Scale-dependent response of the urban heat island to the European heatwave of 2018

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Abstract

Extreme heat continues to be a pressing challenge of the changing climate. The impacts of extreme heat manifest on two different spatio-temporal scales: (1) episodic continent-wide heatwaves (HWs) and (2) the city-scale urban heat island (UHI). As HWs are becoming more frequent, longer, and severe, they pose serious implications of increased public health risks at a city scale, and have adverse impacts on agricultural and terrestrial/aquatic ecosystems on the regional scale. Here we offer a fresh perspective of the HW as a forcing that invokes dynamic, heterogeneous, scale-dependent responses evident in inter and intra-urban heat islets. A numerical simulation of the 2018 European HW including the surface and air temperature-based UHIs of six urban agglomerations, with a high-resolution focus on Paris, serves as our case study. We find that the mean nighttime UHI intensities are reduced for inland cities but increased for coastal cities. Our examination of the heat islets reveals two major findings: (i) the HW homogenizes the intra-urban surface temperatures during the daytime (reduces variance), (ii) the HW impacts are most significant on the scale of large, spatially discontiguous extreme heat islets during nighttime. These results underscore the need to move beyond the prevalent HW-mean UHI intensity characterization and toward intra-urban heat islet analyses that aid targeted mitigation.

1. Introduction

A heatwave (HW) is defined as an anomalously hot spell that lasts several consecutive days, resulting in higher levels of heat-related discomfort, loss of productivity [1], morbidity [2], and mortality [3]. Despite being a slow and silent killer, HWs claim more lives every year than all the other meteorological hazards combined 4. Some of the deadliest and most well-documented examples in the last few decades have been the 2003 European HW [4], 2010 Russian HW [5], and the 2015 Indian HW [6]. These HWs also cause damage to vast expanses of terrestrial and aquatic ecosystems which put further pressure on urban systems by rapidly depleting ecosystem resources in the short term as well as causing the uprooted rural populations to migrate into cities as climate refugees [7]. Such instances are on the rise as HWs get more intense, more frequent, and longer-lasting under the changing climate [8–11].

There is no universal characterization of a HW based on a fixed threshold of air or surface temperature. People in different climatic backgrounds get acclimatized to their local thermal means and extremes, either by natural adaptation or by artificial measures of mitigation such as building air-conditioning. As a result, the threshold for ‘extreme heat’ and the definition for a HW varies for different regions. For instance, the National Oceanic and Atmospheric Administration issues a heat stress warning above 33 °C for some regions in the US,
whereas, in the tropical regions of India, temperatures up to 40 °C do not warrant a warning\(^5\). In the absence of a standard definition, the use of percentile-based thermal thresholds based on local historical records of nighttime minima or daytime maxima has been recommended [12, 13].

On the other hand, urban communities already experience elevated temperatures through out the year due to the urban heat island (UHI) effect [14]. The UHI effect is characterized traditionally using the difference between mean urban and rural temperatures. The interaction between large-scale extreme heat events (such as HWs) and the local-scale UHI has recently attracted considerable scientific interest [15–20]. Prior research has shown that HW-UHI interaction results in a higher amplitude of UHI intensity during a HW period [19, 21, 22]. Contrarily, an absence of correlation [16, 18, 23, 24] as well as a reduction of UHI Intensity under a HW were also observed in some cases [25–27]. This is because external climate forcings play a significant role in influencing the UHI Intensity. Factors such as mean annual precipitation and rural landuse characteristics can influence the UHI Intensity [28, 29]. Prior work has identified the difference in storage heat flux and moisture availability during a HW as a main driver of the synergistic outcome [30, 31]. A limitation of these studies is that they only focus on how the mean urban temperatures behave with respect to mean rural temperatures during a HW.

Recent research has begun to extend the UHI framework to underscore the differences in air and surface temperatures within different types of urban regions themselves [32, 33]; however, there is need to understand the HW impact on the intra-urban thermal variance and the spatial distribution of high heat clusters. Such an understanding is paramount given that spatial heterogeneity of extreme temperatures in cities yield very different impacts on different socio-economic population groups within the same city. For example, at an individual's scale, extreme heat can be mitigated with air-conditioning; however, as the rampant use of air-conditioning in the affluent neighborhoods cool down the buildings internally, it leads to increased anthropogenic heat flux emissions outside, further increasing the ambient temperatures for those who are exposed and vulnerable [34]. Thus, the consequences of extreme heat are borne disproportionately by the disadvantaged lower income population.

