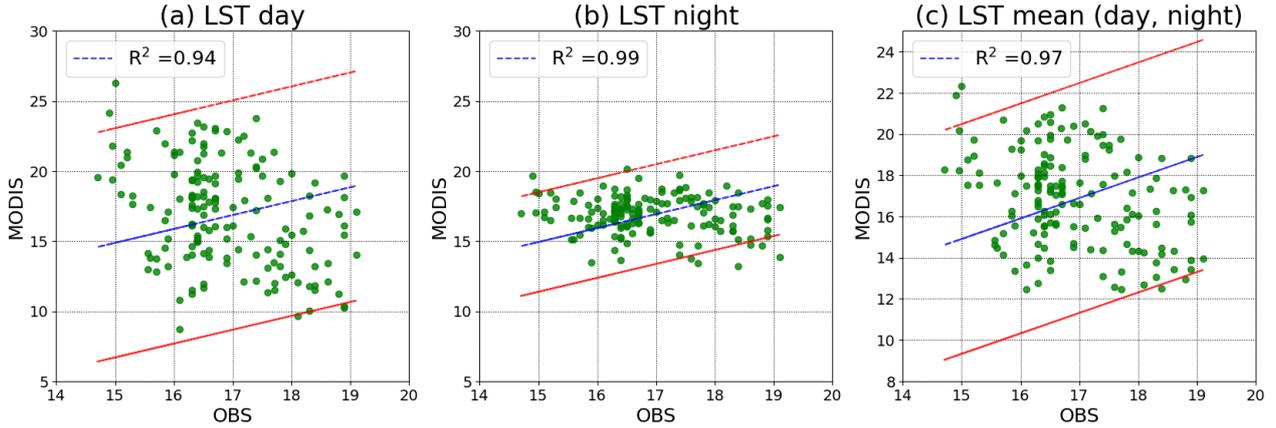


Figure 2: Validation of MODIS LST using stationary observation data for (a) day, (b) night and (c) mean of the day and night. The green dots are the actual data points calculated at 99.9% confidence interval under Ordinary Least Squares (OLS) assumptions. The blue line in the middle is the linear least squares fit with an indicated R-squared values. The upper and lower red lines are for the upper and lower bounds respectively at 99.9% confidence level.

3.2 Representing tropical surface urban heat islands

This study aims to challenge the misconception that tropical cities in developing countries lack urban heat islands (UHIs). This belief stems from the inhomogeneous distribution of buildings and roads in sub-Saharan African cities, where skyscrapers often stand alongside informal settlements. However, the rapid urbanization in these regions, driven by the desire for better education, healthcare, and employment, leads to increased water and energy consumption, releasing anthropogenic heat and moisture into the environment. Despite the spatial heterogeneity, roads, sidewalks, and other impervious surfaces contribute significantly to altering the energy and moisture balance compared to rural areas. These changes, coupled with dense populations and consequent human activities, create distinct weather and climatic conditions, potentially leading to UHIs even in seemingly inhomogeneous landscapes.

Our analysis confirms the presence of Tropical Surface Urban Heat Islands (TSUHIs) in this sub-Saharan African city during summer and autumn seasons (Fig. 3). In these seasons, the central city exhibits significantly higher daytime Land Surface Temperatures (LSTs) compared to its outskirts. As shown in Figs. 3 (c) and (d)), the summer LST reaches 27.5°C at the center, while the edges experience cooler temperatures around 23.5°C. Similarly, autumn daytime LSTs peak at 30.6°C in the center, contrasting with 27.5°C at the city’s periphery.

These temperature differences are visualized by the closed contour lines in Fig.3 radiating outwards from the warmer center. We estimated the TSUHI intensity by subtracting the LST at the city edges from the central values. This reveals a summer TSUHI of 4°C and an autumn TSUHI of 3.1°C, signifying that the city center is warmer than surrounding rural areas during these seasons.

However, the analysis for winter and spring seasons (not shown) doesn’t show similar patterns. Instead, temperature variations follow a latitudinal trend, where temperatures are generally higher near the tropics and decrease at higher latitudes. Consequently, based on these spatial analyses, there are no night time surface temperature variations in all the seasons (Fig. S6) implying that there is no distinct tropical surface urban heat islands during the night in this city based on this spatial analysis.

The cool island in the north western part of the city is nearly adjacent to the city where there is a chain of mountains, as shown by the blue closed contour lines in Fig. 3. The city is surrounded

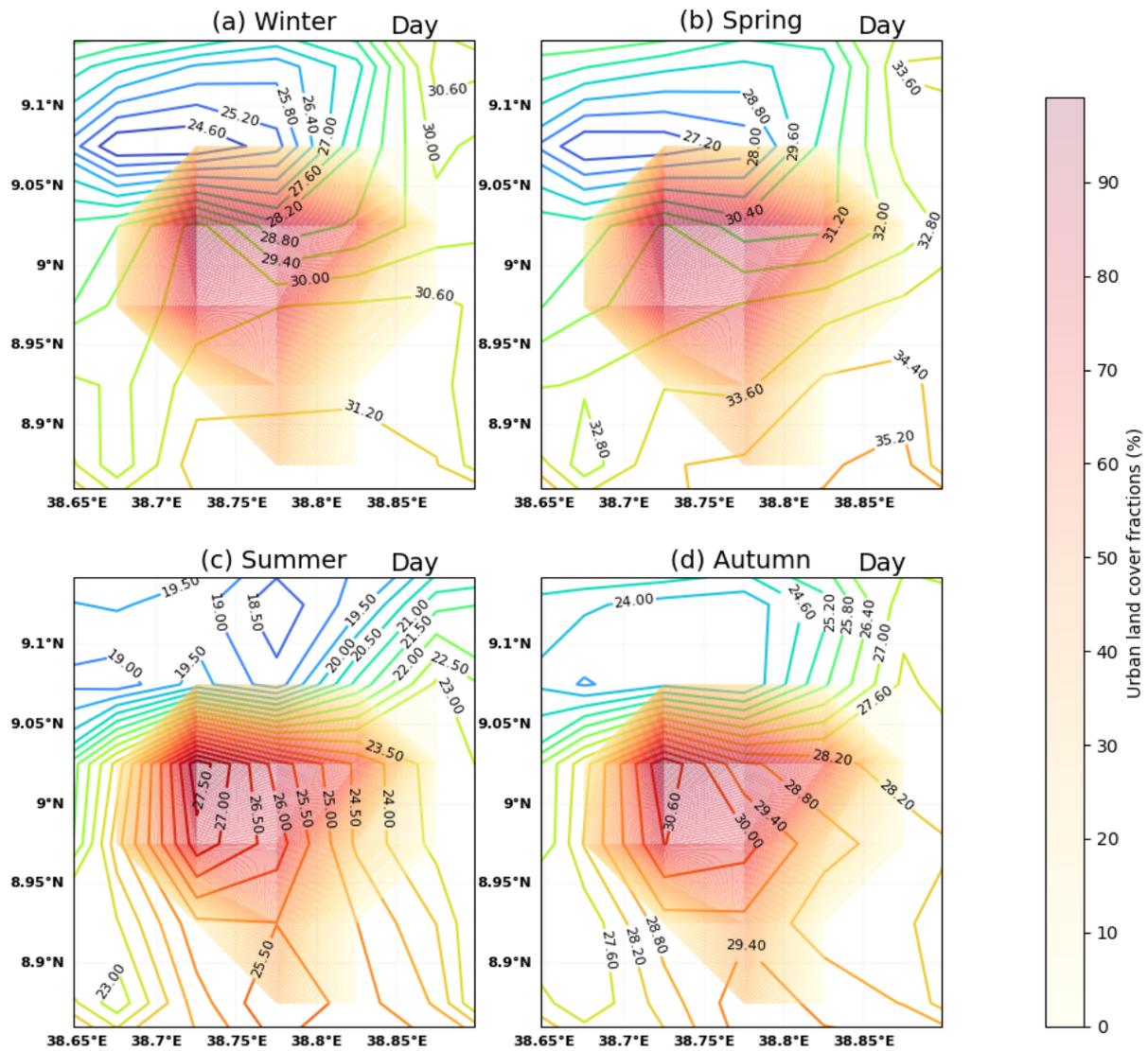


Figure 3: Seasonal mean (2000-2020) MODIS represented land surface temperature contour lines for (a) winter, (b) spring, (c) summer, and (d) autumn seasons during the day light time.

218 by a chain of Entoto mountains in the north where the peak of the mountain reaches 2300 m
219 above sea level extending from the north east to the north west. Most of the terrain of this
220 mountain is covered by eucalyptus trees. The closed blue contour lines in the northern part of
221 the city show cooler islands as a result of the higher topography. In winter, the mountains are
222 colder by at least 3°C, that is from 27.6°C at the edge of the cold center to 24.6°C at the center.
223 In autumn, it is 3.2°C, that is taking the difference from the edge to the center, 30.4°C-27.2°C.
224 The cold center in summer and autumn are around 0.5°C in the Northern part of the city. The
225 center of the city didn't show closed isothermal lines during these two seasons implying that
226 there was no urban heat islands. Generally, the surface cool islands dominate in winter and
227 spring in the northern part of the city pertaining to topographical variations. Furthermore,
228 the tropical surface urban heat islands dominate in the center of the city during summer and
229 autumn seasons.

