



The University of
Nottingham

**Definition of new parameters to develop an improved predictive model for
urban heat island spatial distribution**

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Submitted in partial fulfilment of the conditions for the award of the degree **Doctor of
Philosophy.**

August 2022

Dedication

I dedicate this thesis to the loving memory of my mother Mrs Rosemary Equere, who passed away while I was still on this program. It is in pursuit of this degree, that I was absent from your sight in your last hours here on earth.

The memory of your thoughts and confidence in me have been my constant motivation through this PhD journey, I hope this achievement makes you proud.

Abstract

Urban heat island (UHI) is an urban phenomenon where the inner city experiences a significance elevation in temperature, compared to the suburban areas. UHI formation and intensity, has enormous beneficial and adverse impact on the microclimate of urban spaces. Hence, there is a need to understand how several urban aspects impact on this phenomenon, to enable policy makers and urban planners propose efficient mitigation strategies to adverse the UHI effects and to benefit from its potentially positive impacts. Furthermore, a robust predictive model is necessary to simulate the efficacy of a proposed mitigation or enhancement strategy before any real-world implementation.

This dissertation, thus, investigates the impact of urban elevation aspects on the UHI intensity, and aims to improve the prediction of the spatial distribution of the UHI by proposing two novel urban elevation parameters defined as the Elevation Factor (EF) and Terrain Factor (TF), accounting for urban superstructures and the topographical aspects of cities. The proposed parameters were integrated with other already existing urban parameters in the remote sensing subject area to train and develop predictive models with more accurate predictive performances. An artificial neural network model was developed, which resulted in further improvement of the prediction accuracy.

The associated procedure for retrieving both EF and TF from point cloud LiDAR data. The urban morphology parameters used in this study were derived from two case study cities of North Park and Oak Brook towns in Illinois State, USA. The integration of TF to the training process significantly improved the model's prediction performance of the LST for high terrain variation areas, as the average root mean square error decreased from 1.26 to 0.90°C and R^2 increased from 0.74 to 0.81. The models were then successfully validated against the latter data of the case study cities to predict the LST for parts of the city, which were not initially included in the training process.

Acknowledgement

I want to firstly acknowledge the Almighty God, for giving me strength and divine inspiration to power through these years of academic sojourn.

I give special thanks to my mentor, and principal supervisor Dr Parham Mirzaei, for his tremendous support and pastoral care, within and out of official hours. For being patient and believing in me as I slowly navigated my way through this research journey. I also appreciate my second supervisor Prof. Saffa Riffat, for the support and valuable inputs he made at critical points throughout my study duration.

I also thank the Architecture and Built Environment Department, and indeed the engineering faculty and the entire University of Nottingham, for making every necessary support available and accessible to students at every level of studies.

I also acknowledge the contributions of my colleagues at the Sustainable Research Building postgraduate office, for their support, their genuine concern for my wellbeing, and all the moments we shared, all went a long way to make my time in Nottingham very memorable.

I am forever indebted to my family, particularly my father Mr George Equere, who financial and moral support have been a constant source of motivation for me all through these years in academic sojourn, and to my brother Mr Ubong Equere, for supporting and believing in me.

Publications

Journal

Equere, V., Mirzaei, P. A., Riffat, S., & Wang, Y. (2021). Integration of topological aspect of city terrains to predict the spatial distribution of urban heat island using GIS and ANN. *Sustainable Cities and Society*, 69, 102825. doi:<https://doi.org/10.1016/j.scs.2021.102825>

Equere, V., Mirzaei, P. A., & Riffat, S. (2020). Definition of a new morphological parameter to improve prediction of urban heat island. *Sustainable Cities and Society*, 56, 102021. doi:<https://doi.org/10.1016/j.scs.2020.102021>

Conference

Equere V. Parham M. Saffa R. (2019). "Effect of 3D Morphology Distribution of Cities on Urban Heat Island Formation: A GIS approach" 18th International Conference on Sustainable Energy Technologies, Kuala Lumpur, Malaysia, August 20-22, 2019.

