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SEEDS Sustainability Program

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Executive Summary

The upsurge of climate change has exacerbated urban heat island (UHI) effect, leading to severe consequences for human health, urban livability, and energy demand. Rising temperatures significantly increase the demand for cooling energy, as the cooling load of buildings is heavily influenced by the amount of solar radiation reaching their surfaces. One of the most effective and sustainable strategies is urban greening. These interventions can take various forms, including street trees, urban parks, and vegetation surrounding buildings, all of which contribute to heat relief and improved urban resilience. Trees offer a wide range of ecosystem benefits that improve the climate and habitability of cities, including public spaces, by acting as natural shading and wind-shielding elements around buildings. By blocking solar radiation, trees help lower the energy needed for cooling, especially in buildings with poor window-to-wall ratios.

This project contributes to NCAP's goals by quantifying tree shade on buildings on UBC campus and analyzing its impact on building energy demand. Using high-resolution LiDAR data and sun position data, a Digital Surface Model (DSM) was created to represent campus elevation, and hillshade analysis was employed to simulate shade coverage at 15-minute intervals. Findings revealed that there is a negative correlation between shade coverage and cooling energy demand, highlighting the effectiveness of tree shading as a cooling strategy, as buildings with more shade tend to have lower cooling loads. Also, the analysis, although statistically significant, revealed that other confounding factors affect energy demand in a building, including the age of the building, occupancy level and behaviour, shape and orientation of the building.

The findings highlight the importance of strategic tree planting in urban environments to mitigate the urban heat island effect and enhance energy efficiency. Integrating tree shading into urban planning policies is essential for fostering sustainable and climate-resilient communities. Future research should incorporate real-time occupancy and equipment usage data, quantify transpiration contributions alongside shading effects and how the age of buildings can influence their energy demand over time.

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1. Introduction

The intensification of climate change has exacerbated the urban heat island (UHI) effect, leading to severe consequences for human health, urban liveability, and energy demand (Park et al., 2023; Sun et al., 2022; Zheng et al., 2020). This phenomenon is largely driven by the continuous release of emissions into the atmosphere, making the planet more vulnerable to climate change than ever (Akbari, 2002; Jamei et al., 2020).

Rising temperatures significantly increase the demand for cooling energy, as the cooling load of buildings is heavily influenced by the amount of solar radiation reaching their surfaces (Liu & Harris, 2008; Santamouris et al., 2011). Consequently, the summertime urban thermal environment and its associated energy demands have become a growing concern, particularly given that buildings account for approximately 40% of total energy demand in most developed countries (Hsieh et al., 2018a; Pandit & Laband, 2010; Sun et al., 2022). This calls for the need to pursue more resilient heat mitigation strategies to foster more sustainable and climate-adaptive urban environments (Wu et al., 2022). Among the most effective and sustainable heat mitigation strategies is urban greening, which has demonstrated substantial potential in reducing urban heat (Campbell et al., 2021). These interventions can take various forms, including street trees, urban parks, and vegetation surrounding buildings, all of which contribute to heat relief and improved urban resilience (Srivanit & Hokao, 2013).

1.1 The Cooling Benefits of Tree Shades

Urban trees provide more than just aesthetic value. They offer a wide range of ecosystem benefits that improve the climate and habitability of cities, including public spaces (Akbari et al., 2001; Jamei et al., 2020; Santamouris et al., 2011). One of their most significant functions is reducing urban temperatures by acting as natural shading and wind-shielding elements around buildings. This not only enhances thermal comfort but also reduces cooling energy demand, especially in buildings with poor window-to-wall ratios (Hsieh et al., 2018b, 2018a; Jamei et al., 2020; Morille et al., 2015).

When trees are strategically planted around buildings, they help mitigate solar heat gain by blocking unwanted solar radiation from striking building surfaces (Huang et al., 1987; Morille et al., 2015). This reduces the amount of energy required for cooling, a concept validated by Calcerano & Martinelli (2016). Research consistently shows that shaded urban areas tend to be significantly cooler than areas exposed to direct sunlight (Jamei et al., 2020).

A study by Hsieh et al. (2018b) in Nanjing City examined the impact of tree shading and transpiration on building energy use, finding that tree shade can reduce cooling energy demand by up to 10.3% compared to buildings with no surrounding trees. This result is consistent with

findings from Calcerano & Martinelli (2016) in Rome, where trees were shown to significantly reduce cooling energy demand, with reductions ranging from 11.1% for a single tree to 44.4% for a five-tree configuration. Similarly, Morakinyo et al. (2016) modelled the effects of tree shade on indoor and outdoor thermal conditions, reporting that tree-shaded buildings had temperatures 2.4°C lower than unshaded buildings, which experienced peak temperatures up to 5.4°C in Akure City, Nigeria.

Additional studies confirm these cooling effects. Abdel-Aziz et al. (2015) found that tree shading and transpiration reduced summer temperatures by 1–5°C, leading to significant decreases in cooling loads and energy demand in Mediterranean climates. McPherson & Rowntree (1993) assessed the energy conservation potential of urban tree planting in Chicago, using monitoring data and computer simulations. Their findings estimated that a single 25-foot tree could reduce household heating and cooling energy by 8–12%, translating to an annual nationwide energy savings of \$1 billion.

Further research highlights the importance of tree shade in mitigating heat waves. Wang et al. (2019) found that urban trees reduce temperatures during heatwaves, with a cooling rate of up to 1.336°C per percentage of fractional tree cover (FTC), compared to just 0.022°C per percentage of FTC during cold waves. Schwaab et al. (2020) observed that increasing the proportion of broad-leaved tree species helps lower daily summer temperatures by up to 1.8K in the Atlantic region and 1.5K in the Continental and Mediterranean regions.