230 While spatial analysis offers insights into temperature gradients (Fig. 3), it isn't enough to fully
231 understand the overall impact of urban heat islands (UHIs). Analyzing the mean temperature
232 difference between urban and rural areas provides a more comprehensive picture. Therefore,
233 the area-averaged seasonal temperature differences were calculated between urban and rural
234 areas using three methods: urban and rural fractions within each grid cell (Fig. S5 (a)), urban
235 center vs. surrounding rural areas (Fig. S5 (b)), and urban dynamics (Fig. S5 (c)). After
236 identifying urban and rural Land Surface Temperatures (LSTs), their difference provides the
237 Tropical Surface Urban Heat Islands (TSUHIs). Interestingly, results reveal both heat and
238 cool islands depending on the season (Fig. S5 (d)): TSUHIs are observed in summer and
239 autumn (JJA-SON) seasons with the city experiencing heat islands up to 1.7°C warmer than
240 surrounding areas (Fig. S5 (d)). The city transitions to a cool island from winter to spring
241 (DJF-MAM), with temperatures as much as 1.8°C cooler than rural areas.

242 While methods 1 (red line) and 2 (blue lines) in Fig. S5 (d) show similar patterns, method
243 3 (orange line) deviates significantly during winter. This suggests that methods 1 and 2 are
244 more consistent in capturing the overall TSUHI pattern, except during winter. However, relying
245 solely on temporal observations makes it challenging to definitively identify the best performing
246 method. Therefore, the next section will employ a different approach for a more comprehensive
247 evaluation.

248 3.3 Sensitivity of the methods to represent TSUHIs

249 This study delves into whether the representation of urban heat islands (UHIs) hinges on the
250 specific method employed, or if all methods yield identical results. Understanding this method-
251 ological sensitivity is crucial for the urban climate research community. This analysis reveals
252 remarkable seasonal variations in the mean daytime TSUHIs calculated using three distinct
253 methods (Table S1). For instance, summer TSUHIs range from 0.72°C to 1.03°C, while autumn
254 values span from 0.30°C to 1.29°C. These significant discrepancies across methods highlight the
255 critical dependence of UHI results on the chosen approach and the unique characteristics of the
256 studied urban area. In light of these diverse outcomes, a meticulous evaluation of each method
257 becomes essential to determine its suitability and limitations for representing UHIs in different
258 contexts.

259 To assess the sensitivity of each method in capturing Tropical Surface Urban Heat Islands
260 (TSUHIs), we employed two key tools: Taylor diagram (Taylor (2001)) (Fig. 4 (a)) and box
261 plots (Fig. 4 (b)). By combining these tools, we gain a comprehensive understanding of how
262 each method responds to the complexities of TSUHI representation, ultimately guiding the
263 selection of the most suitable approach for specific research contexts.

264 Analyzing the Taylor diagram (Fig. 4 (a)), Method 3 stands out in capturing TSUHI amplitude
265 variations due to its comparable standard deviation with observation data. Despite a high

266 offset (RMSD), its strong correlation ($\cong 0.35$) suggests a consistent overestimation. Method
 267 2 performs moderately with an intermediate correlation, while Method 1 shows the weakest
 268 relationship with observed values, indicating its relative inferiority.
 269 While Method 3 captures TSUHI variations well (Fig. 4 (a)), its overestimation is evident. Both
 270 Methods 1 and 2 underestimate TSUHIs (Fig. 4 (b)). Interestingly, the average of all methods
 271 (Mean(M1, M2, M3)) shows the best performance due to its minimal spread and symmetrical
 272 distribution. This suggests its suitability for representing TSUHIs in similar rapidly urbanizing
 273 cities, like Addis Ababa (Fig. 4). This aligns with findings from other studies highlighting the
 274 city’s rapid expansion in recent years (Mohamed and Worku (2019), Debelo and Soboka (2022)),
 275 making this method a potential choice for analyzing TSUHIs in similar contexts.

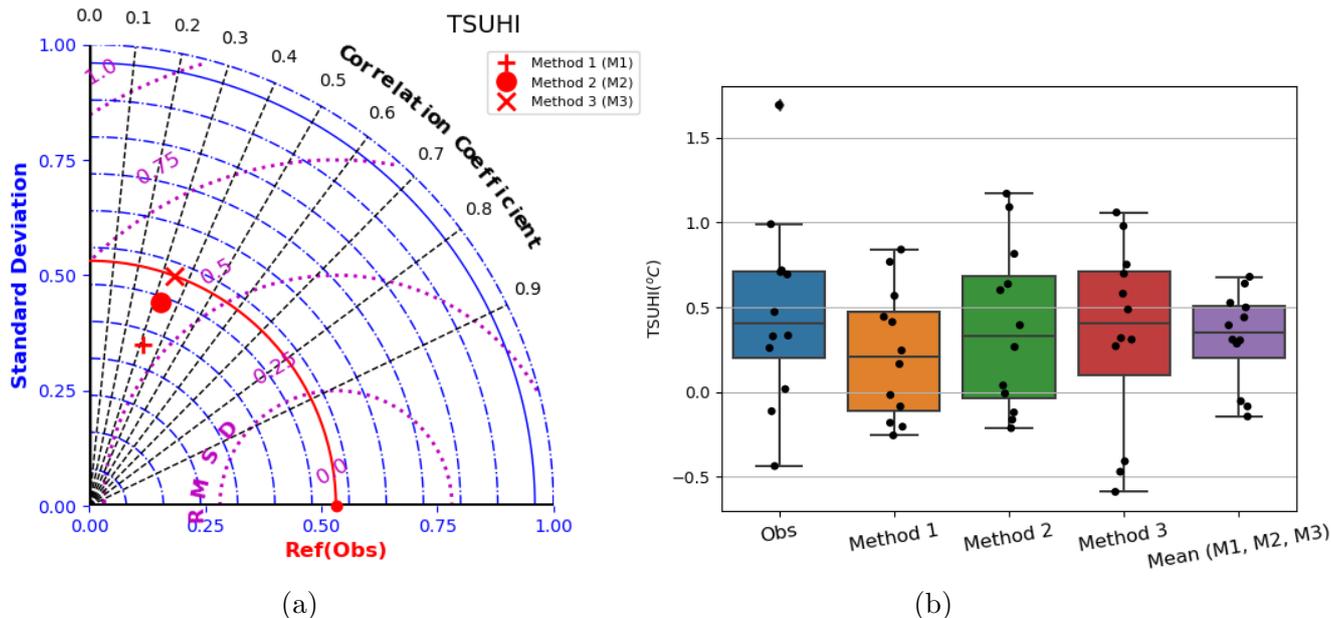


Figure 4: The performance evaluation of the computation methods M1, M2, and M3 relative to the observation in representing the tropical surface urban heat islands using (a) Taylor diagram and (b) box plots.

276 In conclusion, while averaging diverse methods offers robust urban heat island (TSUHI) infor-
 277 mation, specific historical contexts can guide method selection. In rapidly expanding cities, the
 278 ”current vs. past urban morphology” approach excels. Stable, low-growth environments ben-
 279 efit from methods comparing vegetation to impervious surfaces or urban cores to rural areas.
 280 Conversely, areas implementing mitigation like vegetation or albedo changes thrive with the
 281 ”fractional changes in imperviousness, vegetation, and albedo” method for accurate weather
 282 and climate estimation.

283 4 Conclusion

284 This study investigated the nature of tropical surface urban heat islands (TSUHIs) using quali-
 285 tative spatial analysis and quantitative temporal analysis. The spatial analysis employed shaded
 286 or unshaded contour lines to map temperature gradients from the city center to its outer edges.
 287 This visualization revealed how different parts of the city heated up compared to surrounding
 288 rural areas. However, this method wasn’t sufficient to capture the combined impacts of urban
 289 surfaces on weather and climate over time. To address this limitation, the study incorporated
 290 area-averaged temporal analysis. This technique computed the average temperature within the
 291 entire urban area over a specific period. This produced a cumulative view of how the entire

292 city, as a whole, affects surrounding weather and climate patterns compared to rural areas. By
293 combining these distinct analyses, the study paints a more comprehensive picture of TSUHIs
294 in tropical cities.

295 To comprehensively understand the cumulative effects of tropical surface urban heat islands
296 (TSUHIs) in Addis Ababa, the study employed three established urban climate estimation
297 methods:

- 298 • M1: Natural and built-up fractions: This method differentiates urban and rural areas
299 based on land cover and vegetation fractions. Urban areas typically have less vegetation
300 and more impervious surfaces, which is expected to result in higher heat retention and
301 warmer temperatures.
- 302 • M2: Urban center vs. surrounding rural areas: This method focuses on the temperature
303 contrast between the urban center, considered the hottest zone, and the surrounding rural
304 areas. This approach highlights the localized heat island effect within the city.
- 305 • M3: Urban dynamics: This method analyzes land cover transitions from rural to urban
306 over time and space. By tracking these changes, it is possible to understand how ur-
307 ban expansion and development contribute to rising temperatures and altered climate
308 patterns.