Accepted manuscripts

Equere V., Mirzaei P.A., Riffat S., Wang Y., "Development of a predictive urban heat island model using vertical aspect of cities", IBPC2021, Copenhagen, August 2021.

Declaration

The work described in this thesis was carried out at the Architecture and Built Environment Department, University of Nottingham between October 2017 and November 2021. The thesis is my own work, except the work of other authors that has been referenced. No part of this thesis has been submitted for any degree at another University.

A handwritten signature in black ink, appearing to read 'Victor George Equere', with a stylized, overlapping flourish.

Victor George Equere

August 2022

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Notations

ANN Artificial Neural Networks

AUHI Atmospheric Urban heat island

ASTER Advanced Space borne Thermal Emission and Reflection Radiometer

BSC Building Site Coverage

BOA Bottom of Atmospheric

BU Built-up Index

BVD Building Volume Density

CCD Charge-Coupled Device

CFD Computational Fluid Dynamics

DN Digital Number

DTM Digital Terrain Model

EF Elevation Factor

FAD Frontal Area Density

FAR Floor Area Ratio

FFNN Feedforward neural network

FVA Fundamental Vertical Accuracy

GCP Ground Check Points

GIS Geographical Information System

GPS Global Positioning Satellite System

GVF Ground View Factor

HV Height variation

ILHMP Illinois Height Modernization Project

IMU Inertia Navigational Measurement Unit

IS impervious surface

ISDD Impervious Surface Distribution Density

LANDSAT Land Remote-Sensing Satellite (System)

L Layer

LiDAR Light Detection and Ranging

LST Land Surface Temperature

LULC Land Use Land Cover

MAE Mean Actual Error

MH Mean Height

MNLR Multi-nonlinear Regression

ML Machine Learning

MLR Multi-linear Regression

MLP Multilayer perceptron

MSAVI Modified Soil Adjusted Vegetation Index

NAD83 North American Datum 1983

NASA The National Aeronautics and Space Administration

NAVD88 North American Vertical Datum 1988

NDBaI Normalized Difference Bareness Index

NDBI Normalized Difference Built-up Index

NDCI Normalized Difference Composite Index

NDVI Normalized Difference Vegetation Index

NDVI Normalized Difference Vegetation Index

NDWI Normalized Difference Water Index

NME Normalized Mean Error

NMB Normalized Mean Bias

NHV Normalized height variation

NIR Near Infrared Response

OLI Operational Land Imager

OSR Open Space Ratio

OSP Open Space Ratio

RGB Red Green and Blue

RMSE Residual Mean Square Error

RSS Residual Sum of Squares

RVI Ratio Vegetation Index

SAVI Soil Adjusted Vegetation Index

SC Shape coefficient

SEVIRI Spinning Enhanced Visible and Infrared Imager

SUHI Surface urban heat island

SWIR Shortwave Infrared

SVF Sky view factor

SVR Support Vector Regression

TF Terrain Factor

TIRS Thermal Infrared Sensor

TOA Top of atmospheric

UAV Unmanned Aerial Vehicle

UCM Urban Canopy Model

UHI Urban Heat Island

UMBAs Urban Main Built up areas

UTFVI urban thermal field variance index

L_λ At-sensor spectral radiance ($W \cdot m^{-2} \cdot sr^{-1} \cdot \mu m^{-1}$)

ML band specific multiplicative rescaling factor

AL The band specific additive rescaling factor

T_B is the brightness temperature (in degrees)

K₁ and **K₂** coefficients determined by effective wavelength of a satellite sensor

ε the spectral emissivity

T_s is the LST (in Celsius)