1.2 Relevance of the study to UBC Neighbourhood Climate Action Plan

In June 2024, the University of British Columbia (UBC) approved the Neighbourhood Climate Action Plan (NCAP), which emphasizes ecological systems and ecosystem services, including the role of tree shade in urban environments. This project contributes to the goals of the NCAP by quantifying tree shade on buildings in a selected UBC neighbourhood and analyzing its impact on building energy demand.

This study builds on the 2024 Shade Mapping for Neighbourhood Climate Adaptation and Community Wellbeing project, which identified areas of UBC with limited shade. This study takes it a step further by comparing the cooling energy demand of buildings based on their shade coverage levels. The study will enhance our understanding of how tree shade regulates ambient and surface temperatures in built environments and its role in reducing building cooling loads.

To achieve these objectives, the study employed geospatial analysis and statistical modelling. LiDAR point cloud data was processed to generate a series of shade rasters, which were then stacked into a single layer and overlaid onto building footprints to compute shade statistics for each selected building. Simple linear regression models were used to examine the relationship between tree shade coverage, temperature, and building cooling energy demand. Based on the statistical findings, tree planting recommendations were proposed to enhance the cooling benefits of trees in UBC neighbourhoods.

2. Study Area and Data Description

2.1 Study Area and Climate Description

The study was conducted at the University of British Columbia (UBC) Vancouver Campus, situated at the western tip of the Point Grey Peninsula in Vancouver, Canada, at 49.2606° N, 123.2460° W. The region experiences an average daily temperature of approximately 18°C during the summer and around 8°C in the winter (UBC Weather Summary, n.d.). According to the UBC Social Ecological Economic Development Studies (SEEDS) Program, the predominant vegetation in the study area includes western red cedar, red alder, Douglas fir, black cherry, and Norway maple, which are characteristic of a moderate oceanic climate (Gülçin et al., 2021). Understanding the distribution of tree species was essential, as different species provide varying levels of cooling through shading (Hsieh et al., 2018b; Morakinyo et al., 2016). Additionally, local temperature variations influence the ambient air temperature, which in turn affects the cooling loads of buildings (Zheng et al., 2020). Thus, assessing the temperature dynamics within the study area was necessary for evaluating microclimate impacts.

The housing stock at UBC comprises residential, commercial, institutional, and office spaces that accommodate thousands of students and other residents within the university community (PLAN_UBC_ClimateActionPlan, 2020). This study focused on four institutional buildings within the academic campus characterized by similar geographic and climatic conditions. Data on the buildable area of each house, construction type, roofing structure, and the presence of cooling systems were obtained from the UBC SEEDS Sustainability Program and UBC Campus + Community Planning.



Figure 1. Map of the University of British Columbia (UBC) Vancouver campus showing building locations and the legal boundary. The buildings selected for this study are highlighted in red for easy identification.

2.2 LiDAR Point Cloud Data

LiDAR, which stands for Light Detection and Ranging, is a remote sensing technology that measures highly accurate distances by emitting laser pulses onto the Earth's surface to create 3D maps of the target objects and landscapes (Park et al., 2023; Roussel et al., 2020). This technology provides precise and detailed three-dimensional data about topography and surface features (Tooke et al., 2009). In forestry, LiDAR is commonly used for forest mapping and assessment (Roussel et al., 2020), while in urban planning, it supports applications such as land use planning and infrastructure development (Dawood et al., 2017).

For this study, the LiDAR dataset was sourced from the City of Vancouver Open Data Portal. The data was acquired on September 7th and 9th, 2022, and covers an area of approximately 134 square kilometres, including the City of Vancouver and the UBC Endowment Lands (LiDAR 2022, n.d.). The point cloud data is classified into several categories: unclassified, bare earth, low grass, low vegetation, high vegetation, water, buildings, other, and noise (which includes noise points, blunders, and outliers) (LiDAR 2022, n.d.). The dataset is characterized by an average point density of 49 points per square meter, a vertical accuracy of 0.081 meters at a 95% confidence level, and a minimum sidelap of 60% in both the north-south and east-west directions.

Out of the 181 tiles in the dataset, 12 tiles covering the UBC campus were selected for this study. The LiDAR point cloud data was utilized to generate a high-resolution digital surface model (DSM) of the UBC campus, excluding buildings and other features except trees, at a 1-meter spatial resolution. The DSM enabled the generation of shade rasters necessary for shading analysis (Park et al., 2023). The high precision and resolution of this data were critical for performing accurate shade simulation and meeting the study's objectives (Calcerano & Martinelli, 2016; Park et al., 2021, 2023).

2.3 Sun Position Data

The Sun position data is essential for shade simulating and analyzing the shading patterns cast by trees on buildings (Calcerano & Martinelli, 2016; Park et al., 2021). This dataset was sourced from the National Research Council of Canada's Sunrise/Sunset Calculator, which generates solar parameters for specific dates and times(Canada, 2012). The data provides information on the solar azimuth (direction), solar altitude (height above the horizon), shadow length factors and the hour angle for every 15 minutes. The Solar altitude represents the sun's height above the horizon, while solar azimuth indicates the compass direction of the sunlight. The shadow length factor is a multiplier used to determine the length of a shadow based on the height of the object casting it. The hour angle indicates the time difference from solar noon, with each hour corresponding to 15 degrees.

Table 2. Sample of Sun position data for Vancouver, BC, on July 21, 2024, recorded at 15minute intervals between 9:00 AM and 9:30 AM. The data includes the hour angle, solar altitude, solar azimuth, and shadow length factor for each time interval.