309 A qualitative spatial analysis of this tropical city revealed the presence of surface urban heat
310 islands in summer and early autumn, peaking at 4°C and 3.1°C respectively. This analysis
311 compared the urban center's temperature grid to those at the city's edge, representing the
312 maximum achievable heat island intensity. However, nighttime urban heat islands weren't
313 detectable through this method alone. To gain a more comprehensive understanding, the
314 study incorporated a composite mean value computation using three established methods,
315 complementing the initial spatial analysis.

316 The mean TSUHI values vary depending on the method of computation under consideration.
317 The two methods, M1 and M2 have almost similar patterns while method 3 is slightly different in
318 capturing the seasonal variations of the TSUHIs. Nevertheless, all the methods show maximum
319 heat islands in late summer and autumn (JJA-SON) seasons. As such, the surface urban heat
320 islands in these seasons reach a maximum of 1.7°C . The cool island reaches a minimum of -1.8°C
321 during the spring (MAM) season. During the night time, the city exhibits surface urban heat
322 islands all the time except during the August month. The night time surface urban heat islands
323 during the early autumn and early winter seasons reach a maximum of 1.2°C . The cool island
324 in August reaches a minimum of -0.4°C . Nevertheless, the surface urban heat islands dominate
325 the cool islands during the day and night times. The mean TSUHIs obtained using the three
326 methods are 0.72°C , 1.03°C , and 0.74°C in the summer, and 0.92°C , 1.29°C and 0.30°C in the
327 autumn seasons, implying that the results are sensitive to the methods used and are dependent
328 on the characteristics of the specific urban area.

329 The study went beyond simply identifying the presence of urban heat islands. It also aimed
330 to determine which method among the three employed was most effective in representing the
331 city's unique urban climate. To achieve this, this study utilized Taylor diagrams and box plots.
332 As such, the analysis revealed that the mean composite of all the three methods collectively
333 offered the best representation of the city's urban climate. This suggests that combining diverse
334 approaches can yield more accurate results compared to relying on a single method. However,
335 among the individual methods, method 3, which considered dynamic urbanization (land cover
336 transitions from rural to urban), consistently outperformed the others. This indicates that
337 for rapidly growing cities like the one studied, methods that account for the evolving urban
338 landscape are particularly valuable.

339 The study emphasizes the benefits of using multiple methods to assess urban heat island charac-
340 teristics. This allows for a more comprehensive understanding of the complex factors influencing
341 urban climate. In cases where data limitations restrict the use of multiple methods, careful
342 consideration of the city’s development history is crucial for selecting the most suitable single
343 method. This is specially advisable to urban climate studies in developing countries where
344 the availability of data for the applicability of various methods is challenging. For cities ex-
345 perencing rapid urban expansion, method 3, which leverages the dynamics of urbanization,
346 is likely to provide the most accurate results. Similar performance can be expected in cities
347 with comparable growth patterns. These findings highlight the importance of tailoring urban
348 climate assessment methods to the specific characteristics of each city. As cities continue to
349 grow and evolve, developing robust and adaptable methods for understanding and managing
350 their unique climates will be essential.

351 Acknowledgments

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354 (ICDC), CEN, University of Hamburg for data support.

355 Data Availability

- 356 a. The MODIS land surface temperature and urban land fractions are obtained from the
357 Integrated Climate Data Center (ICDC, [icdc.cen.uni-hamburg.de](https://www.cen.uni-hamburg.de)) University of Ham-
358 burg, Hamburg, Germany. It is available freely for anyone from [https://www.cen.
359 uni-hamburg.de/en/icdc.html](https://www.cen.uni-hamburg.de/en/icdc.html).
- 360 • MODIS land surface temperature is available from [https://www.cen.uni-hamburg.
361 de/en/icdc/data/land/modis-landsurfacetemperature.html](https://www.cen.uni-hamburg.de/en/icdc/data/land/modis-landsurfacetemperature.html).
 - 362 • MODIS urban land surface fractions are extracted from [https://www.cen.uni-hamburg.
363 de/en/icdc/data/land/modis-landsurfacetype.html](https://www.cen.uni-hamburg.de/en/icdc/data/land/modis-landsurfacetype.html).
- 364 b. The temperature data from the meteorological stations was obtained from the National
365 Meteorology Agency (http://www.ethiomet.gov.et/data_access/information) and
366 the Berkley Earth Database ([https://data.berkeleyearth.org/locations/8.84N-38.
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Seasons	Mean daytime TSUHI values			
	Method 1 (M1)	Method 2 (M2)	Method 3 (M3)	Mean(M1,M2,M3)
Summer	0.72°C	1.03°C	0.74°C	0.83°C
Autumn	0.92°C	1.29°C	0.30°C	0.84°C
Winter	-0.29°C	-0.28°C	0.89°C	0.11°C
Spring	-0.87°C	-0.97°C	-0.58°C	-0.81°C

Seasons	Mean nighttime TSUHI values			
	Method 1 (M1)	Method 2 (M2)	Method 3 (M3)	Mean(M1,M2,M3)
Summer	0.22°C	0.33°C	0.30°C	0.28°C
Autumn	0.53°C	0.76°C	0.30°C	0.53°C
Winter	0.81°C	1.07°C	0.89°C	0.92°C
Spring	0.56°C	0.78°C	-0.58°C	0.25°C

Table S1: This table shows the different mean TSUHI values for each of the methods, M1, M2, and M3. The observation TSUHI estimation and the mean of the methods, Mean(M1,M2,M3) are also shown for comparison.

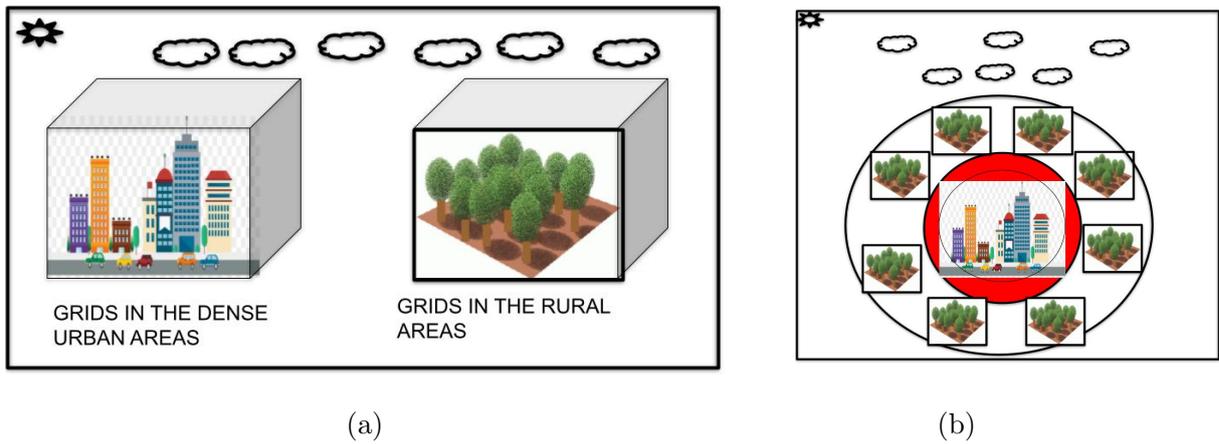


Figure S1: The figure depicts two common approaches to representing urban and rural areas in urban climate studies: (a) separate grids for urban and rural regions, (b) urban area at the center surrounded by rural grid cells.

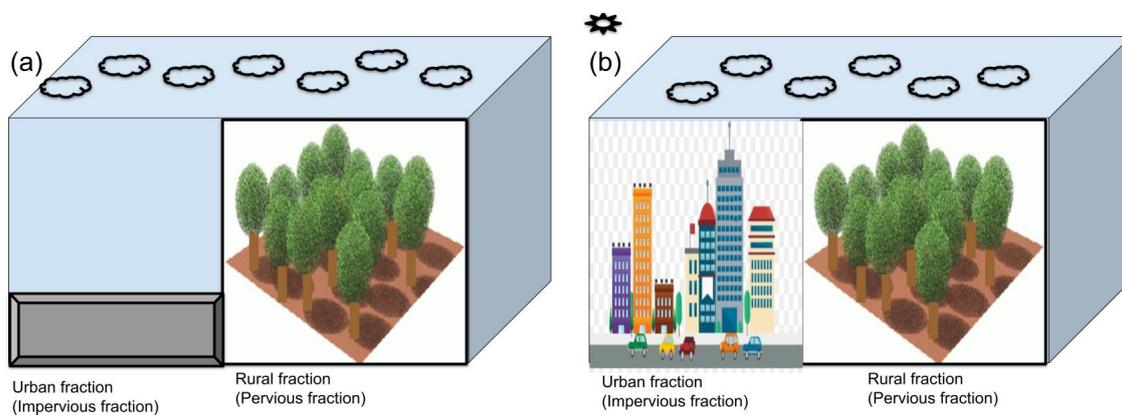


Figure S2: The figure compares two approaches to incorporating urban features into a combined urban-rural grid: (a) a simplified model with adjustments for impervious surfaces like pavement, and (b) a more detailed representation including buildings, roads, and other impervious elements.

