Evaluating the Urban Parks Cooling Extent Using Satellite Observations: An Alternative Approach

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Abstract: Green infrastructure is the cooling hub of the built environment in urban settings. These interactions could contribute towards the reduction of the rise in temperature due to urban heat island effects. It is common practice to evaluate the cooling extent using onsite observations. Alternatively, satellite data could be a possible source to perform the former. We analyse and evaluate the extent using the satellite observations. Intuitively, as we go further from a park, the cooling effect will decrease but this need to be quantified. We analyse Landsat-8 images to generate a temperature distribution in urban environment. The Land Surface Temperature (LST) was derived from Landsat-8 and downscaled from 30 m to 10 m using the Sentinel-2 spectral indices in the Greater London area. This gives a relatively high resolution LST variation in urban environment. A profile over a park was extracted to observe the extent of cooling from the green infrastructure extends towards the build environment. The cooling effect varies with the park and the effect extends up to 300 m. These observations contribute towards the urban planners to maximise the cooling benefits of urban parks to promote urban resilience and sustainability.

1 INTRODUCTION

The urbanisation and expansion of built environment in cities are putting a lot of loads to the heat sinks such as parks, woodlands, and street trees, collectively called green infrastructure (GI) (Jeyachandran et al., 2010; Tessema et al., 2023). As a result, problem such as the Urban Heat Iceland (UHI) effect and extreme weather conditions are observed in cities (Almeida et al., 2021). A high temperature in cities, poses risks to the public health (Nieuwenhuijsen, 2021). GI play a vital role in mitigating the UHI and moderate the thermal variations in urban settings. Quantifying the extent of GIs in absorbing the heat and improving thermal comfort of the environment is essential. In this regard, in addition to the in-situ measurements of temperature, Earth Observation (EO) satellites can be used as a tool to investigate surface temperature variations in urban environments (Mackey et al., 2012). There are various studies that have evaluated the GIs effect at different scales (Almeida et al., 2021; J. C. Jiménez-Muñoz et al., 2014; Mackey et al., 2012; Vieira Zezzo et al., 2023).

Microscale weather variability study is essential in urban environment for the wellbeing of the population live in the cities (Almeida et al., 2021; Vieira Zezzo et al., 2023). The extreme temperature above the normal climate range should be monitored to reduce the impact on public health (Nieuwenhuijsen, 2021). In addition, the data analysis on macroscale would contribute to the urban planners and city councils to plan reducing the extreme heat in urban settings.

Figure 1: Location map of the study area.

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In this study, we investigate the variability in temperature in the urban areas and the effect of the green areas and parks in reducing the variability. As a show case, we focus on the Greater London area (Figure 1). The city has a very diverse land use, functions, and vitality. The GI cooling effects was quantified based on hyperspectral images of optical observation satellites. The spatial extent of cooling effect of selected green space was analysed. Landsat-8 and Sentinel-2 satellite data was used to analyse the temperature variation in the city.

2 MATERIAL AND METHOD

2.1 Data

In this research, multispectral satellite imageries of the Landsat mission by NASA and the Sentinel-2 mission by ESA that are acquired over the London area were used. The Landsat data is available from 2013 and the Sentinel-2 mission is available from 2015, we used here the overlapping period. Landsat-8 OLI/TIRS has a native spatial resolution of 30 m for the eight reflective bands (B1-B7, B9), 15 m for the panchromatic band (B8), and 100 m for the thermal bands (B10-B11) (Storey et al., 2014). The Landsat-8 collection 1 Level-2 surface reflectance product was used to generate spectral indices in 30 m spatial resolution. The Sentinel-2 MSI Level-2A imagery was used, and the mission has no thermal band. But it provides multispectral imagery at a spatial resolution of 10 m and with a temporal resolution of 5 days (Drusch et al., 2012). We use the Sentinel-2 data to analyse and optimize the Landsat-8 data to higher spatial resolution. The percentage cloud cover over the images was also considered when we select the images.

2.2 Method

The heat distribution in urban areas is controlled by a diverse land cover distribution. The interaction between the built environment and the green spaces determines partly the heat dynamics of urban areas. The thermal band from Landsat-8 allow us to map the surface thermal radiance at 100 m ground sampling resolution. The final distribution of the thermal band is resampled to 30 m spatial resolution by the United States Geological Survey. LST measures the emission of thermal radiance from the land surface where the incoming solar energy interacts with and heat the ground (Hulley et al., 2019). The surface thermal radiance of the Landsat thermal band can be used to calculate the Land Surface Temperature (LST). LST can be computed using an empirical relationship between TOA brightness temperatures in a single TIR channel (Freitas et al., 2013).

$$\mathrm{LST} = \mathrm{A_i}\frac{\mathrm{Tb}}{\varepsilon} + \mathrm{B_i}\frac{1}{\varepsilon} + \mathrm{C_i} \tag{1}$$

Where Tb is the TOA brightness temperature in the TIR channel, and ε is the surface emissivity for the same channel. The coefficients $(\mathrm{A_i}, \mathrm{B_i}, \mathrm{C_i})$ are determined from linear regressions of radiative transfer simulations.