Time	Hour Angle	Solar Altitude	Solar Azimuth	Shadow Length Factor
9:00	-3.31	41.4	107.8	1.13
9:15	-3.06	43.7	111.4	1.04
9:30	-2.81	46	115.2	0.97

2.4 Building Energy Demand Data

Energy demand data for each building were sourced from UBC Energy and Water Services and made publicly accessible through the SkySpark platform. This platform comprises a suite of four applications that provide comprehensive access to energy and utility data (Home – Lobby – SkySpark, n.d.). The four applications available to guest users are:

- **Building App**: Gives an overview of the performance of each building on the UBC campus and allows users to download utility data.
- Energy App: Provides detailed information, enabling comparisons of energy usage between buildings.
- **Historian App**: Allows users to view multiple trends and perform simple regression modelling.
- Weather App: Presents current, forecasted, and historical weather data snapshots.

Students and researchers use this data to monitor the energy-saving performance of different building types, which helps inform best practices for future construction projects. For this study, data obtained from the Energy App were used to analyze and monitor the monthly energy demand of UBC campus buildings

3. Methods

In order to quantify the effects of tree shade on building cooling energy demand on campus, it is essential to calculate the extent of tree shade coverage on buildings and compare the energy demands for cooling in these buildings during summer. To do this, the shade simulation was conducted using the Hillshade tool in ArcGIS Pro with DSM and Sun position data sourced from the National Research Council of Canada's Sunrise/Sunset Calculator, which provided parameters such as solar altitude, azimuth, and shadow length factors. The methods section involves several interconnected steps as summarised in Fig. 2, the workflow diagram.



Figure 2. Workflow diagram for the reprocessing of LiDAR point cloud data, DSM generation, shade simulation, and statistical analysis.

3.1 Preprocessing LiDAR Point Data

LiDAR data is essential for creating accurate 3D models of trees and buildings. This data provides detailed measurements of tree canopy spread, tree height, and building height, crucial for modelling shade. The LiDAR point cloud data covering UBC was filtered to remove all the unclassified and noisy points using the lidR package in R Studio. Also, all the buildings were filtered since the study was interested in simulating shades from trees and not buildings. The classification process was necessary to avoid distortions and segregate the point cloud data into meaningful categories like buildings, vegetation, and ground, ensuring that only relevant features are included in the analysis (Park et al., 2021; Zhang et al., 2016).

3.1 Digital Surface Model

Digital Surface Model(DSM) is a raster layer that represents the highest elevation of ALS returns of non-normalized points (Leigh et al., 2009; Priestnall et al., 2000; Roussel et al., 2020). The DSM for this study was generated from the LiDAR points at 1-meter resolution using the pit-free algorithm proposed by Khosravipour et al., 2014. This algorithm comprises a series of sequential height thresholds where Delaunay triangulations are applied to the first returns. The height thresholds applied in this study include 0, 2, 5, 10, and 15. Additionally, the subcircle option, part of the pit-free algorithm, was applied with a radius of 0.2 meters using the **lidR** package. This ensured that the output DSM was free of pits without using any post-processing or correction methods.



Figure 3. Digital Surface Model (DSM) of UBC Campus. The shaded areas with values from 44.604 to 154.67 indicate variations in elevations of objects, with darker shades (lower value) representing lower elevations and lighter shades (higher value) representing higher elevations. Source of basemap: Eri, Maxar, Earthstar Geographics, and the GIS User Community.

3.3 Solar Altitude and Azimuth

Simulating shade coverage requires precise sun position data, including solar altitude, azimuth, hour angle, and shadow length at various time intervals. As noted in the data summary section, this information will be sourced from the National Research Council of Canada (NRC) sunrise/sunset calculator. This tool calculates sunrise and sunset times throughout the year and provides sun position data for the 21st day of any given month when the sun reaches its most extreme positions. It also allows users to customize calculations by selecting the longest daylight day, the same day each month, or specific days within selected months. Since the primary objective of this study is to assess the impact of tree shade on cooling energy demand during summer, the analysis focused on the cooling degree days during summer. These dates are typically among the hottest days of their respective months and represent periods when the sun reaches its most extreme positions (Canada, 2012).

3.4 Estimating Cooling Degree Days

Temperature levels are key factors in assessing the impact of shading on indoor climate conditions. In addition to selecting the 21st day of the three summer months for analysis, other days were chosen based on Cooling Degree Days (CDD) thresholds in British Columbia. CDD measures the extent to which a day's average temperature exceeds a base temperature, indicating the need for cooling. It is calculated as:

$CDD = T_m - T_b$

where T_m is the mean daily temperature and T_b is the base cooling temperature (Al-Hadhrami, 2013).

CDD is a key metric for estimating air conditioning demand, as cooling energy demand rises with higher outdoor temperatures. A threshold of 18°C is considered a comfortable indoor temperature, and values above this threshold require cooling for thermal comfort and health (Heating & Cooling Degree Days - Environmental Reporting BC, n.d.). The selection of these specific days for analysis was informed by a similar study conducted by Morakinyo et al. (2016). Temperature data collected at 15-minute intervals from the UBC Earth, Ocean, and Atmospheric Sciences (EOAS) Rooftop Weather Station for June, July, and August were filtered to include only CDD values, ensuring that the analysis captured periods when cooling was relevant. The CDD values for each month were computed and used as a proxy for indoor temperature due to the absence of ground-level and indoor temperature data.



Figure4. Daily temperature trends with a baseline indicating cooling degree days (CDD). The dashed red line represents the 18°C threshold, above which temperatures contribute to cooling energy demand.