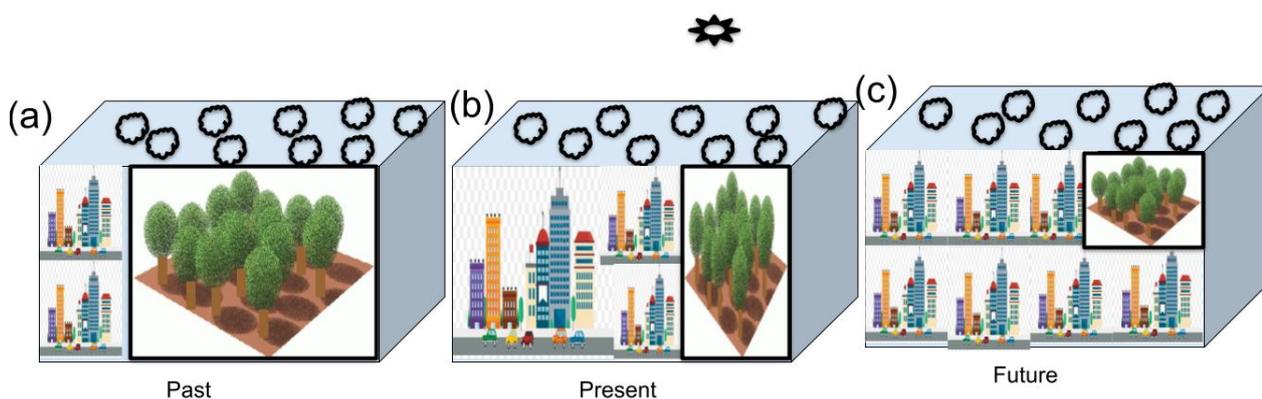


Figure S3: A diagrammatic representation of the hypothetical urban and rural grids in the (a) past (b) present and (c) future. The rural grids decrease from the past to the future as more urban areas are expected to replace most of the natural fractions.

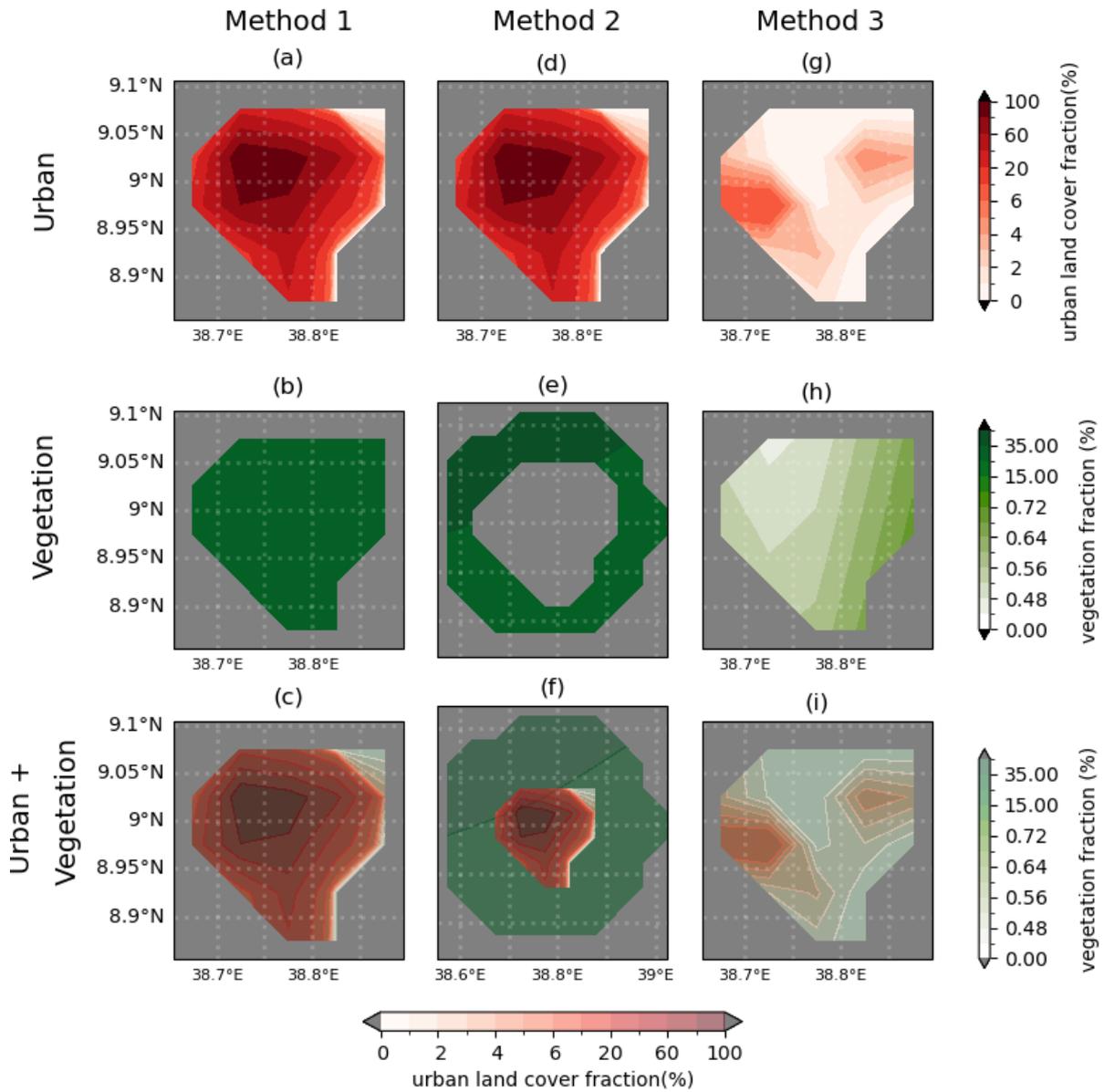


Figure S4: Three frequently used methods to quantify urban and rural properties, Method 1: Urban land cover fractions (a) and vegetation fractions (b) are used to differentiate urban and rural areas, whereas the combined urban and vegetation fractions are shown in (c), Method 2: urban at center (d) and rural areas surrounding it (e) are used to quantify urban and rural properties, whereas the combined Urban and vegetation fractions are shown in (f), and Method 3: Urban dynamics: the differences between urban land cover (g) and vegetation fraction (h) in the first few years (2000-2010) when urban development was low and the next few years (2011-2020) after the city had gone through huge urban development, whereas the combined urban and vegetation dynamics is shown in (i).

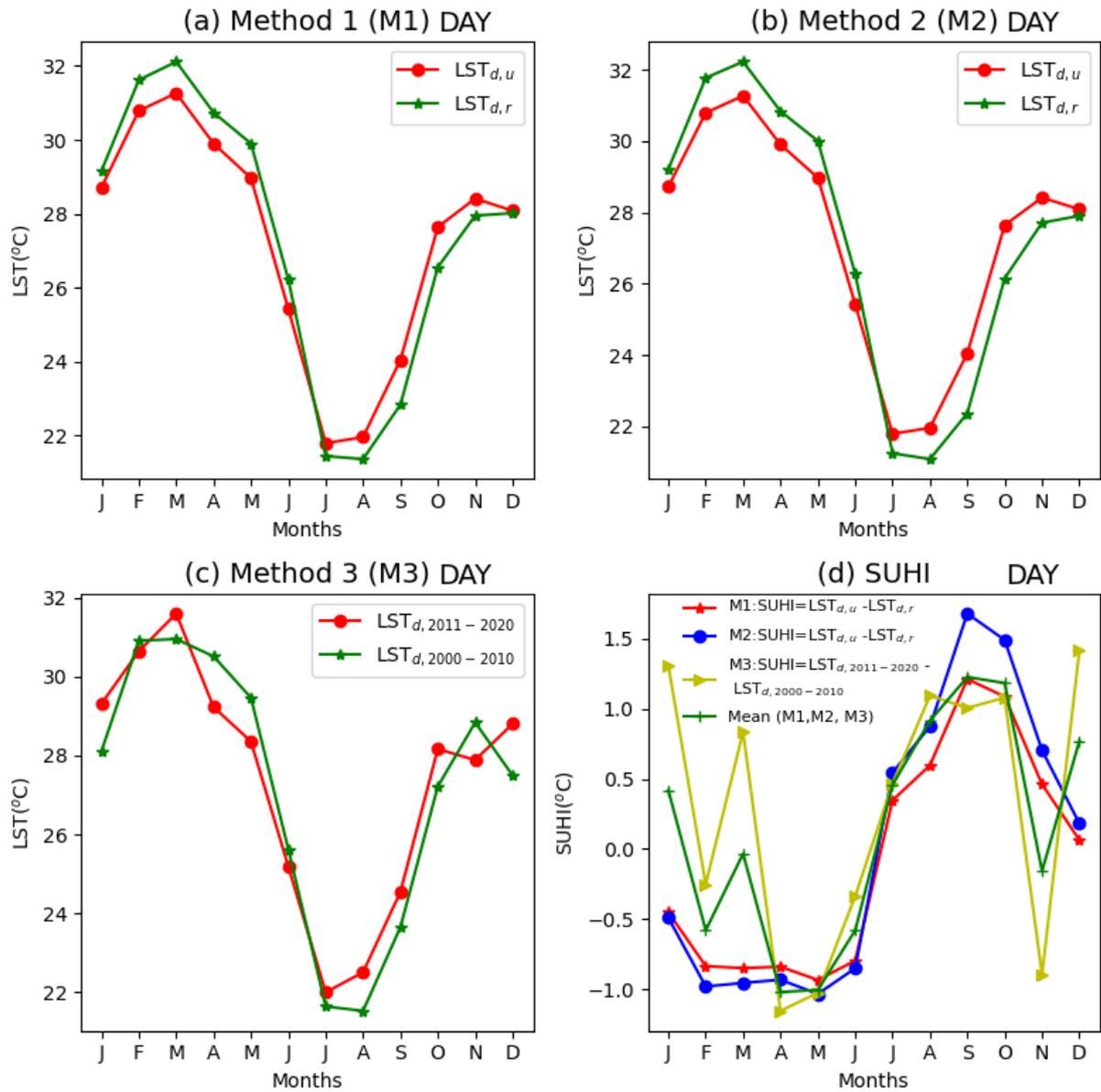


Figure S5: The different methods, (a) method 1, (b) method 2 and (c) method 3, to compute the urban and rural land surface temperature annual cycles. The tropical surface urban heat islands shown in (d) are calculated based on these methods and compared with TSUHI computed from the ground based observation.