To this end, the primary goal of this study is to investigate the heterogeneous, scale-dependent response of the UHI to a HW forcing. We integrate the recently introduced concept of intra-urban heat islets with that of HWs [33, 35]. To identify intra-urban heat islets, the temperature (air or surface) spatial fields are treated analogously to topography in digital elevation models, where the temperatures substitute for elevation [33]. Percentile-based thermal thresholds are chosen for identifying the relative hottest regions within the urban areas, and then the spatially connected hot regions are grouped into clusters that we collectively refer to as a heat islets.

We use the Weather Research Forecast (WRF) model to simulate the 2018 European HW at three nested scales with a high-resolution focus on metropolitan Paris (detailed in sections 2 and 3). Using the heat-islet framework, we examine the changes in the spatial organization of extreme temperatures (section 4.3). We then corroborate our findings by extending the analysis to coastal cities (Rotterdam and London), and inland cities (Frankfurt, Cologne, and Essen) that experienced the same HW. Lastly, we introduce new UHI metrics that address the problem at varying degrees of complexity and explore their diurnal interdependence and co-evolution during a HW (section 4.4). We close with a discussion (section 5) of the implications of our findings to mitigation planning to reduce adverse impacts of UHI and HW.

2. Case study: 2018 European HW over Paris

The European HW of 2018 was one of the warmest and driest in recent history and spread widely throughout the continent. The land surface temperature anomalies were record-breaking and deemed the highest in the last 519 years [36]. More importantly, these warm temperatures were accompanied by an extreme drought in central and northern Europe resulting in major economic and ecological setbacks [37]. Recent research has attributed these HW conditions to large-scale, stationary, upper-level high-pressure systems that arrest the circulations below and effectively trap the heat near the surface. Such a phenomenon is referred to as atmospheric blocking [38, 39] and results in low near-surface wind speeds and cloud cover leading to increased exposure to incoming solar radiation and ultimately, higher and more persistent near-surface temperatures [40]. Thus, the European HW of 2018 is of great scientific as well as societal relevance.

For the high-resolution analyses, we focus on Paris because it is a large inland mega-city with conspicuous intra-urban variability, and the UHI effect is captured in the numerical simulation conducted here. Paris is set in a mild temperate climate zone and has been of interest to several extreme heat vulnerability studies due to the massive death toll during the 2003 HW [4, 41–44]. Furthermore, the availability of observational towers in Paris allowed us to validate

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\(^5\) Source: https://www.weather.gov/safety/heat-index.
the results from the numerical simulation of the HW event.

3. Model description: WRF simulation

The WRF model was used to simulate the HW over western Europe. To choose the period of simulation, the air temperatures obtained from National Center for Environmental Prediction-National Center for Atmospheric Research reanalysis dataset for 2018 were compared against the expected temperature for each day. The expected temperature was calculated by averaging the air temperature values from 2006 to 2016 for that day and then applying a 7-day moving average (SI figure D1 (available online at stacks.iop.org/ERL/16/104021/mmedia)). Subsequently, a sample set of 11 days corresponding to two distinct HW episodes from 23 July to 27 July and then from 3 August to 7 August (figure 2) were identified as the HW periods. The week after the HW was used to represent non-HW days.

A triply nested domain structure was designed such that the smallest domain (horizontal grid-spacing = 1 km) is centered on the city of Paris, the mid-sized domain (horizontal grid-spacing = 3 km) covers several other European cities such as London, Frankfurt, Amsterdam, etc and the largest domain (horizontal grid-spacing = 9 km) encompasses western Europe (figure 1(a)). The simulations were driven by ERA-Interim reanalysis data provided by European Centre for Medium-Range Weather Forecasts at 6-hour intervals as atmospheric boundary conditions and the surface boundary conditions were derived from MODIS (figure 1(b), further details in Appendix A). Lastly, the simulated air temperatures were compared with those from observational towers in urban and rural locations around Paris and derived from the Integrated Surface Database maintained by NOAA’s National Climatic Data Center to validate the simulated temperatures (SI figure A1).