3.4 Shade Simulation

The objective of the shade analysis is to simulate the interaction between sunlight, trees, and buildings using the Hillshade tool in ArcGIS Pro. This tool is widely used for modelling shade on both built structures and landscapes. It generates a 3D representation of the terrain surface by incorporating the sun's relative position and topographic features (Park et al., 2023). Specifically, the Hillshade tool computes shading and illumination based on solar altitude and azimuth, producing raster outputs where pixel values range from 0 (fully shaded) to 255 (fully illuminated) (Park et al., 2023).

For this study, a digital surface model, along with solar altitude and azimuth values at 15minute intervals, was used as input data. Shade simulations were performed at 15-minute intervals during peak periods, with each selected time step generating a corresponding hillshade raster. The resulting hillshade values, ranging from 0 (completely shaded) to 254 (fully illuminated), represent variations in shading intensity throughout the day. These raster layers capture shade distribution at different time intervals during the simulation period. To facilitate further analysis, the hillshade rasters were reclassified into binary rasters, where shaded areas (low illumination values) were assigned a value of 0, and unshaded areas (high illumination values) were assigned a value of 1.

To assess overall shade dynamics, all binary rasters from multiple shade simulations at different time intervals were combined into a single raster stack for each month. This composite raster enabled the identification of key shade attributes, including total shade coverage, average shade duration, and the timing of shade throughout the day. Within this framework, the duration

of shade for each pixel was quantified as the number of time steps during which the pixel remained shaded during the shade simulation period, with values ranging from 0 (never shaded) to 1 (always shaded). Additionally, the aerial coverage of each shaded pixel corresponded to the pixel's cell area, allowing for spatial analysis of shade distribution and coverage.



Figure 5. Comprehensive shade frequency map for the UBC. This map illustrates the proportion of time each pixel is shaded during the selected shade simulation period. The values range from 0 (never shaded) to 1 (always shaded), representing the frequency of shade across the UBC campus.



Figure 6. Shade Patterns on August 21, 2024, at 18:00. This map illustrates the direction and length of the shadows cast by trees on the UBC campus, estimated from the digital surface model. The shade patterns represent the shadow positions at 18:00 on the 21st day of August 2024.

3.7 Shad Analysis

To quantify shade coverage on buildings, a spatial overlay analysis was conducted using the Spatial Analyst tools in ArcGIS Pro. The stack raster layers generated from the shade simulations were superimposed onto the selected building footprints (polygons) within the study area. This overlay analysis facilitated the assessment of shade coverage on individual buildings. The statistical measures of the shade distribution and coverage, including the mean, standard deviation, maximum and minimum shade frequency statistics, were derived using the Zonal Statistics as Table tool. This analysis provided key metrics, including mean shade frequency, standard deviation, minimum shade frequency, and maximum shade frequency. The mean shade frequency represents the average proportion of time each building area remains shaded throughout the day. A higher mean indicates greater and better shade coverage, whereas a lower mean suggests reduced or less shade coverage. Standard Deviation quantifies the variability and consistency of shade coverage. A higher standard deviation implies that shade is unevenly distributed and likely concentrated in certain areas, whereas a lower standard deviation suggests a more uniform shade distribution across the building. Minimum Shade Frequency identifies the lowest proportion of time any part of the building remains shaded, while Maximum Shade Frequency indicates the highest proportion of shading experienced by any section of the building. These statistical measures provided a temporal and spatial understanding of shade dynamics across different buildings in the study area throughout the shade simulation period.

3.8 Statistical Analysis

Following the shade frequency analysis, a comparative assessment of energy demand was conducted between several buildings with varying levels of shade coverage but similar structural and environmental characteristics. The buildings selected for this analysis include the Chan Centre, Orchard Commons, Asian Centre, Fred Kaiser Building, Music Building, and Allard Hall, all located within the same geographical zone on the UBC campus.

All the selected buildings are equipped with central cooling systems comprising chillers, condensers, and evaporators, which work together to regulate indoor temperatures and maintain thermal comfort. These systems operate under the supervision of the Building Management System (BMS), which enables centralized monitoring, scheduling, and performance optimization across the facilities.

To examine the relationship between tree shade, temperature, and energy demand, a linear regression analysis was performed as used in a similar study by Pandit & Laband (2010). Additionally, correlation analysis (using Pearson or Spearman correlation coefficients) was

performed to assess the strength and direction of relationships between key variables. Model performance was evaluated using the coefficient of Determination (R²), which measures the proportion of variance in energy demand explained by tree shade and temperature and the Root Mean Square Error (RMSE) to evaluate model accuracy and goodness of fit. These statistical analyses provided valuable insights into the impact of tree shade on cooling energy demand, contributing to a broader understanding of urban microclimate regulation and energy efficiency.

4. Result

4.1 Shade Frequency Statistics

The shade simulation analysis for June, July, and August revealed significant variations in shade coverage across buildings on the UBC campus. The minimum shade coverage recorded was 0, indicating that certain areas of the buildings remained unshaded throughout the simulation period, while the maximum shade coverage was 1, meaning some locations were fully shaded 100% of the time. The buildings analysed include Allard Hall, Fred Kaiser Building, Music Building, and Chan Centre for the Performing Arts.

In June, the Chan Centre recorded the highest mean shade frequency of 0.3800, meaning it was shaded 38% of the time during the simulation period. In contrast, Allard Hall had the lowest shade frequency (0.1400), indicating that only 14% of its surface received shade on average. The Fred Kaiser Building and Music Building both recorded moderate levels of shade coverage with mean values of 0.2271 and 0.2250, respectively, indicating that these buildings experienced more shading than Allard Hall but less than the Chan Centre.