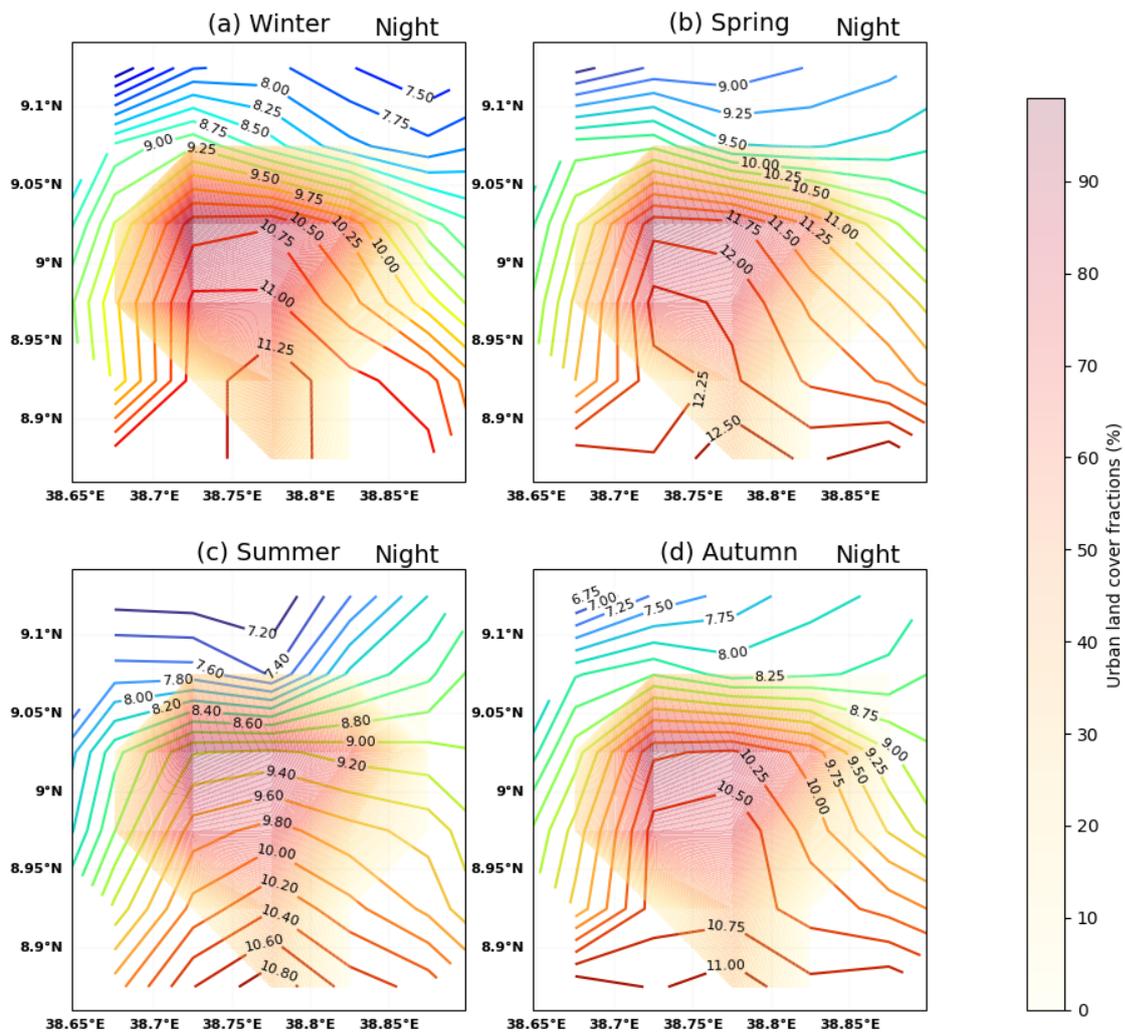


Figure S6: Seasonal mean (2000-2020) MODIS represented land surface temperature contour lines for (a) winter, (b) spring, (c) summer, and (d) autumn seasons during the night time.

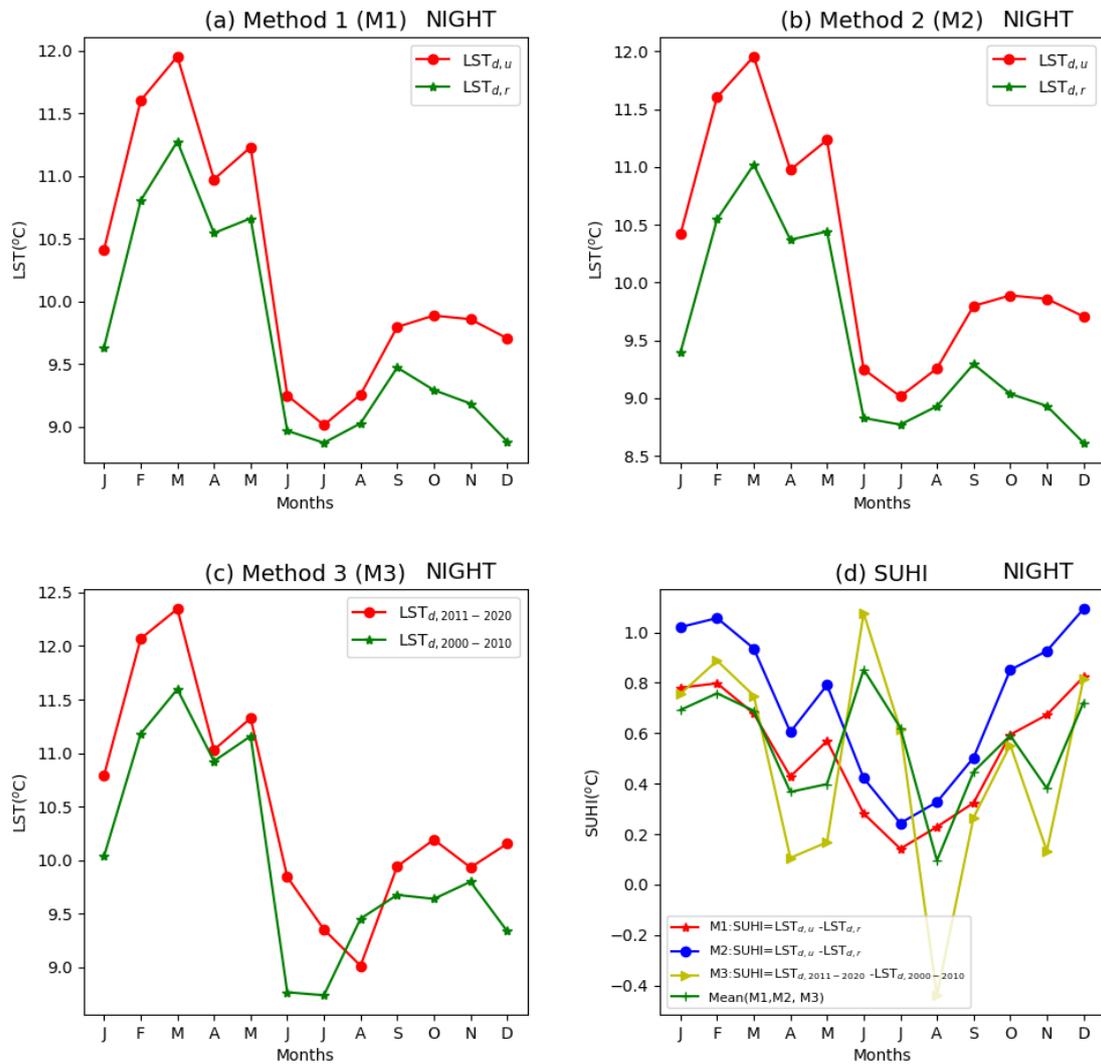
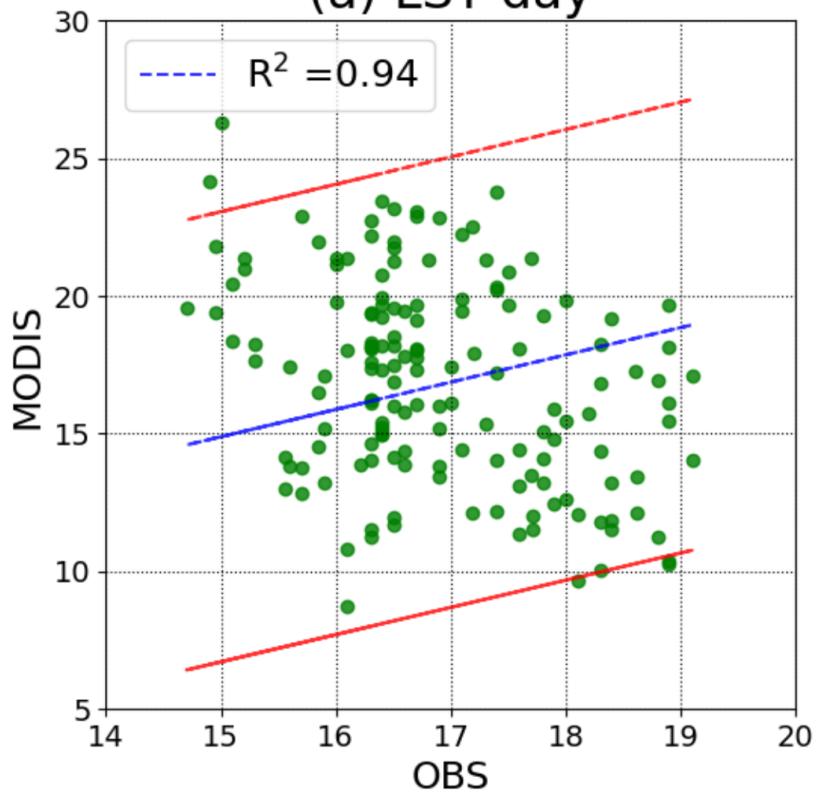