4. Results

4.1. Mean UHI intensity

UHI intensity is defined as the difference between the mean of urban air temperature (estimated at the height of 2 m above the street level and referred to as T2 in WRF) and the surrounding rural air temperatures (estimated as an average over all other types of surfaces except water within a bounding box containing each city; shown in figure 1). Analogously, the difference between Land Surface Temperature (estimated a representative skin temperature for all surfaces within a grid cell and referred to as LST) is the surface UHI (SUHI) Intensity. While the LST and T2 thermal fields are correlated [45], there is a hysteresis in T2 due to delayed heating (figure 2). During the daytime, the surface temperature is higher than air temperature due to incoming shortwave solar radiation, whereas the air temperature is higher during nighttime due to the delayed outgoing longwave as well as anthropogenic heat fluxes [46] (SI figure D2, see section 4.4 for an in-depth discussion). This can also be seen as the distinctly hotter urban region from heat stored in
urban surfaces with high thermal mass that appears during daytime in the LST plots and during nighttime in the T2 plots (figure 2). We use an hour-specific averaged time-series of domain-wide mean temperatures, UHI Intensities, and intra-urban thermal variances (discussed in section 4.2) to focus on the consistent diurnal trend alone (figure 3).

4.1.1. Paris
We observe that in the case of Paris, the UHI Intensity is strongest during nighttime and negative during the day, i.e. urban temperatures are less than rural temperatures (figure 3(e)). Conversely, a weak but positive SUHI Intensity is present during the nighttime, which intensifies further during the day (figure 3(b)). The impact of HWs on both of these metrics can be most strongly and consistently observed during the nighttime wherein the UHI Intensities decrease by ∼1 °C on average during the night time. Our findings are in contradiction with the reported synergistic union between HWs and UHIs in some cases [19, 21, 22]. The absence of HW-induced amplification was also noted in other regions such as India, wherein the rural soil moisture was found to be less than that of the urban area [26]. This is consistent with our results as well (SI figure B4). We also conducted a surface energy budget analysis to compare with the existing literature on urban heat fluxes (see Appendix B for the discussion).

4.1.2. Other European cities
In addition to Paris, six other urban agglomerations were captured in the WRF simulation (domain 2, figure 4). We mainly analyze them from a perspective of inland urban agglomerations (that comprise German towns and cities contiguous to Essen, Cologne, and Frankfurt respectively) versus coastal cities (London, which not strictly coastal but influenced by a central river and its proximity to the coast, and Rotterdam-Hague agglomeration). Both UHI and SUHI Intensities were mostly unaltered by the HW during the daytime. The SUHI Intensities for the coastal cities, Rotterdam and London, were an exception to this trend. Unlike the inland cities, the variability in the diurnal pattern of SUHI Intensity under the non-heat wave scenario (shown in blue in figure 4(c) for these coastal cities is only ∼1 °C. Furthermore, the difference in SUHI intensity between an HW and non-HW scenario is larger (∼2.2 °C). These differences may be attributable to the land-sea breeze that occurs in cities with close proximity to the ocean. Past research has shown that the land-sea breeze gets arrested by the high-pressure system during a HW and the lack of circulation can aid in the exacerbation of near-surface temperatures [30]. Likewise, in the case of UHI Intensities (figure 4(d)), during nighttime, a reduction of nearly 1 °C was observed for all inland cases. Conversely, for the coastal cities of London and Rotterdam, the UHI intensity increased during the HW when compared to the non-HW scenario. This serves to show that despite the difference in rural backgrounds of Paris (which is mostly croplands) and the German cities (which are closer to forests), no synergistic influence of HW was observed on the UHI of the inland cities during the European HW of 2018.
4.2. Intra-UHI variance
The variance of LST and T2 (\( \text{Var}(\text{LST}) \) and \( \text{Var}(\text{T2}) \) respectively) were calculated for the regions corresponding only to urban areas, where the temperature fields nearly follow a Gaussian distribution. For the case of Paris, we find that the \( \text{Var}(\text{LST}) \) is higher during the daytime (same as SUHI Intensity) under non-HW conditions but it decreases significantly under HW (figure 3(c)). During the nighttime, \( \text{Var}(\text{LST}) \) is only slightly higher during the HW: \( \text{Var}(\text{T2}) \) increases during nighttime as well, but the changes during daytime are not statistically significant.