ε_{OLI} is the ground emissivity

λ is the wavelength of emitted radiance

σ is the Boltzmann's constant

h is the Planck's constant

c is the velocity of light

3D Three Dimension

2D Two Dimension

Chapter 1

Introduction

1.1 Background of study

As the world population continue to increase, the pace of urbanization has even become faster. A prominent consequence of this rapid urbanization is the rising temporal pattern of Urban Heat Island across the globe. UHI effects as illustrated in [Figure 1.1](#), has adverse consequences on our cities, in terms of the health of cities' residents ([Clare Heaviside, Macintyre, & Vardoulakis, 2017](#); [Shahmohamadi, Che-Ani, Etessam, Maulud, & Tawil, 2011](#)), the indoor and outdoor climate ([Mirzaei et al., 2012](#)), building energy demand ([Calice, Clemente, Salvati, Palme, & Inostroza, 2017](#); [Karatzas & Katsifarakis, 2018](#); [Mirzaei et al., 2012](#)), and the risk increase of a natural disasters such as flood ([Hester & Bauman, 2013](#)). However, UHI can be beneficial in regions and seasons of extreme cold, where increased energy demand, thermal discomfort and increased temperature related mortality are also predominant ([Hajat, Kovats, & Lachowycz, 2007](#); [Lowe, 2016](#)). Hence, there is a need to better understand the major causative factors of this phenomena to better maximize its benefit or effectively mitigate its associated adverse effects.

In a bid to gain more understanding of UHI driving factors, researchers often adopted the approaches of correlating the morphological characteristics of a given urban climate with the temperature profile, either air or land surface temperature ([Ho et al., 2014](#); [Su, Foody, & Cheng, 2012](#)), in order to assess their thermal behaviour. For the large scale UHI mapping, the use of remote-sensed derived urban morphology indices has simplified the process of urban morphological information retrieval, through the automatic mapping of morphological features ([Polydoros & Cartalis, 2015a](#)). However, despite this advantage of simplifying the urban morphological information retrieval, these conventional urban indices such as the Normalized Difference Built-up Index (NDBI) ([Zha, Gao, & Ni, 2003](#)), and the Normalized

Difference Vegetation Index (NDVI) (Yan, Zhang, Ling, & Han, 2022) has been considered weak in providing sufficient vertical information about an urban space, thereby limiting their ability to fully explain the spatial variation of UHI across any given urban space (Mirzaei & Haghighat, 2010). Hence, there is a need to develop an index to account for the vertical aspects of the urban spaces, so as to improve the mapping of UHI.

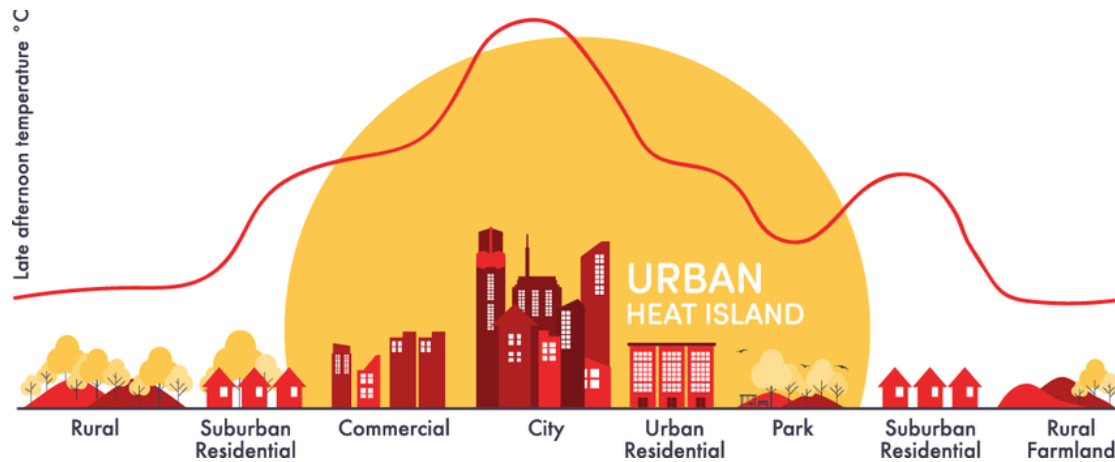


Figure 1.1 Pictorial illustration of a city's temperature profile, showing the UHI effect (WorldMeteorologicalOrganization, 2021).