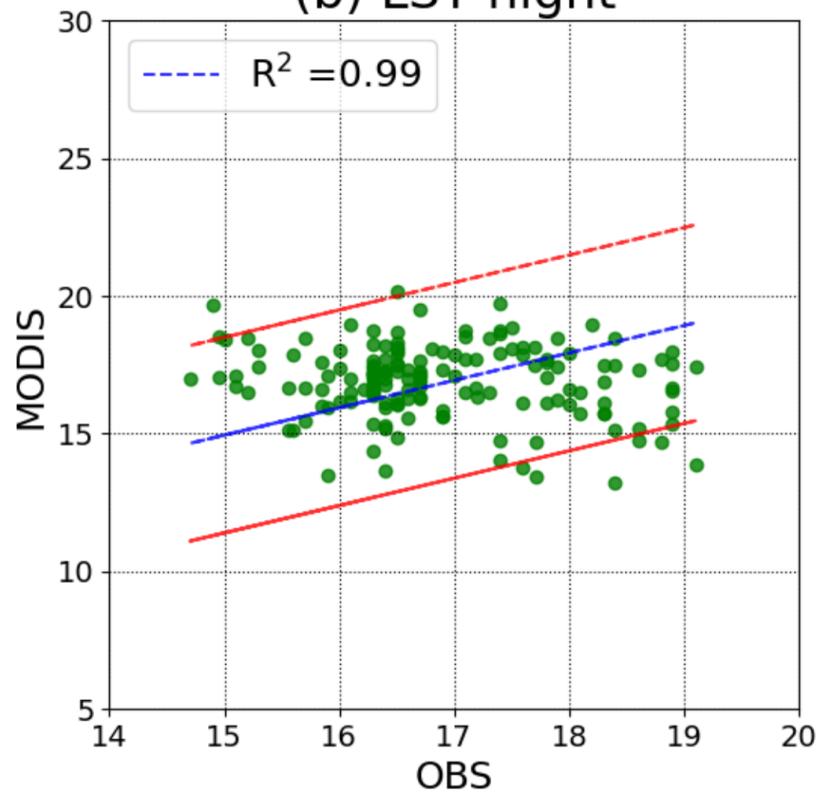
Figure S7: The different methods, (a) method 1, (b) method 2 and (c) method 3, to compute the urban and rural land surface temperature annual cycles during the night. The corresponding nighttime tropical surface urban heat islands are shown in (d).

Figure 2.

(a) LST day



(b) LST night



(c) LST mean (day, night)

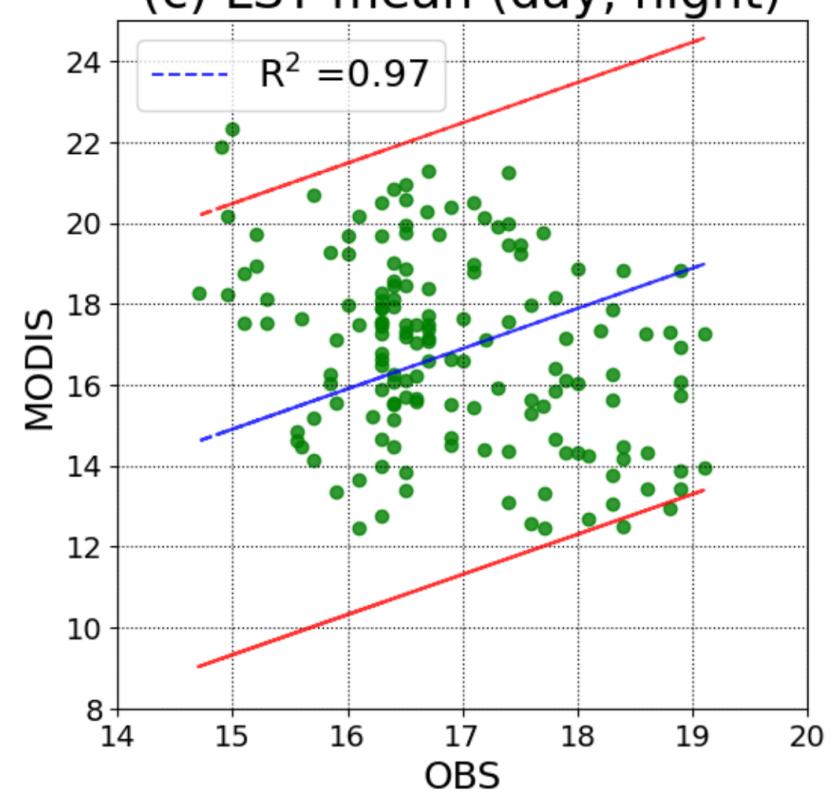


Figure 4 (a).