In the six other urban agglomerations as well, the intra-urban variance analysis shows that the HW reduced \( \text{Var}(\text{LST}) \) and homogenized the urban surface temperatures for all urban areas, except Rotterdam (SI figure E1). This is because its coastal region maintains cooler temperatures during the HW while the more inland regions heat up. This results in an increased intra-urban thermal variance (in both LST and T2). For all other cities, any impact of the HW on \( \text{Var}(\text{T2}) \) is statistically insignificant (SI figure E2).

4.3. Scale-dependent impact on intra-urban heat islets
Variance alone does not offer any information about the spatial organization of the heat islets. Therefore, we used the 2D power spectral density (PSD) to extract the information on variance contributed by each of the constituent spatial scales. The radially averaged PSD algorithm is applied to the LST map of Paris (domain 3) obtained at every time step (1 hourly) and the diurnal evolution for a single day is shown in figures 5(a) and (b) (Detailed methodology is given in Appendix C).

We find that the most notable impact of the HW manifests as an increased variance within the larger spatial scales (corresponding to 32–163 km wavelength), which correspond to the size of the city. The diurnal variability at these spatial scales, evident in figure 5(a), are absent under a HW scenario, indicating large heat islet structure throughout the day and night. On the other hand, the tail of power spectra (corresponding to 1–5 km wavelength in figure 5(b)) is indicative of systematic intra-urban diurnal variability. These smaller spatial scales correspond to smaller heat islets, which increase in number during the daytime. This observation was consistent for other HW days as well (figure 5(b)).

A representative PSD plots are shown in figures 5(c) and (d), for nighttime and daytime respectively. We find that the most notable difference manifests at the larger wavelength (54–163 km) during the night time, which indicates larger contiguous patches of elevated temperature. While these spatial scales correspond to the entire width of the city, figure 3 illustrates that the SUHI is not persistent at nighttime and in fact, decreases relative to T2 during a HW. Thus, we conclude that the large contiguous patches of heat do not correspond to the urban and rural boundaries. Instead, these are the manifestation of the HW itself at these scales. On the other hand, during the daytime (shown in figure 5(d)) the PSD corresponding to city-scale wavelength does not vary due to the HW. This is because the SUHI is significantly dominant during the daytime irrespective of the HW. This finding is also consistent with the
SUHI Intensity analysis wherein the impact of HWs was negligible during the daytime (figure 3). Only the smaller spatial scales corresponding to 1–5 km show an increased variability due to the HW.

As intra-urban heat islets have a fractal spatial structure [33], its PSD follows an inverse power law and can be characterized by its slope. We use this property to comprehensively represent the size distribution across all length scales. Our analysis of air temperatures revealed higher slopes (ranging from 1.75 to 2.75) than LST (ranging from 1.5 to 2.5), indicating less variance in smaller-scale features. This is because air temperatures tend to be more homogeneous and have smoother gradients due to turbulent mixing, whereas LST can have sharp thermal changes due to sharp changes in LULC and associated emissivity [47]. The diurnal trend, however, is consistent with that of LSTs, where the most dominant impact of HWs is the persistence of large contiguous patches of heat during nighttime. The persistence of contiguous
Figure 5. Radially averaged 2D power spectral densities (PSDs) of LST fields are shown. PSD for every hour of a single day is shown for (a) non-HW scenario, and (b) HW scenario. Here, the color bar represents the hour of the day with 0 corresponding to midnight. The PSD value obtained for (c) nighttime (from 9 pm to 7 am), and (d) daytime (from 8 am to 8 pm) within the period of interest are then averaged by wavelength to obtain the representative PSD values for HW (in red) and non-HW (in blue) scenario. The details of slope fitting are described in ?? The time series of PSD slopes of (e) LST and (d) T2 is shown in the light-colored lines for HW (in red) and non-HW (in blue) scenario. Hour-specific average slopes for each time of day overlaid in dark lines.

regions of high heat impedes effective thermal dissipation due to increased distance from nearby heat sinks. This results in a homogeneous expanse of persistent high temperatures which is consistent with the low values of \( \text{Var}(\text{LST}) \) observed during daytime HWs (figures 3(c) and (f)).