1.2 Research problem and hypothesis

To propose a suitable countermeasure strategy against the UHI, testing the efficiency of that strategy before its full implementation should be employed to prevent other possible side-effects on microclimates. This is due to the significant causative factor for the UHI may vary across different cities. Hence the need to develop a robust predictive model with a high accuracy is required to enable the researchers and policy makers measure the impact of prescribed strategies as variables can easily be altered.

The main Hypothesis of this thesis is that, integrating the vertical aspects of urban cities in a model training process, will improve the learning of the proposed model and improve its prediction performance. The term vertical aspects of an urban domain within the context of this study, refers to the height information of the morphological features within the study domain.

1.3 Research Aim and Objectives

The overall aim of this thesis is to explore the extent of impact of the elevation aspect of cities on the urban heat island intensity and formation, and, also to propose an improved urban heat island predictive model.

Objectives

The aim of this study will be achieved through the implementation of the below objective:

- Definition of new urban elevation parameters, accounting for on-surface and topographical features.
- Establish a procedure for retrieving on- surface and topographical urban elevation parameters.
- Establish the correlation between the defined urban elevation parameters and urban heat island intensity and formation.
- Development of a UHI predictive model with improved predictive performance and its validation.

1.4 Thesis structure

The remainder of this thesis is structured as follows:

- Literature review: This chapter covers in-depth definitions of UHI, causes, effects, UHI predictions, and lastly methods of investigating UHI.
- Definition of two novel parameters: A detailed review of the current literature focused on the integration of the elevation aspect of cities to UHI studies is firstly presented. Then the research gap associated with this research area of urban elevation in UHI study is outlined as a justification for the definition of these two novel parameters. The procedure for retrieving these parameters from the LiDAR point cloud data and associated steps for further processing of this data into raster files and 3D models are equally outlined.

- **Methods:** This section of the thesis describes the framework adopted for the proposed model development. Starting from the raw data collection stage, through the data processing stages and then lastly the actual model development details including the input parameters, the model configuration, and model performance testing.
- **Case study areas:** This section of the thesis describes the study areas where the morphological parameters used to develop the proposed model were derived and tested on. The justification for their selection, and detailed description of each morphological parameter retrieved including the exact amount of pixels used for model training, testing and validation for each area are presented.
- **Results and discussion:** This section of the thesis reports the results for all the tests and analysis conducted in this research including the Pearson correlation test, the model performance evaluation, the Pareto factor characterization test and lastly the model validation. The presented results are discussed in depth in this section.
- **Conclusion:** This chapter summarises the main insights of the work and including specific suggestions for further research questions.

Chapter 2

Literature Review

2.1 Definition of Urban Heat Islands

Urban heat island is essentially a phenomenon where the urban areas experience elevated temperature in relation to their surroundings rural areas. In the context of an urban climate, urban heat island phenomena is discussed in two forms, namely atmospheric urban heat island (AUHI) and surface urban heat island (SUHI) ([Dewan et al., 2021](#)). This classification is based on the height above the ground where the UHI is observed ([Oke, 1982](#)). AUHI is discussed in terms of the difference in air temperature, between the urban areas and the surrounding regions, usually the sub-urban areas, and its primarily measured using air temperature records ([Mirzaei & Haghighat, 2010](#); [Oke, 1982](#); [Taha, 2004](#)). Surface urban heat island (SUHI) is mainly discussed in terms of the temperature difference of the surfaces (roofs, roads, grass, etc.) in the inner city neighbourhood in relation to the surface temperature of urban features in the country side, and its mainly measured using land surface temperature (LST) data ([Erdem Okumus & Terzi, 2021](#); [Masson, Lemonsu, Hidalgo, & Voogt, 2020](#); [Z. Yu, Yao, Yang, Wang, & Vejre, 2019](#)).