In July, the Chan Centre again had the highest mean shade coverage (0.3800), while Allard Hall remained the least shaded building (0.1584). Fred Kaiser Building and Music Building experienced minor increases in their mean shade frequencies, with values of 0.2271 and 0.2475, respectively, indicating slight improvements in shading over the month.

August showed an overall increase in shading across all buildings. The Chan Centre recorded a significant rise in shade frequency to 0.5300 (53%), the highest observed in the study. This was followed by the Music Building, which showed an increased mean shade frequency of 0.4500. Fred Kaiser Building recorded a small increase in shading to 0.3173. This increase may be attributed to factors such as changes in the sun's azimuth or variations in tree canopy density. However, Allard Hall continued to have the lowest mean shade coverage at 0.1792, reflecting a continued lack of significant shading compared to the other buildings.

The Fred Kaiser building		Chan Centre for Performing Arts (130)		
June	Mean shade coverage	Average daily energy demand	Mean shade coverage	Average daily energy demand
2024-06-08	0.30	174.13	0.38	122.70
2024-06-20	0.29	242.01	0.37	117.94
2024-06-21	0.25	239.81	0.25	135.36
2024-06-22	0.29	185.92	0.37	119.43
July				
2024-07-05	0.25	240.81	0.41	110.37
2024-07-07	0.26	192.30	0.41	108.92
2024-07-09	0.26	264.85	0.41	134.11
2024-07-11	0.26	261.03	0.42	109.16
2024-07-13	0.27	193.51	0.42	81.37
2024-07-15	0.27	252.59	0.42	137.43
2024-07-17	0.28	270.15	0.42	109.21
2024-07-21	0.25	192.03	0.25	130.14
August				
2024-08-01	0.31	233.19	0.44	118.16
2024-08-02	0.32	258.08	0.46	100.43
2024-08-05	0.33	229.35	0.46	31.68
2024-08-10	0.35	206.77	0.48	86.42
2024-08-21	0.32	200.27	0.32	99.65
2024-08-31	0.42	197.10	0.54	87.84
Allard Hall				
	Allard Hall		N	lusic Building (575)
June	Allard Hall Mean shade coverage	Average daily energy demand	Nean shade coverage	lusic Building (575) Average daily energy demand
June 2024-06-08	Allard Hall Mean shade coverage 0.32	Average daily energy demand 170.38	Mean shade coverage 0.53	lusic Building (575) Average daily energy demand 55.86
June 2024-06-08 2024-06-20	Allard Hall Mean shade coverage 0.32 0.32	Average daily energy demand 170.38 221.61	Mean shade coverage 0.53 0.52	lusic Building (575) Average daily energy demand 55.86 52.77
June 2024-06-08 2024-06-20 2024-06-21	Allard Hall Mean shade coverage 0.32 0.32 0.14	Average daily energy demand 170.38 221.61 228.02	Mean shade coverage 0.53 0.52 0.25	lusic Building (575) Average daily energy demand 55.86 52.77 59.51
June 2024-06-08 2024-06-20 2024-06-21 2024-06-22	Allard Hall Mean shade coverage 0.32 0.32 0.14 0.32	Average daily energy demand 170.38 221.61 228.02 171.51	Mean shade coverage 0.53 0.52 0.25 0.52	Statistic Building (575) Average daily energy demand 55.86 52.77 59.51 54.39
June 2024-06-08 2024-06-20 2024-06-21 2024-06-22 July	Allard Hall Mean shade coverage 0.32 0.32 0.14 0.32	Average daily energy demand 170.38 221.61 228.02 171.51	Mean shade coverage 0.53 0.52 0.25 0.52	lusic Building (575) Average daily energy demand 55.86 52.77 59.51 54.39
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Table 2. Breakdown of shade coverage and corresponding daily energy demand for selected days in June, July, and August 2024 across the Chan Centre, Fred Kaiser Building, Music Building, and Allard Hall.

4.5 Statistical Analysis

To quantify the relationship between the mean shade coverage and average daily energy demand, correlation and a simple linear regression analysis were performed. Correlation analysis measures the strength and direction of the relationship between shade coverage and energy demand, while linear regression models the extent to which variations in shade coverage explain changes in cooling energy use. The results were evaluated using statistical metrics, including the correlation coefficient to indicate the strength and direction of the relationship, the p-value to assess the statistical significance, the root mean square error (RMSE) to measure the average magnitude of prediction error, and the R-squared value to represent the proportion of variance in cooling energy demand explained by shade coverage.

4.5.1 Correlation and Regression Modelling

The results for the Fred Kaiser building showed a strong negative correlation (r = -0.76) between mean shade coverage and cooling energy demand. This suggests that increased shade coverage is significantly associated with lower cooling energy demand. The relationship was statistically significant, with a p-value of 0.00027, providing a high level of confidence in the findings. The regression model also indicated an excellent predictive accuracy, with a Root Mean Square Error (RMSE) of 0.04, indicating minimal prediction error. The R-squared value of 0.57 shows that 57% of the variance in cooling energy demand was explained by shade coverage. This highlights the considerable influence of tree shading in reducing cooling energy demand.