4.4. Temporal dynamics of intra-urban heat islets
Cities often collect data on air temperatures and UHI intensity at a limited number of locations. However, there are little to no in situ observational datasets detailing the spatial intra-urban thermal variability. To this end, we seek to explore if the aforementioned PSD slope can be derived as a function of temperature or UHI Intensity and understand how their relationship co-evolves in time.

4.4.1. Air temperature-based analyses
In figure 6(a), the diurnal trajectory of UHI Intensity as a function of mean air temperature is evaluated. During the early morning hours, as the Sun rises, the rural air temperatures start rising faster than that of the urban areas due to different thermal inertia of urban building materials. As a result, as the mean temperature increases, UHI Intensity decreases reaching minima at 1 pm. In the afternoon hours, once the urban air heats up due to longwave radiation emissions from the hotter urban surfaces, the UHI Intensity steadily increases while T2 peaks at about 4 pm before declining. After sunset, urban and rural T2 continue to decrease through the night, the difference between the two remains large during the night because of the release of storage heat flux from urban building materials. Thus, the difference in heat capacity between the urban and rural regions leads to a hysteresis in the response of urban T2, which manifests as an anticlockwise circular trajectory of UHI Intensity as a function of mean T2. While the anti-clockwise trajectory of UHI Intensity as a function of mean T2 is consistent under a HW, the increased range of diurnal T2 results in a larger range of UHI intensity as well (figure 6(b)). This results in lower UHI Intensity during the night and early morning hours.

Figure 6(c) depicts the trajectory of slope as a function of UHI intensity. The slope decreases as the absolute value of UHI intensity increases (either positive or negative). When the UHI is near zero, the temperatures are homogeneous across the rural-urban boundaries. This manifests as the reduction of small-scale variabilities, in other words, a steeper PSD slope. When the urban temperatures deviate from that of the surroundings, the variances manifest at every scale resulting in a decrease of the slope. This reveals a quadratic nature of the relationship between the UHI intensity and the slope. Note that the first crest at dawn corresponds to zero UHI; however, the second crest that occurs at dusk shows a hysteresis and corresponds to a positive UHI value. Moreover,
the quadratic relationship between Slope and UHI Intensity is disrupted by the HW in the morning hours (figure 6(d)). Further research on the consistency of such a pattern for other environmental conditions and other cities is needed to study the precise relationship.

4.4.2. Surface temperature-based analyses
Unlike UHI, the SUHI does not have a delayed response to solar radiation. As a result, SUHI Intensity is more positively correlated with mean LST (figure 6(e)). As the Sun rises, the mean LST immediately increases steeply; however, the SUHI intensity first decreases for about an hour before rising later. This subtle offset in behavior between the urban and rural areas results in a similar anti-clockwise trajectory despite the notable positive correlation. Under a HW, the range of mean LST, as well as SUHI Intensity, increases by $\sim 1^\circ C$, resulting in a more elongated hysteresis pattern (figure 6(f)).

Another interesting pattern emerges from the analysis of slope vs SUHI Intensity under a HW scenario (figure 6(h)). As discussed previously in the case of UHI Intensity, the minima of slope occur when the absolute value of SUHI Intensity is the largest. As there are no negative values of SUHI Intensity, this manifests as a monotonic negative correlation, wherein the maximum slope value occurs near zero SUHI Intensity. This is also because near-zero values of SUHI Intensity imply that the temperatures are homogeneous across the rural-urban boundaries. This reduction of small-scale variabilities manifests as a steeper PSD slope. As near-zero values of SUHI Intensity are not prevalent in non-HW scenarios, this relationship is only evident under a HW (figure 6(g)). As SUHI Intensity increases, the variances show up at every scale thereby lowering the PSD slope. Thus, using the hourly trajectory plots for pairs of these variables, we present a novel perspective that complements the time series analysis.