The spectral indices such as NDVI (normalised difference vegetation index), built-up index (NDBI), and water index (NDWI) are determined from both Landsat-8 and Sentinel-2 data (Defries & Townshend, 1994; Gao, 1996; Onačillová et al., 2022). The 10 m spatial resolution of indices from Sentinel-2 have given an opportunity to spatially downscale the products from Landsat-8. The downscaling is important in urban and semi-urban areas to analyse parameters such as LST in high resolution. In this research, we used the method proposed by Onačillová et al., (2022) to downscale the spatial resolution of the LST calculated from Landsat-8.

3 RESULTS AND DISCUSSION

The hyperspectral images were used to calculate land cover indices such as NDVI, NDBI and NDWI (Defries & Townshend, 1994; Gao, 1996; Varshney, 2013). From these indices, surface reflectance products are derived to determine the land surface temperature (LST) using Landsat-8. In addition to this, the Sentinel-2 images were used to derive similar land cover indices with 10 m resolution. Figure 2 shows the Sentinel-2 NDVI derived from green, red, and near-infrared band, and the LST derived from the green, red, near-infrared, and infrared bands from the Landsat-8 (J. C. Jiménez-Muñoz et al., 2014). We considered images from both satellites with a maximum cloud coverage of 20%. As a result of high cloud cover, we selected very limited images from the archive. The variation in NDVI in Figure 2 (a) varies from 0 to -1 from built environment to water bodies and 0 to +1 from built environment to vegetations. The NDVI index contributes for dividing the land cover based on the chlorophyl content of the vegetations. The white part in NDVI image represents the built environment. Figure 2 (b) shows the LST derived from Landsat-8 with a spatial resolution of 30

m. The temperature variation shows the average temperature over the 2023 summertime over the Greater London area. The temperature represented in the figure is in degree Celsius and varies from 15 °C in water bodies and up to 45 °C in places dominated by buildings.

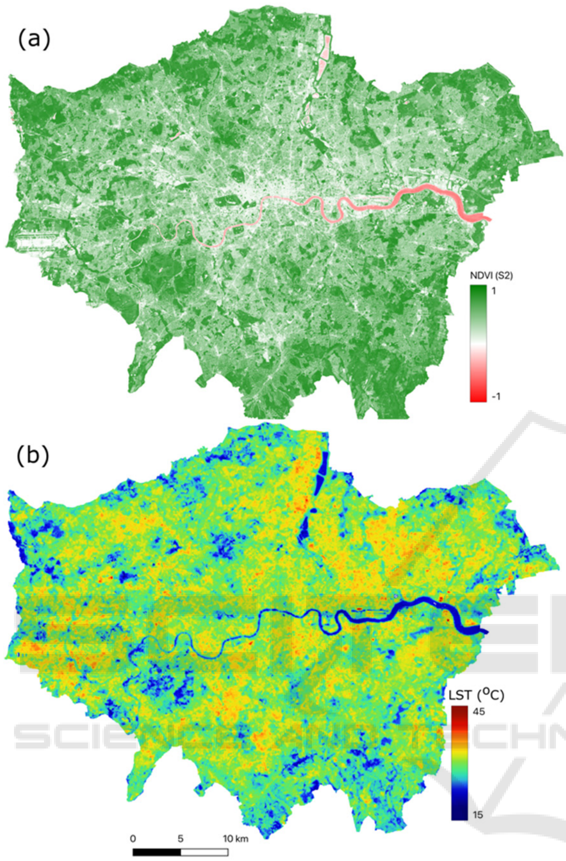

Figure 2: NDVI and LST map for Greater London. (a) NDVI using Sentinel-2 with a 10 m spatial resolution. (b) The LST derived from Landsat-8 with a 30 m spatial resolution. The temperature varies from 15 °C in water.

To see the variation in temperature at the microscale, we selected the Central London area as outlined in the black rectangle in Figure 3 (b). The LST calculated from the Landsat-8 has a spatial resolution of 30 m and the derived temperature variation Figure 3 (a) and (c) acquired on May 26, 2023, and September 15, 2023, respectively. The temperature difference between these dates on average is about 5°C. The cooling effect of parks are significant in May as compared to September. The temperature in the parks in May on average was 15-20 °C but in September the average temperature rises to 30 °C. The cooling effect of parks in September is very much reduced and limited to water bodies and areas with dense trees.

LSTs in Figure 3 (b) and (d) are the downscaled version which shows relatively variable temperature. The downscaled map shows clear demarcation temperature in the parks, built environments, and linear civil structures. Hyde Park in Central London, UK, was selected based on its size and complexity.