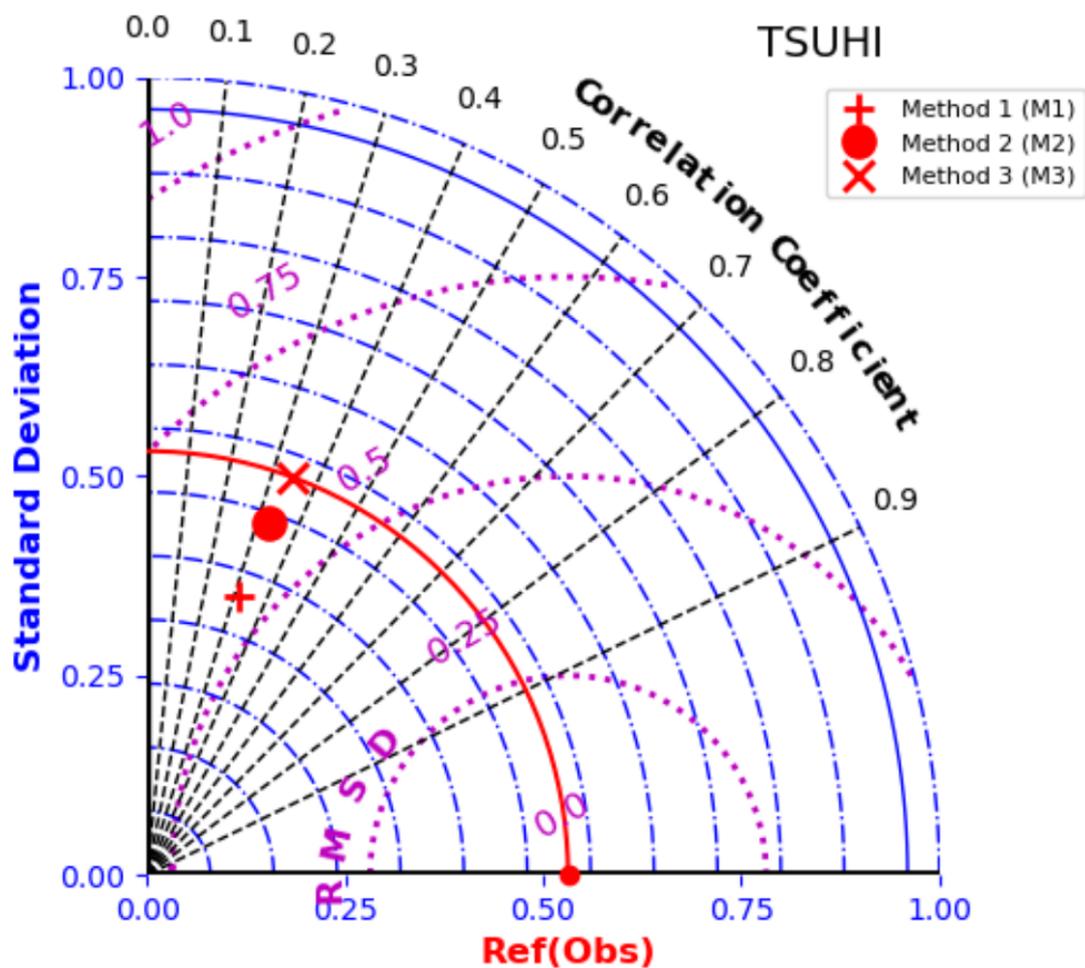
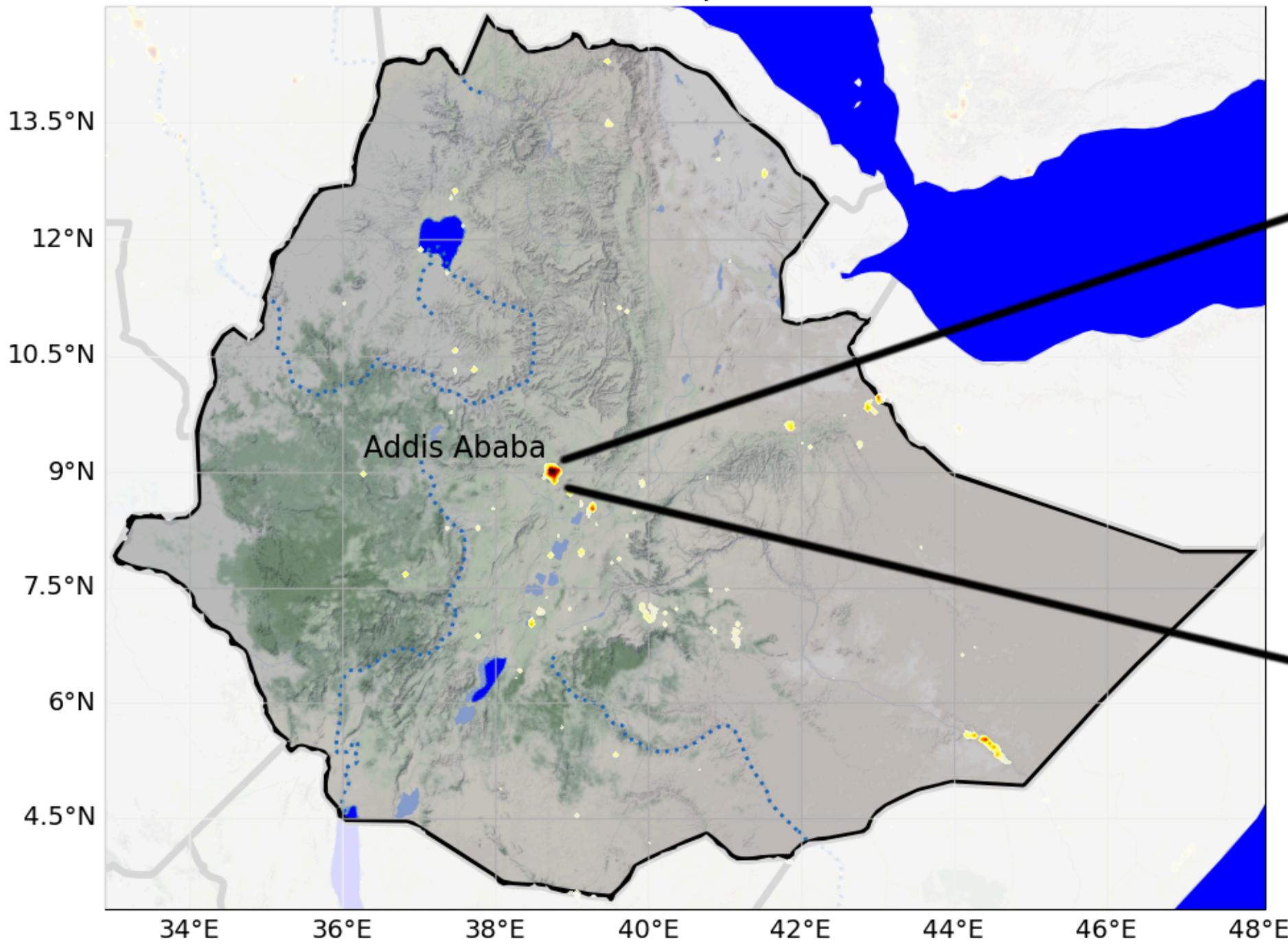


Figure 1.

Ethiopia



Addis Ababa

urban land fraction (%)

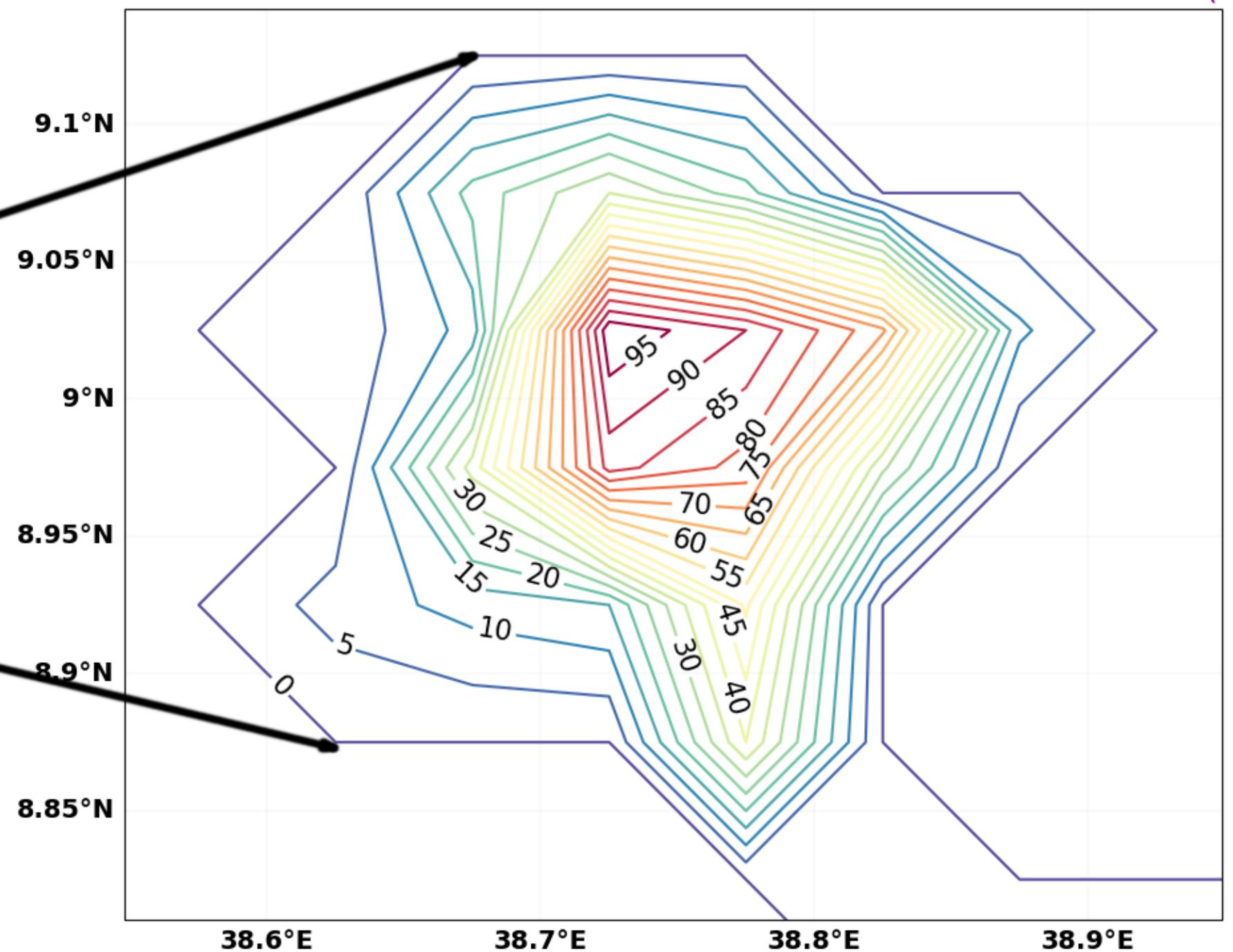


Figure 4 (b).

