Hyperlocal Thermal Modeling with IoT Sensors and UMEP in London's Queen Elizabeth Olympic Park

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Summary

Urban thermal modeling is often constrained by the limited availability of high-resolution spatiotemporal data. In London's Queen Elizabeth Olympic Park, we deployed a network of 15 bespoke IoT temperature sensors across various land cover types. We compared the measured air temperature (T_{air}) with UMEP modeled mean radiant temperature (T_{mrt}). A rank analysis indicated a significant positive correlation for daytime which confirms the sensors' ability to resolve microclimate variations, but a weaker correlation for nighttime, indicating limitations of current thermal modelling methods. Results demonstrate the value of the cost-effective IoT sensors in detecting, monitoring and remediating thermal hotpots.

KEYWORDS: [Urban Heat Modeling, Internet of Things, Hyperlocal Temperature Data, Climate Mitigation Planning, GIS Analysis]

1. Introduction

Rapid urbanization and climate change have intensified the need for fine-scale thermal modeling to inform urban planning, mitigate extreme heat, and promote public health. While satellite-derived land surface temperature data provides spatially explicit insights and serves as a boundary condition for urban energy balance, it is often employed in health risk assessments more for its ease of mapping than its relevance to human heat exposure (Ho et al., 2016). In contrast, mean radiant temperature (T_{mrt}) and near-surface air temperature (T_{air}) offer finer resolution and direct relevance to human thermal comfort, making them indispensable for capturing hyperlocal temperature dynamics (Venter et al., 2020). Previous research (Ma, 2024) in east London demonstrated that IoT sensor networks' ability in providing real-time, high spatiotemporal T_{air} data. Additionally, the Urban Multi-scale Environmental Predictor (UMEP), is available for modeling the influence of urban morphology and vegetation on thermal comfort and estimating T_{mrt} (Lindberg et al., 2018). In this paper, we compare sensor measured T_{air} and UMEP-modeled T_{mrt} data for 15 zones in London's Queen Elizabeth Olympic Park on 12th August 2024 to explore their utility for advancing GIS-based microclimate modeling and urban thermal comfort assessments.

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2. Methodology

2.1. Direct Measurement of T_{air}

The study focuses on Queen Elizabeth Olympic Park (QEOP) in London, a diverse urban park with varying land cover types, including green spaces, paved surfaces, and built-up areas. A network of 15 bespoke, solar powered devices have been deployed across the park since 1st August 2024, on a variety of land cover types, utilizing existing infrastructure like lamp posts, trees, and bridges. These sensors collect real time air temperature and humidity data at five-minute intervals and communicate directly with the cloud via a citywide Long Range Wide Area Network (LoRaWAN) (**Figure 1**).

Figure 1 Solar-Powered IoT Sensor Deployed in QEOP for Microclimate Monitoring

2.2 UMEP Modelling of T_{mrt}

UMEP and its processor SOLWEIG (Solar and Longwave Environmental Irradiance Geometry) were used to model T_{mrt} across the QEOP using QGIS. SOLWEIG requires five categories of land cover types: paved, buildings, grass, bare soil, and water. Tree cover is integrated via a separate canopy digital surface model. Classifications of land cover used OpenStreetMap data and Bluesky tree data (location, height, canopy size, and type). Sky view factors (SVF) quantify the openness of the sky at each location, accounting for shading effects from buildings and trees. Meteorological inputs including air temperature, humidity, wind speed, and solar radiation, were obtained from the Copernicus ERA5 dataset for 12th August 2024, a hot day selected for its high thermal variability. SOLWEIG then calculates T_{mrt} by simulating the effects of both solar and longwave radiation under varying urban geometry and surface properties. A 30m x 30m zone was defined around each sensor location to facilitate the T_{mrt} comparison, aligning with Landsat satellite image resolution for potential future work.