In contrast, the results for Allard Hall, the music building, and the Chan Center for Performing Arts showed not very strong correlations, indicating that while shade coverage influences cooling energy demand, its effect is less pronounced compared to the Fred Kaiser Building The music building had a correlation coefficient of -0.55 and a p-value of 0.017, signifying a statistically significant relationship. However, the RMSE of 5.68 and the R-squared value of 0.31 indicate that only 31% of the variation in cooling energy demand was explained by shade coverage. The Chan Centre for Performing Arts had a correlation coefficient of -0.53 and a p-value of 0.025, also indicating a statistically significant relationship. Despite this, the model's RMSE of 20.19 and an R-squared value of 0.28 suggest relatively high prediction error and lower explanatory power. Similarly, Allard Hall showed a correlation coefficient of -0.29 with

a p-value of 0.25. The model's RMSE of 32.7 and R-squared value of 0.08 imply that shade coverage accounted for 8% of the variability in cooling energy demand.



Figure 10. Scatter plot illustrating the relationship between mean shade coverage and average daily cooling energy demand for Allard Hall.

4.6 Demand for energy in summer vs spring

The analysis of average daily energy demand for the Music Building shows clear seasonal differences between spring and summer. During summer, the average daily energy demand is **4,912.65 kW/day**, which is higher than the **4,768.79 kW/day** recorded in spring shown in the bar chart. This means an additional **143.86 kW** of energy is needed per day to operate the building in summer compared to spring. The increase is mainly due to higher cooling needs as outdoor temperatures rise.

The **boxplot** highlights these differences. In summer, the **median energy demand is higher**, and the range of values is wider, showing greater variation in energy use. The longer whiskers in the plot suggest occasional spikes in energy demand, likely due to **cooling degree days**, when outdoor temperatures rise and require more cooling. In spring, energy demand is more stable, with a **lower median value and a narrower range**. There are no extreme values, which suggests that cooling needs are lower and energy use remains more consistent.



Fig 11. Average daily energy demand in Summer compared to Spring in the music building.

Similar to the music building, energy demand in the Fred Kaiser building is higher in summer with an average daily demand of 20,741.7 kW, which is higher than the 20,235.5 kW recorded in spring. This results in an increase in energy demand of 506.2 kW per day in summer, mainly due to the need for more cooling as temperatures rise. The boxplot shows that summer has greater fluctuations in energy demand, with occasional peaks likely linked to hotter days. In contrast, spring has a more consistent pattern, with lower average daily energy demand.



Fig 12. Average daily energy demand in the Fred Kaiser building in summer vs Spring

The same trend was observed in the demand for energy in the Chan Centre for Performing Arts. The average daily demand in summer is 20,741.7 kW, compared to 20,235.5 kW in spring, resulting in an increase of 599 kW per day in summer due to the higher cooling requirements



Fig 13. Average daily energy demand in the Chan Centre in Summer vs Spring

5. Discussion

The study assessed the impact of tree shade on building cooling energy demand during summer. We analyzed the amount of shade provided by different tree species at various ages across campus to determine whether there is a statistical correlation between tree shade and building energy use. The results in Section 4 demonstrate that tree shade coverage has a statistically significant negative correlation with cooling energy demand, supporting the hypothesis that tree shading contributes to energy savings. Buildings with greater tree shade coverage recorded lower cooling energy use, which is consistent with the findings of Akbari et al. (2001), who showed that increased vegetative cover in urban environments can lead to cooling cost reductions of up to 50%, depending on tree placement and species. For instance, on average, an additional 150 kWh of energy was demanded in a day to operate the Music Building during the summer compared to the spring. The Chan Centre, which had the highest mean shade coverage (0.53 in August), recorded significantly lower cooling energy consumption compared to Allard Hall, which had the lowest mean shade coverage (0.1792). The findings also align with previous modelling and experimental studies that emphasize the importance of trees in mitigating urban heat and reducing energy demand (Donovan & Butry, 2009; Hsieh et al., 2018).

5.1 Variability in Shade Coverage and Energy Demand

One key observation was that while shade generally reduced cooling energy demand, its effectiveness was influenced by several factors, such as tree species, canopy density, and the placement of trees relative to buildings. The statistical analyses in the results section also revealed an inverse relationship between mean shade coverage and cooling energy demand. For the Fred Kaiser building, the analysis was statistically significant with a p-value of 0.00027, minimal prediction error (RMSE of 0.04), and an R-squared value of 0.57, indicating that 57% of the variance in cooling energy demand is explained by shade coverage. Similar analyses for other buildings show varying degrees of effectiveness, with the Music Building showing a correlation coefficient of -0.55, a p-value of 0.017, RMSE of 5.68, and an R-squared value of 0.025, RMSE of 20.19, and an R-squared value of 0.28. The analysis for Allard Hall presented a weaker correlation coefficient of -0.29, a p-value of 0.25, RMSE of 32.7, and an R-squared value of 0.08. This analysis was not statistically significant, indicating that other confounding factors, such as building characteristics, occupancy level, shape and orientation of the building,

and the age of the building, also influence energy demand. The findings align with the study by Ali-Tagba et al. (2024), which emphasized that cooling energy demand was driven not only by external shading but also by the interaction of multiple internal and external factors, including window-to-wall ratio, material reflectivity, and air infiltration rates. These findings suggest that tree shading, while beneficial, should be considered alongside improvements in insulation, ventilation strategies, and optimized HVAC system performance to achieve the greatest energy savings from trees.

5.4 Implications for Neighbourhood Climate Adaptation

Beyond direct energy savings, the implications for urban planning and climate action are significant. Effective tree planting strategies should prioritize species with high shading potential, focusing on optimal placement to maximize energy savings. As urban centers experience rising temperatures due to climate change and the urban heat island (UHI) effect, tree shading presents a cost-effective, nature-based adaptation strategy. Hsieh et al. (2018) demonstrated that species such as Cinnamomum camphora and Ilex chinensis Sims, which have relatively high transpiration rates, can reduce ambient air temperature by 1–2°C through evaporative cooling. Urban forestry initiatives should prioritize species with high leaf area index (LAI) and dense canopies to maximize shading coverage. Additionally, optimizing tree placement, particularly around west- and south-facing facades, can substantially enhance energy savings, as supported by findings from McPherson & Simpson (2003) and Donovan & Butry (2009). The integration of these strategies into urban planning policies can provide significant long-term benefits in reducing cooling energy demand, enhancing energy savings and overall environmental sustainability.