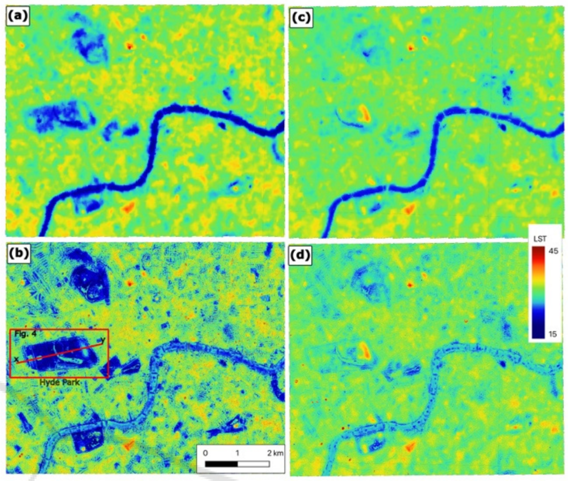

Figure 3: LST in Central London. On 26-05-2023, (a) is LST 30 m resolution and (b) LST downscaled using Sentinel-2 indices. On 15-08-2023, (c) is LST 30 m resolution and (d) LST downscaled using Sentinel-2 indices.

The LST profile was extracted across the park as shown in Figure 4. Figure 4 (a) and (b) shows the temperature variation in end May and September respectively. The LST relatively smoothly vary in the 30 m resolution (the red lines) image profiles and showed similar pattern in both dates. The downscaled LST shows a high frequency variability in temperature but follows a similar general trend with the 30 m spatial resolution LST profile.

The other important aspect of downscaling of the LST is that it enables us to identify pocket areas of anomalously high or low LST areas. For instance, in Figure 4a and b, the dome shaped high temperature anomaly at a distance from 2.8 to 3 km on the profiles is the Winter Wonderland in Hyde Park. Places such as train stations, large shopping centres and public centres produces high heat anomaly in the urban settings.

4 CONCLUSIONS AND FUTURE DEVELOPMENT

In this study, we used Landsat thermal signal and Sentinel-2 observations to calculate the LST. The LST generated from Landsat at 30 m resolution is downscaled to 10 m by implementing the spectral indices of Sentinel-1 to calibrate the Landsat LST. We compared two dates at the beginning and ending months of the summer 2023. The LST profile across the park was extracted and the extent of the cooling effect was determined.

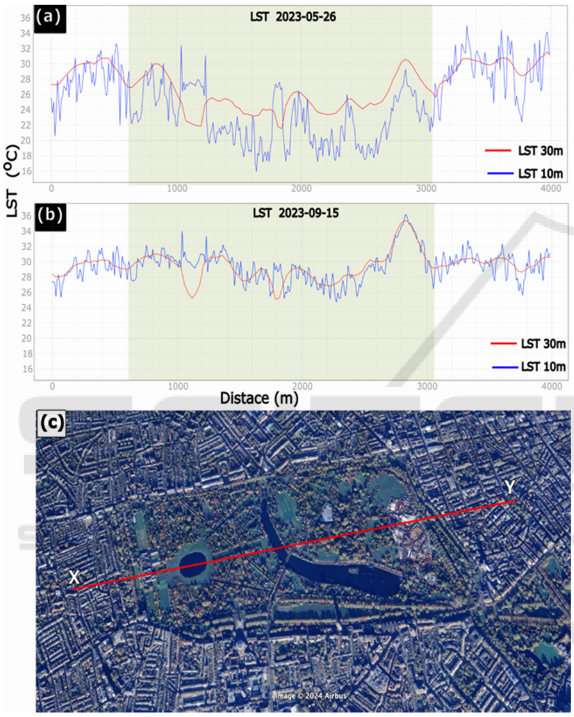

Figure 4: LST profile on Hyde Park in Central London, UK, the park extent is highlighted the profile plots with shaded rectangle. (a) shows the LST in May 2023 and (b) shows the LST in September 2023, (c) shows the profile and the RGB image of the area, the profile is shown by the XY red line.

The cooling effect can be extending up to 300 m from the border of the park. In addition, our profile analysis showed that there is a temperature variation within the park. The limitation in the data coverage is the percentage of the cloud cover during this period, and the availability of Landsat images in study area. This work would also help authorities in developing countries to support fast growing cities and help them to balance the urban development and the use of parks and public spaces towards sustainable and comfort-oriented practices.

This research will be further developed based on geostatistical analysis of cooling effects and the dynamics with the built environment. Validation of the results with the in-situ weather station database and other measurement will be done to evaluate the accuracy of the freely available satellite data for urban temperature monitoring. The newly launched thermal satellites such as the UK based satellite SatVu (SatelliteVu,2024), which has 3.5 m resolution thermal images would be a potential for further research endeavors.

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