In general, the urban heat island is the temperature difference between two reference points in an urban climate. However, to establish a scope for these reference points, ([Taha, 2004](#); [Voogt & Oke, 2003](#)) have defined two major scales, including canopy layer and boundary layer. The canopy layer heat island mainly occurs below the roof level or within the urban canyons while the boundary layer heat island can extend up to the urban plume as shown in [Figure 2.1](#).

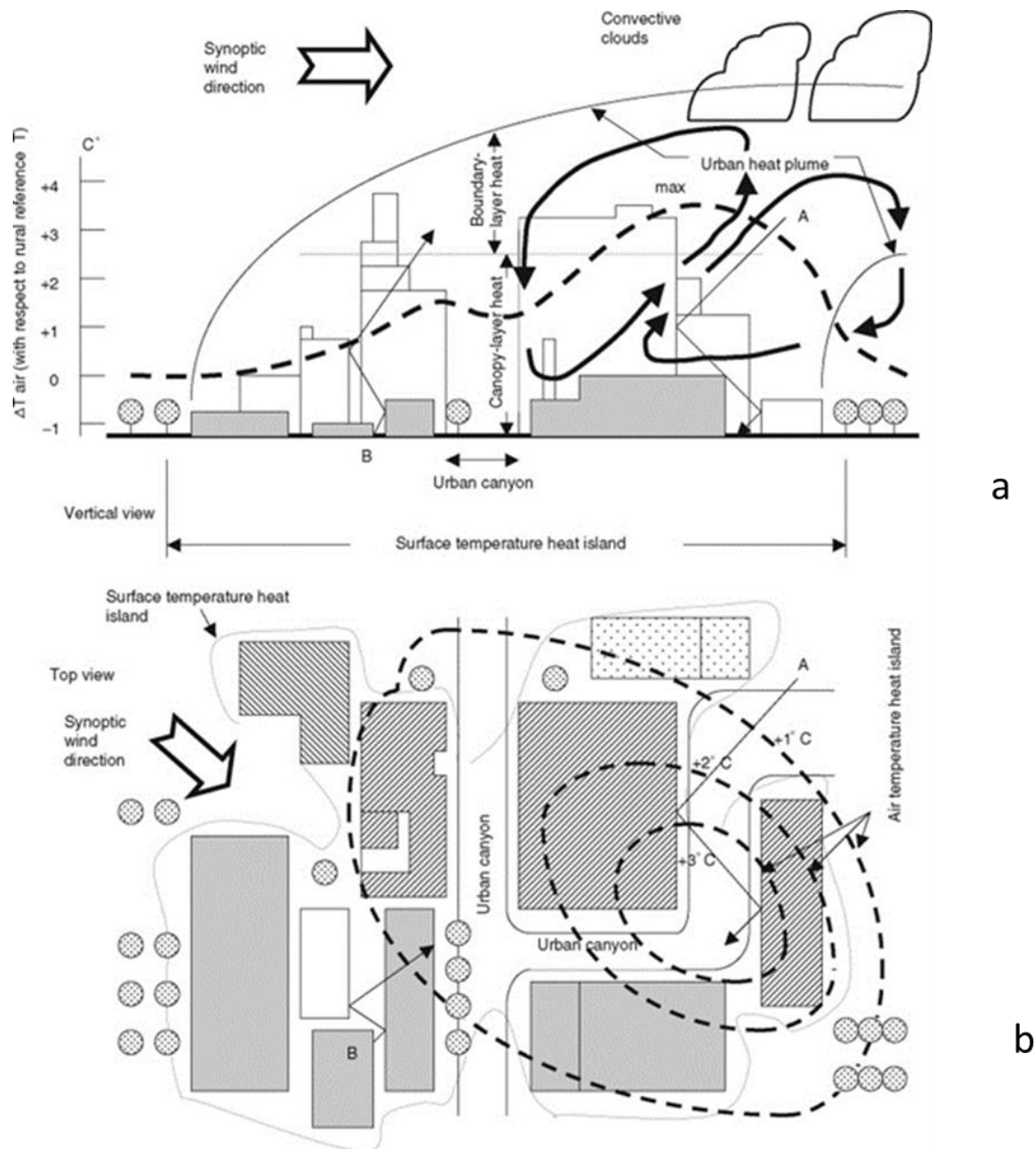


Figure 2.1 Schematic of an urban heat island, showing the canopy-layer heat island and the boundary-layer heat island in a) a vertical and b) plan view (Taha, 2004).