5. Discussion
What is the utility of focusing on the interaction between UHI and HWs? More specifically, how will the portfolio of mitigation strategies change if there is synergy [19, 21, 22], or anergy [25–27], or no interaction [16, 18, 23, 24] between UHI and HW? Does a lack of synergy (as seen in this study) imply that cities like Paris need not invest in heat mitigation since the UHI reduces during a HW?

Here, we argue that the UHI Intensity is not a useful index for aiding mitigation planning in the context of HW. In our analysis of the 2018 European HW over several cities, we see that in the case of a HW, the diurnal fluctuations in the rural areas are higher than their urban counterparts. The rural LST and T2 are highly sensitive to the fluctuations in the soil water storage variations, whereas the urban temperatures remain driven by the dynamics of sensible heat flux and storage heat flux [22, 23]. A reduction in UHI and SUHI Intensity under a HW scenario does not imply better thermal comfort for an urban resident, who is only impacted by the local temperature and humidity. Rather, it merely reflects elevated rural background temperatures during the HW, which is
often accompanied by drought conditions [37]. On the contrary, in coastal regions, UHI Intensity is normally lower than in other cities as the land-sea breeze dissipates some of the built-up heat [48]. But during a HW, the UHI intensities increase during the daytime as the high-pressure HW system arrests the land-sea interactions [25, 30]. This leads us to conclude that UHI Intensity is not an adequate metric to evaluate the impact of HW on urban areas.

As a solution, we recommend a shift of focus to the intra-urban thermal variance, or more specifically the intra-urban heat islets framework [33]. Here, we investigated the UHI-HW interactions for multiple cities that experienced the European HW in 2018 with an emphasis on intra-urban heterogeneity. We find that Var(LST) reduces during the HW period, yielding large clusters of homogeneous heat. The persistence of large expanses of high heat especially during nighttime would result in prolonged exposure for people moving outdoors. This finding is all the more significant given that in Paris, the intra-urban spatial pattern of nighttime temperatures was most strongly correlated with heat-related deaths during the 2003 HW [41]. This underscores the importance of fragmenting or removing the large night-time heat clusters. In mild temperate climates like Paris, local blue-green architectural interventions are shown to yield good results in urban cooling [29, 49]. However, in a dense megacity, the availability of land and water resources poses a limit to such strategies. Moreover, under a long HW spell, the benefits of greening were found to diminish [43]. Lastly, urban greening alone may not be sufficient if the co-location of vulnerable populations is not considered [44]. Thus, it is important to understand how urban designs and practices impact the co-location between the heat sources/sinks and the urban zones/populations that are vulnerable.

While the spatially optimized allocation of heat sinks for urban regions across the globe is the ultimate motive, we recognize the practical limitations of running high-resolution simulations or obtaining high-fidelity observations for all possible urban/rural agglomerations—especially in the developing countries. High-resolution remotely sensed data is one such solution to obtaining insights on surface temperatures at a consistent resolution with low estimation uncertainty. Novel missions such as ECOSTRESS6 provide the capability to collect LST data at a 70 m resolution making it possible to study the diurnal trajectory of intra-UHI [50]. Additional upcoming missions such as SBG7, LSTM8, and TRISHNA9 will be able to provide a near-daily coverage (at ∼50 m resolution) of most urban areas by the end of this decade, thus paving the way for more accurate spatial optimization and improved urban planning [51–54].

Understanding, quantifying, and evaluating the net impact of extreme heat on an urban resident and the surrounding ecosystems is imperative given the uncertainty surrounding the interactions between the HW, UHI, and global warming. Due to the increasing scarcity of resources, it is important to revisit the conclusions of the prior studies based on the mean temperatures alone, and adapt our mitigation strategies to target resources toward the most vulnerable regions [10, 55, 56]. As we enter a climate paradigm where the local temperatures breach the limits of human adaptability to heat stress [57, 58], it becomes critical that we study the heterogeneity and local extremes within urban temperatures. Rethinking the HW-UHI interactions as a scale-dependent, heterogeneous, dynamic interaction is a step in this direction.

Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

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6 ECOSTRESS: ECOsystem Spaceborne Thermal Radiometer Experiment.
7 SBG: Surface Biology and Geology.
8 LSTM: Land Surface Temperature Monitoring.
9 TRISHNA: Thermal infrared Imaging Satellite for High-resolution Natural resource Assessment.
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