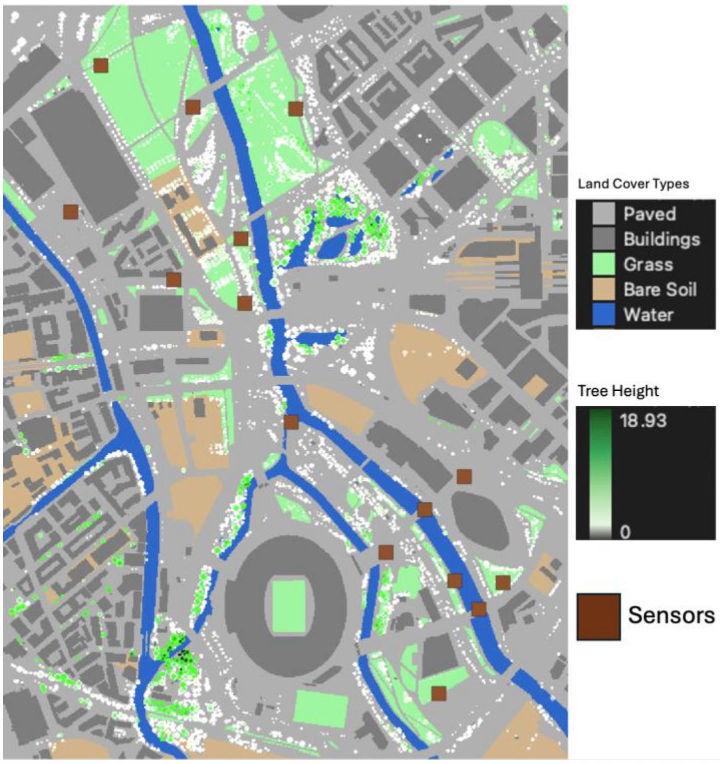

Figure 2 Land Cover Classification Map of QEOP for UMEP Modelling

3. Preliminary Results

The zonal mean T_{mrt} across the 15 zones was calculated (**Figure 3**) and compared with actual T_{air} measured by the sensors using rank analysis (**Table 1)**. Spearman's Rank Correlation showed significant positive correlation for daytime (R_s = 0.5714, p=0.05), with weaker correlation at night (R_s= 0.2929, p=0.5).

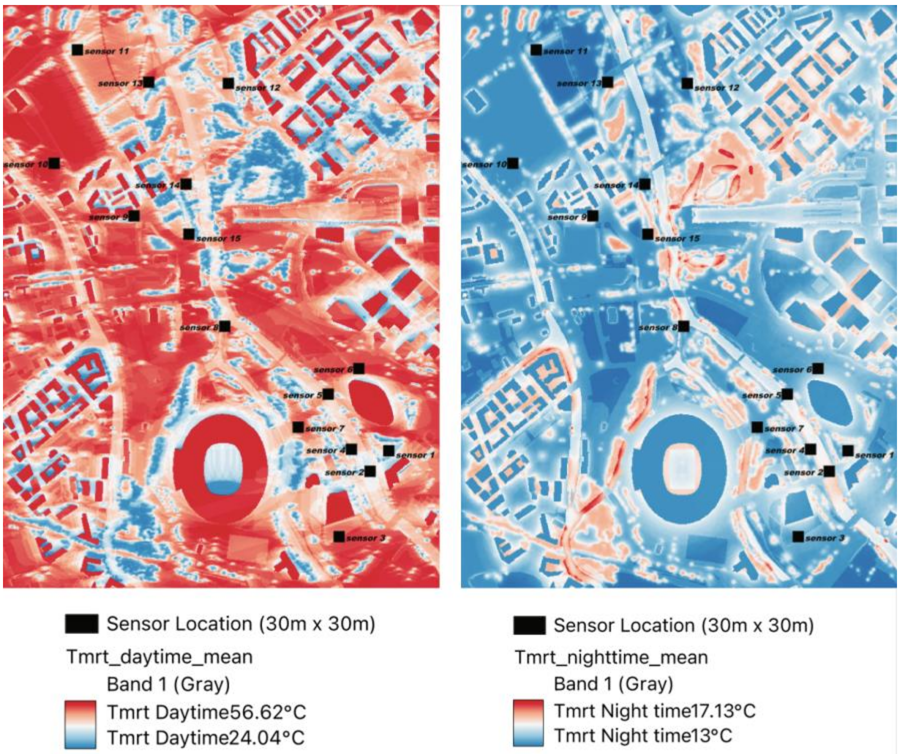

Figure 3 Heat Map of QEOP on 12th August 2024 using SOLWEIG modelled T_{mrt}

Table 1 Rank Analysis (from hottest to coldest) of T_{mrt} and T_{air} for daytime and night time

Zone	Mean Daytime T_{air} (6am-9pm) (°C)	T_{air} Rank	Mean Daytime T_{mrt} (6am-9pm) (°C)	T_{mrt} Rank
sensor1	28.206	15	38.572	15
sensor2	28.534	12	40.969	14
sensor3	28.641	9	51.104	4
sensor4	28.250	14	41.006	13
sensor5	28.499	13	47.204	7
sensor6	28.867	7	52.545	2
sensor7	29.022	5	51.342	3
sensor8	28.553	11	46.701	8
sensor9	28.963	6	48.976	5
sensor10	29.179	3	54.276	1
sensor11	28.833	8	43.349	12
sensor12	28.607	10	43.740	11
sensor13	29.813	1	48.269	6
sensor14	29.174	4	44.483	9
sensor15	29.365	2	43.888	10
	$R_s = 0.5714$, $p = 0.05$			

Zone	Mean Nighttime T_{air} (0am-6am, 9pm-11pm) (°C)	T_{air} Rank	Mean Nighttime T_{mrt} (0am-6am, 9pm-11pm) (°C)	T_{mrt} Rank
sensor1	20.061	12	14.324	5
sensor2	20.449	1	14.653	2
sensor3	20.267	6	13.810	11
sensor4	20.271	5	14.958	1
sensor5	20.204	10	14.049	7
sensor6	20.389	3	14.010	9
sensor7	20.372	4	13.648	14
sensor8	20.249	7	14.548	3
sensor9	20.420	2	14.306	6
sensor10	20.034	13	13.438	15
sensor11	20.247	8	14.041	8
sensor12	19.983	14	13.776	13
sensor13	20.227	9	13.942	10
sensor14	20.129	11	13.779	12
sensor15	19.898	15	14.506	4
	$R_s = 0.2929$, $p = 0.5$			