2.2 Causes of UHI intensity

The growing intensity of the UHI across various cities of the world has warranted the need to investigate into identifying key drivers of this phenomenon and further to enable policy makers and urban designers to plan effective urban mitigation strategies (Equere, Mirzaei, Riffat, & Wang, 2021). Despite the variations in the climatic, demographic, and morphological features across various cities in the world, causative factors of the UHI intensity can be categorised

into two main groups, which are controlled and uncontrolled variables ([Kotharkar, Bagade, & Ramesh, 2019](#); [Nwakaire, Onn, Yap, Yuen, & Onodagu, 2020](#)).

Factors classed under the controlled category refer to those urban characteristics, mostly resulting from the urbanization effects and, hence, can be modified slightly or extensively for the purpose of mitigating or enhancing the intensity of UHI within a given area. The growing world population has been identified by many studies as the major driver of the urbanization ([Grimm et al., 2008](#); [Stempihar, Pourshams-Manzouri, Kaloush, & Rodezno, 2012](#)). Under the controlled UHI driver category, which are mainly factors resulted from urbanization which can be further grouped these factors into anthropogenic and structural ([Nwakaire et al., 2020](#)).

As urbanization expands, the diversity and complexity of the human activities within an urban space equally increases. The phenomena associated with these diverse human activities is classed as anthropogenic source. For instance, increased use of air-conditioning systems to cool indoor spaces can contribute to outdoor temperature elevations as the heat from indoor space is flushed to outdoor environments ([Hirano & Yoshida, 2016](#)). Also, emissions from diverse transportation means, necessary to serve an urban spaces, contribute to both outdoor temperature elevation and poor air quality ([Evola et al., 2017](#)). On the other hand, the amount of heat resulting from human metabolism increases with the growing population of urban dwellers, which exacerbate the elevation of surrounding temperature ([Kotharkar et al., 2019](#)).

A more obvious consequence of the expanded urbanization is the geometrical transformation that occurs where natural surfaces are replaced with artificial ones either by buildings, bridges, roads, or other facilities that should serve the urban dwellers. The impact of these changes on the outdoor temperature constitutes the structural sources of the UHI. For instance, building heights, shapes and orientations, can impact on sky view factors, wind speed and direction alterations, aspect ratio variations, and solar radiation balance changes, which can result in the UHI intensity ([Equere, Mirzaei, & Riffat, 2020](#); [Giridharan & Emmanuel, 2018](#); [Mirzaei, Olsthoorn, Torjan, & Haghighat, 2015](#)). Furthermore, densely located buildings in addition to replacement of natural vegetation with artificial surfaces can result in increasing of night time

temperatures ([Nwakaire et al., 2020](#)) and solar absorption by surfaces as well as reducing of reflective coolings ([Shahidan, Jones, Gwilliam, & Salleh, 2012](#)).

The uncontrolled drivers of the UHI intensity refers to phenomena, which are naturally occurring while their impact on an urban space cannot be modified. For example, precipitations have been identified to significantly influence the UHI intensity ([Gu & Li, 2018](#)). Rainfall amount and duration have also shown significant influence on the UHI intensity according to ([Hong, Hong, Kwon, & Yoon, 2019](#)); rainfall helps urban cooling and a reduction in rainfall can intensify the UHI in a given urban space. Furthermore, a phenomena like heat wave, which is associated with excessively hot humid weather, can exacerbate the UHI effect on cities with frequent occurrence ([Fei & Zhao, 2019](#)).