5.5 Limitations

Data quality and availability: Despite the valuable insights from the study, certain limitations should be noted. A key limitation in this study was the availability and quality. The energy consumption for each building was calculated using the formula $E=P\times t$, where energy is the product of power and time. The energy consumption data was not disaggregated by end-use categories such as cooling, heating, lighting, and others. Consequently, it was not possible to isolate the specific energy demand of the cooling systems. Instead, only the total energy consumption per building was available, and this aggregate value was used for the analysis under the assumption that it sufficiently represents overall energy use, including cooling. Although these assumptions provided a useful approximation of real-world conditions, they could also introduce a degree of uncertainty into the analysis.

Lack of Control for Confounding Variables: The study did not control for the other confounding factors that could cause differences in the amount of energy demanded in these buildings. Additionally, variations in HVAC system efficiencies across buildings were not explicitly controlled, potentially affecting the observed relationship between shade and energy consumption.

Use of Outdoor Temperature as a Proxy: Due to the absence of indoor temperature data, outdoor temperature was used as a proxy for estimating the cooling degree days. Reliance on outdoor temperature data as a proxy for cooling demand, while a common practice, could be improved by incorporating direct indoor temperature measurements.

5.6 Recommendations for Future Research

Future research should integrate real-time occupancy and equipment usage data into the prediction models. This methodological improvement would enhance the predictive accuracy of future studies. Additionally, this study primarily focused on tree shading effects without explicitly quantifying transpiration contributions. Given that transpiration accounts for nearly half of the total cooling effect, future research should explore quantifying the contribution of transpiration alongside shading effects.

Moreover, reliance on outdoor temperature data as a proxy for cooling demand, while common, could be improved by incorporating direct indoor temperature measurements.

A multi-year analysis would also provide deeper insights into interannual variations and longterm trends in tree shading effectiveness, particularly under projected climate change scenarios. 6. Conclusion

This study provides empirical validation of tree shading as an effective strategy for reducing cooling energy demand, reinforcing its role as a climate adaptation tool. The results confirm that shade from trees mitigates solar heat gain, thereby lowering energy consumption for cooling and dense shade provides significantly more cooling during summer than light or moderate shade. By leveraging both shading and transpiration effects, urban planners and policymakers can develop nature-based solutions to mitigate rising urban temperatures and improve energy savings. Future research should focus on refining predictive models and further distinguishing the contributions of shading and transpiration. The insights gained from this study have direct applications in shaping urban greening policies to enhance sustainable building designs, tree planting recommendations and foster climate resilience through nature-based interventions.

7. Bibliography

Abdel-Aziz, D. M., Shboul, A. A., & Al-Kurdi, N. Y. (2015). Effects of tree shading on building's energy consumption-the case of residential buildings in a mediterranean climate. *American Journal of Environmental Engineering*, 5(5), 131–140. https://www.researchgate.net/profile/Dania-Abdel-

Aziz/publication/314388937_Effects_of_Tree_Shading_on_Building's_Energy_Consum ption_-

The_Case_of_Residential_Buildings_in_a_Mediterranean_Climate/links/58c14d97aca27 20944011085/Effects-of-Tree-Shading-on-Buildings-Energy-Consumption-The-Case-of-Residential-Buildings-in-a-Mediterranean-Climate.pdf

- Akbari, H. (2002). Shade trees reduce building energy use and CO2 emissions from power plants. *Environmental Pollution*, 116, S119–S126. https://doi.org/10.1016/S0269-7491(01)00264-0
- Akbari, H., Pomerantz, M., & Taha, H. (2001). Cool surfaces and shade trees to reduce energy use and improve air quality in urban areas. *Solar Energy*, 70(3), 295–310. https://doi.org/10.1016/S0038-092X(00)00089-X
- Calcerano, F., & Martinelli, L. (2016). Numerical optimisation through dynamic simulation of the position of trees around a stand-alone building to reduce cooling energy consumption. *Energy and Buildings*, *112*, 234–243. https://doi.org/10.1016/j.enbuild.2015.12.023
- Campbell, I., Sachar, S., Meisel, J., & Nanavatty, R. (2021). *Beating the heat: A sustainable cooling handbook for cities*. United Nations Environment Programme.

Canada, G. of C. N. R. C. (2012, August 7). *Sunrise/sunset calculator*. https://nrc.canada.ca/en/research-development/products-services/softwareapplications/sun-calculator/