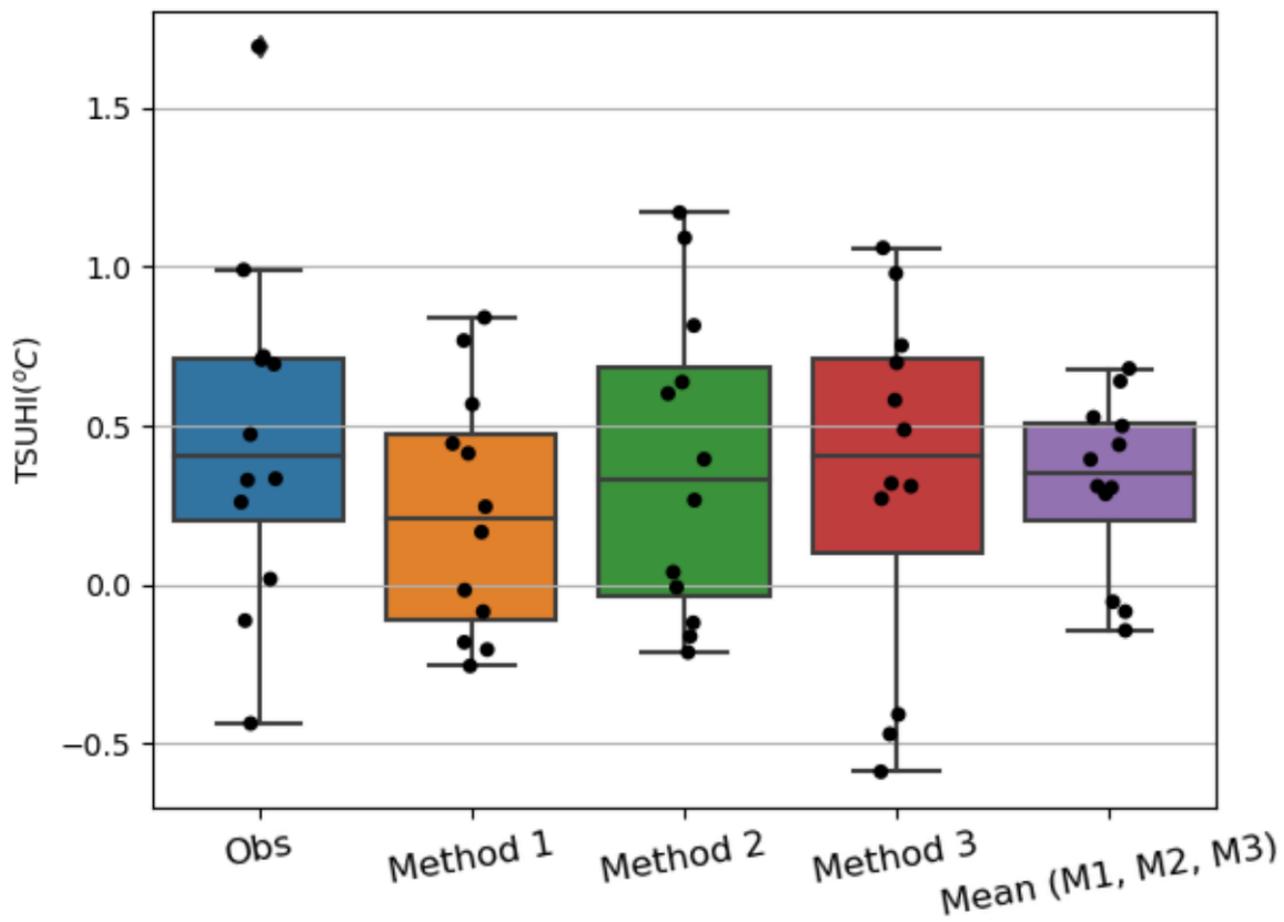
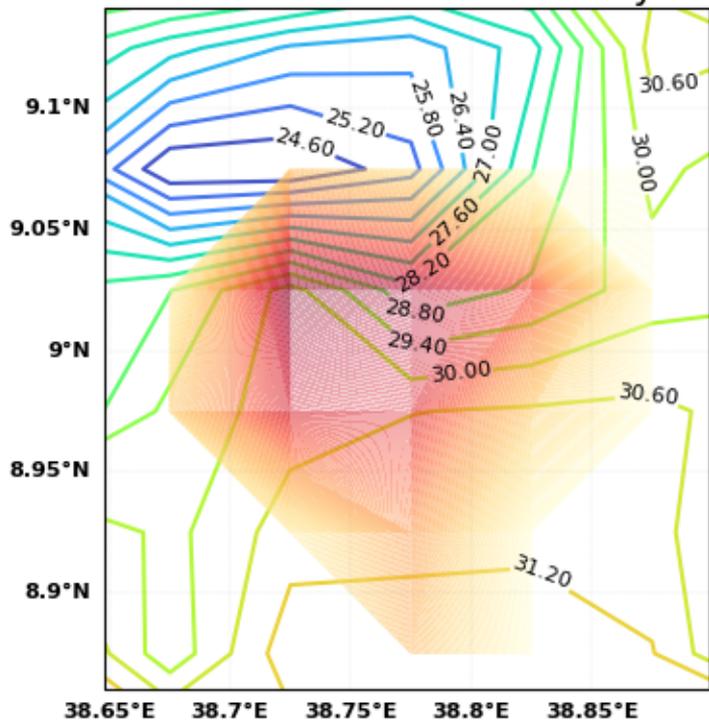
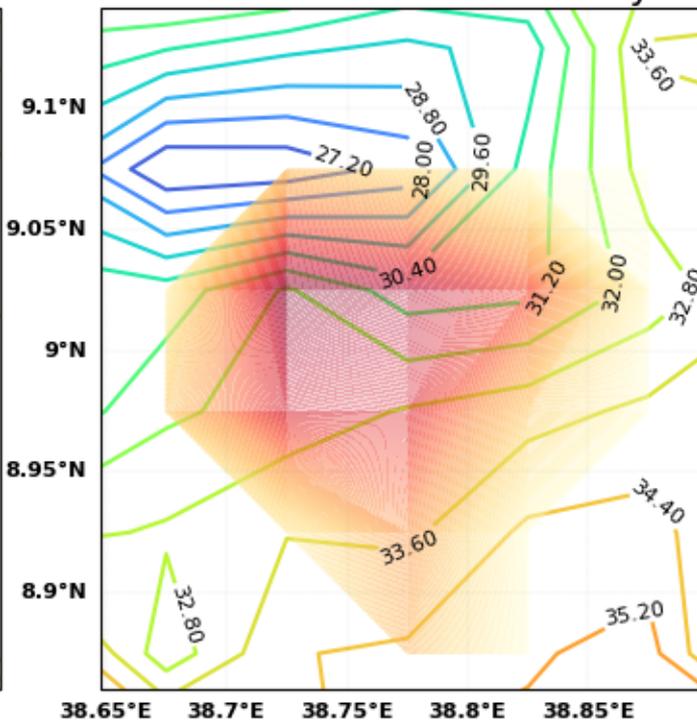


Figure 3.

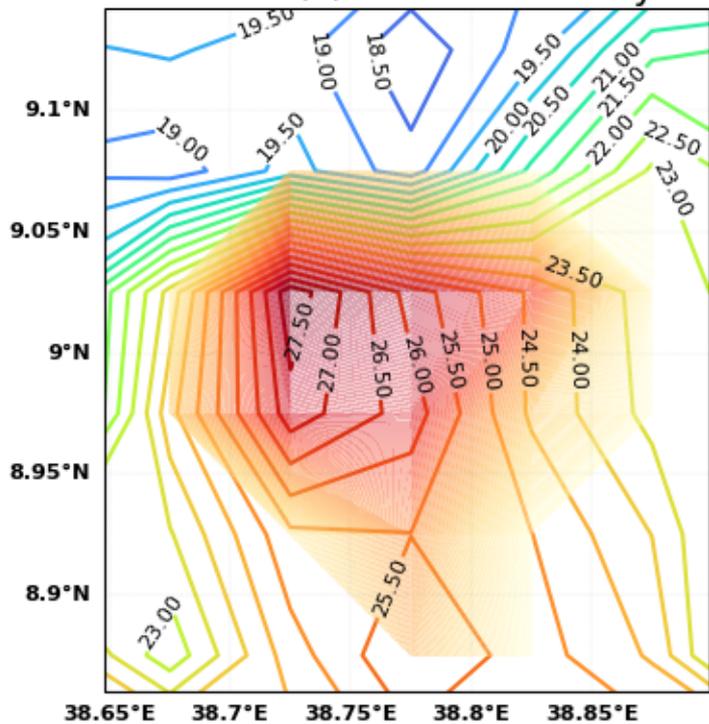
(a) Winter Day



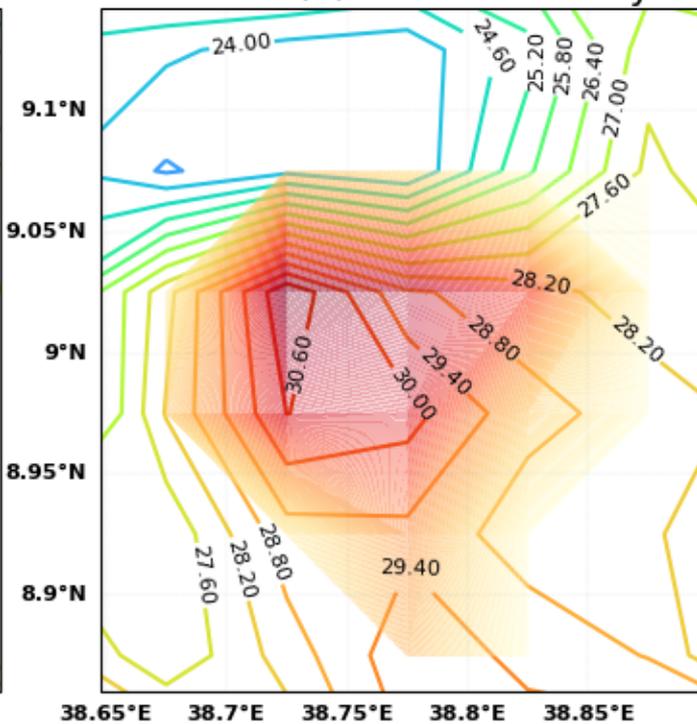
(b) Spring Day



(c) Summer Day



(d) Autumn Day



Urban land cover fractions (%)

90

80

70

60

50

40

30

20

10

0