Based on the various factors on the alteration of the UHI intensity, it is clear that the UHI intensity results from a collective contribution of all the features of an urban area. Hence, to successfully develop a robust UHI predictive model, there is need to expand the scope of the parameters employed in the model training, to account for the various aspects of the urban space.

2.3 Effects of UHI

The impact of the UHI intensity on an urban climate is generally best discussed in terms of the beneficial and adverse impact observed. On a beneficial note, studies have shown that the intensity of UHI would invariably result in energy saving, and thermal comfort improvement in cold regions or during colder seasons as the latent heat discharged at night-time would reduce the need for mechanized heating solutions in buildings. Also, a further benefit of UHI effect is the modulation of outdoor temperature, which prevent it from experiencing extreme cold ([Gasparri et al., 2015](#); [Hajat et al., 2007](#); [Lowe, 2016](#); [Skelhorn, Levermore, & Lindley, 2016](#)).

On the adverse effect of urban heat island, the following aspects can be addressed, which are health of urban residents, energy demand, greenhouse gas and air quality, thermal comfort and climate change.

Urban Heat Island has been identified as a significant driver for the increased heat related mortality especially during the summer. According to (C. Heaviside, Vardoulakis, & Cai, 2016), UHI contributed to about 50% of the total heat-related mortality during the 2003 heatwave in the West Midlands. (Clare Heaviside, 2020) also highlighted the exacerbation of minor illnesses, poor occupational performance, and high risk of hospitalization as some of the health risk posed to urban residents due to the UHI intensity.

The adverse impact of UHI on building energy demand has gained significant attention within the built environment research community. Many researchers have linked the elevated temperature of an urban space associated with the UHI intensity to the rising energy demand in buildings within urban areas (Mirzaei et al., 2012; Salvati, Coch Roura, & Cecere, 2017).

With elevated temperature as a paramount evidence of the UHI intensity within an area buildings within such areas experience high indoor temperatures, and would invariably resort to mechanical means to achieve thermal comfort within the buildings (Dell et al., 2014; Spang, Holguin, & Loge, 2018). This wide spread dependency on mechanical cooling systems results in heavy release of greenhouse gases, which contribute to global warming and compromise the air quality (Maxwell, Grambsch, Kosmal, Larson, & Sonti, 2018).

2.4 UHI Prediction

The enormous impact of the UHI effects on different critical aspects of a city has warranted the need to develop robust models for urban heat island predictions. A robust model with a high predictive accuracy can equip policy makers and urban planners with the opportunity to more accurately evaluate the efficacy of any proposed urban intervention strategy to control UHI effects (O'Malley, Piroozfar, Farr, & Pomponi, 2015). Also, the development of a robust UHI prediction model may help researchers and planners to determine more accurate boundary conditions for building energy simulation (BES) tools where outdoor surface temperature data are not available (Roman, O'Brien, Alvey, & Woo, 2016). For this reason, many researchers have adopted various approaches to develop new UHI predictive models

or to enhance the performance of the conventional models. The two widely used methodologies for developing UHI predictive models are microclimate models and correlation models.

2.4.1 Microclimate Models

The available microclimate models are mostly developed to simulate major atmospheric processes that affects an urban microclimate based on the fundamental laws of fluid mechanics and thermodynamics (Ali-Toudert & Mayer, 2006). These models have become popular for research that seek to propose a UHI mitigation strategy in an urban area. For example, (Noro & Lazzarin, 2015) used an microclimate model called Envi-met to simulate their proposed UHI mitigation strategy for Padua in Italy. Furthermore, microclimate models have proven to be efficient in complex modelling and detailed investigation of urban microclimate (Emmanuel, Rosenlund, & Johansson, 2007). Another advantage of this modelling approach is related to its user-friendliness, and lower computational cost associated with the availability of software packages (Roth & Lim, 2017). A major drawback to this approach is grid dependence of the available software packages, which prevents the modelling of large scale scenarios with high-level of details (Crank, Sailor, Ban-Weiss, & Taleghani, 2018).