- Dawood, N., Dawood, H., Rodriguez-Trejo, S., & Crilly, M. (2017). Visualising urban energy use: The use of LiDAR and remote sensing data in urban energy planning. *Visualization in Engineering*, 5(1), 22. https://doi.org/10.1186/s40327-017-0060-3
- Hsieh, C.-M., Li, J.-J., Zhang, L., & Schwegler, B. (2018a). Effects of tree shading and transpiration on building cooling energy use. *Energy and Buildings*, 159, 382–397. https://doi.org/10.1016/j.enbuild.2017.10.045
- Hsieh, C.-M., Li, J.-J., Zhang, L., & Schwegler, B. (2018b). Effects of tree shading and transpiration on building cooling energy use. *Energy and Buildings*, 159, 382–397. https://doi.org/10.1016/j.enbuild.2017.10.045
- Jamei, E., Ossen, D. R., Seyedmahmoudian, M., Sandanayake, M., Stojcevski, A., & Horan, B. (2020). Urban design parameters for heat mitigation in tropics. *Renewable and Sustainable Energy Reviews*, 134, 110362. https://doi.org/10.1016/j.rser.2020.110362
- Khosravipour, A., Skidmore, A. K., Isenburg, M., Wang, T., & Hussin, Y. A. (2014). Generating Pit-free Canopy Height Models from Airborne Lidar. *Photogrammetric Engineering & Remote Sensing*, 80(9), 863–872. https://doi.org/10.14358/PERS.80.9.863
- Leigh, C. L., Kidner, D. B., & Thomas, M. C. (2009). The Use of LiDAR in Digital Surface Modelling: Issues and Errors. *Transactions in GIS*, 13(4), 345–361. https://doi.org/10.1111/j.1467-9671.2009.01168.x
- LiDAR 2022. (n.d.). Retrieved December 19, 2024, from https://opendata.vancouver.ca/explore/dataset/lidar-2022/

- Liu, Y., & Harris, D. J. (2008). Effects of shelterbelt trees on reducing heating-energy consumption of office buildings in Scotland. *Applied Energy*, 85(2), 115–127. https://doi.org/10.1016/j.apenergy.2007.06.008
- Morakinyo, T. E., Dahanayake, K. W. D. Kalani. C., Adegun, O. B., & Balogun, A. A. (2016).
 Modelling the effect of tree-shading on summer indoor and outdoor thermal condition of two similar buildings in a Nigerian university. *Energy and Buildings*, *130*, 721–732.
 https://doi.org/10.1016/j.enbuild.2016.08.087
- Morille, B., Lauzet, N., & Musy, M. (2015). SOLENE-microclimate: A Tool to Evaluate Envelopes Efficiency on Energy Consumption at District Scale. *Energy Procedia*, 78, 1165–1170. https://doi.org/10.1016/j.egypro.2015.11.088
- Pandit, R., & Laband, D. N. (2010). Energy savings from tree shade. *Ecological Economics*, 69(6), 1324–1329. https://doi.org/10.1016/j.ecolecon.2010.01.009
- Park, Y., Guldmann, J.-M., & Liu, D. (2021). Impacts of tree and building shades on the urban heat island: Combining remote sensing, 3D digital city and spatial regression approaches. *Computers, Environment and Urban Systems*, 88, 101655. https://doi.org/10.1016/j.compenvurbsys.2021.101655
- Park, Y., Zhao, Q., Guldmann, J.-M., & Wentz, E. A. (2023). Quantifying the cumulative cooling effects of 3D building and tree shade with high resolution thermal imagery in a hot arid urban climate. *Landscape and Urban Planning*, 240, 104874. https://doi.org/10.1016/j.landurbplan.2023.104874

PLAN_UBC_ClimateActionPlan. (n.d.).

- Priestnall, G., Jaafar, J., & Duncan, A. (2000). Extracting urban features from LiDAR digital surface models. *Computers, Environment and Urban Systems*, 24(2), 65–78. https://doi.org/10.1016/S0198-9715(99)00047-2
- Roussel, J.-R., Auty, D., Coops, N. C., Tompalski, P., Goodbody, T. R. H., Meador, A. S., Bourdon, J.-F., De Boissieu, F., & Achim, A. (2020). lidR: An R package for analysis of Airborne Laser Scanning (ALS) data. *Remote Sensing of Environment*, 251, 112061. https://doi.org/10.1016/j.rse.2020.112061
- Santamouris, M., Synnefa, A., & Karlessi, T. (2011). Using advanced cool materials in the urban built environment to mitigate heat islands and improve thermal comfort conditions. *Solar Energy*, 85(12), 3085–3102. https://doi.org/10.1016/j.solener.2010.12.023
- Srivanit, M., & Hokao, K. (2013). Evaluating the cooling effects of greening for improving the outdoor thermal environment at an institutional campus in the summer. *Building and Environment*, 66, 158–172. https://doi.org/10.1016/j.buildenv.2013.04.012
- Sun, M., Han, C., Nie, Q., Xu, J., Zhang, F., & Zhao, Q. (2022). Understanding building energy efficiency with administrative and emerging urban big data by deep learning in Glasgow. *Energy and Buildings*, 273, 112331. https://doi.org/10.1016/j.enbuild.2022.112331
- UBC Weather Summary. (n.d.). Retrieved December 21, 2024, from https://weather.eos.ubc.ca/wxfcst/users/Guest/ubcrs_withicons/index.php?location=3510
- Wu, W.-B., Yu, Z.-W., Ma, J., & Zhao, B. (2022). Quantifying the influence of 2D and 3D urban morphology on the thermal environment across climatic zones. *Landscape and Urban Planning*, 226, 104499. https://doi.org/10.1016/j.landurbplan.2022.104499

- Zhang, W., Qi, J., Wan, P., Wang, H., Xie, D., Wang, X., & Yan, G. (2016). An Easy-to-Use Airborne LiDAR Data Filtering Method Based on Cloth Simulation. *Remote Sensing*, 8(6), 501. https://doi.org/10.3390/rs8060501
- Zheng, S., Guldmann, J.-M., Liu, Z., Zhao, L., Wang, J., & Pan, X. (2020). Modeling of shade creation and radiation modification by four tree species in hot and humid areas: Case study of Guangzhou, China. Urban Forestry & Urban Greening, 47, 126545. https://doi.org/10.1016/j.ufug.2019.126545