4. Discussion

T_{air} and T_{mrt} are both key variables in urban thermal studies but measure different thermal dynamics. T_{air} refers to ambient air temperature at pedestrian level (normally 1.5-2m), influenced by atmospheric conditions, surface heat exchange, and convection (Liu et al., 2017). T_{mrt} quantifies the radiant heat exchange between a human body and its surroundings, incorporating both shortwave and longwave radiation, making it a better measure of the thermal comfort than macroscopic air temperature (Lindberg et al., 2016). Thus, the absence of quantitative agreement between T_{air} and T_{mrt} is expected. However, at the hyperlocal scale, the radiation fluxes underlying T_{mrt} will also influence the local air temperature, which explains the observed correlation, which does give confidence that the sensors are capturing hyperlocal thermal dynamics rather than fluctuations caused by measurement uncertainty (±0.3°C) of the sensors.

Differences between thermal modelling of T_{mrt} and the T_{air} measurements highlight limitations in SOLWEIG, which is primarily a radiation model; tree canopy data is used to calculate shadows, but not evapotranspiration effects. The effect of different land cover types is incorporated via their albedo

(Lindberg et al., 2016), but not their heat storage capacities. In addition, no account is taken of heat generated by human activities. These latter factors may explain the weaker correlation between T_{mrt} and T_{air} at night. The T_{air} sensor data suggests SOLWEIG underestimates the cooling effect of bodies of water, perhaps due to the omission of evapotranspiration. This limitation is important because it affects the accuracy particularly for modelling nighttime heat stress and urban heat islands. One potential approach for improving accuracy is integrating sensor data to refine modeled T_{mrt} estimates to improve the accuracy of urban heat modeling. This could help create a more consistent temperature representation across the entire study area, improving its applicability for urban heat risk assessments and climate-responsive urban design.

5. Conclusion

This study validates the bespoke IoT sensor network's ability to capture microclimate variations, identifies limitations in SOLWEIG, and demonstrates the strong cooling effect of water on air temperature. Future work will explore different land covers' impact on thermal environment and to further investigate the relationship between T_{air} and T_{mrt} in this urban park. Overall, we explored how IoT sensing can enhance urban microclimate modeling, providing hyperlocal insights in detecting, monitoring and remediating thermal hotpots. Our findings highlight the potential of our cost-efficient bespoke heat sensors as a complementary tool to GIS analysis on urban heat modeling and supporting the development of future climate-resilient cities.

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References

Ho, H.C., Knudby, A., Xu, Y., Hodul, M., Aminipouri, M., 2016. A comparison of urban heat islands mapped using skin temperature, air temperature, and apparent temperature (Humidex), for the greater Vancouver area. Sci. Total Environ. 544, 929–938.

Lindberg, F., Grimmond, C. S. B., Gabey, A., Huang, B., Kent, C. W., Sun, T., Theeuwes, N. E., Järvi, L., Ward, H. C., Capel-Timms, I., Chang, Y., Jonsson, P., Krave, N., Liu, D., Meyer, D., Olofson, K. F. G., Tan, J., Wästberg, D., Xue, L. and Zhang, Z. (2018). 'Urban Multi-scale Environmental Predictor (UMEP): An integrated tool for city-based climate services'. Environmental Modelling & Software, 99, pp. 70–87. doi: 10.1016/j.envsoft.2017.09.020.

Lindberg, F., Onomura, S. and Grimmond, C.S.B., 2016. Influence of ground surface characteristics on the mean radiant temperature in urban areas. *International journal of biometeorology*, *60*, pp.1439-1452.

Liu, S., Su, H., Tian, J., Zhang, R., Wang, W. and Wu, Y., 2017. Evaluating four remote sensing methods for estimating surface air temperature on a regional scale. *Journal of Applied Meteorology and Climatology*, *56*(3), pp.803-814.

Ma, D., Brousse, O., De Jode, M., & Hudson-Smith, A (2024) 'Using Bespoke LoRaWAN Heat Sensors to Explore Microclimate Effects within the London Urban Heat Islands– A Pilot Study in East London'. 32nd Annual GIS Research UK Conference (GISRUK), Zenodo. doi: 10.5281/zenodo.10897767.

Venter, Z. S., Brousse, O., Esau, I. and Meier, F. (2020). 'Hyperlocal mapping of urban air temperature using remote sensing and crowdsourced weather data'. Remote Sensing of Environment, 242, p. 111791. doi: 10.1016/j.rse.2020.111791.

Biographies

Dongyi Ma is a PhD student in Connected Environments Lab in UCL. Her research focuses deploying the first London wide real time microclimate network using bespoke IoT sensor systems to measure and communicate Urban Heat Islands and urban microclimates for input into urban policy and climate mitigation planning.

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Andrew Hudson-Smith is a Professor of Digital Urban Systems at CASA, University College London. He focuses on real-time data, VR and the Internet of Things. He is an elected Fellow of the Royal Society of Arts, The Academy of Social Sciences and the Royal Geographic Society.