2.4.2 Correlation Models

The use of correlative models for the development of UHI predictive modes and improving existing ones have become very popular in the built environment sector, majorly because of their excellent performance in future UHI predictions (Mirzaei, 2015). A basic type of this correlative model used in UHI predictions is the regression technique. For instance, (Equere et al., 2020), integrated the vertical aspect of an urban area to train a multi linear regression model in order to develop a SUHI model with an improved predictive accuracy. Similarly, (Chun & Guldman, 2014) used regression analysis to explore urban UHI determinants, and to develop a predictive model to simulate the temperature effects of different greening scenarios. Also, (Su et al., 2012) used weighted-regression model to assess the effect of

spatial non-stationarity relationships between land cover and surface temperature on TaoYuan city, Taiwan. However, these regression modes are generally seen to be weak in explaining complex nonlinear relations such as the relationship between UHI determinants and UHI. Although there are statistical methods that have competence in explaining non-linear data (e.g., non-linear regression methods), an iterative processes of fitting different types of mathematical functions to determine the best fits in a given dataset is often required (Oh, Ngarambe, Duhirwe, Yun, & Santamouris, 2020).

To overcome these limitations, advanced techniques such as the machine learning techniques have been extensively applied in the development of a robust model to predict the UHI phenomenon. This is because the machine learning algorithms generally provide better fitted models than conventional statistical techniques, because of their ability to learn and mimic highly complex non-linear data. For instance, (Equere et al., 2021) integrated the impact of urban terrain variation to an ANN training network to improve the prediction accuracy of SUHI in Dupage, Illinois, USA. Also, (Mathew, Sreekumar, Khandelwal, & Kumar, 2019) also combined enhanced vegetation index, road density and elevation parameters to train a support vector regression (SVR) model and to predict SUHI.

2.4.3 Using LST as a UHI indicator

Land surface temperature (LST) is a fundamental parameter in the explanation of surface energy and water balance at local and global scales (Z. L. Li & Duan, 2018). LST measures the emission of thermal radiance from the land surface. This thermal radiance often results from the interaction between the ground, or the surface of the canopy, and the incoming solar energy. The quality of LST being sensitive to changing surface conditions, makes it able to provide information on the energy partitioning into latent and sensible heat fluxes at a spatial scale (land surface-atmosphere boundary) (Hulley et al., 2019). Based on these highlighted characteristics, LST have become widely adopted as a suitable indicator of UHI in many studies.

However, according to (Mirzaei & Haghighat, 2010) actual UHI occurs in the atmosphere. Hence, using LST as an indicator for UHI can be misleading since the LST and the ambient air temperature can be significantly different. Despite this drawback, the use of LST as an indicator of UHI has remained preferable because its retrieval from remotely sensed thermal infrared data, provides an easy access to spatially continuous LST measurements with global coverage (Z. L. Li & Duan, 2018), as opposed to the complexities associated with obtaining an air temperature measurement of a similar scale.

2.5 Scales of studying UHI

The concept of scales in UHI studies describes the level of interaction between elements of an urban surface with the adjacent atmospheric layer (John, 2003). According to (Mirzaei, 2015) the available scales for studying UHI can be classed into three main groups, including building-scale model, micro-scale model, and city-scale model.

2.5.1 Building-scale

These models developed based on this scale have the assumption that other morphological features, for example, roads, buildings, trees, etc. within the neighbourhood, have little or no impact on the energy performance of the case study building. Hence, these models are developed to only account for the energy balance within the building envelop and only consider the impact of prevalent climatic factors as inputs (Mirzaei, 2015). While such models excel at providing great level of detail on the impact of climatic variations on the energy performance of the building (Oliveira Panão, 2014; Pyrgou, Castaldo, Pisello, Cotana, & Santamouris, 2017), neglecting the impact of the neighbourhood morphological features still remains a major drawback as recent studies confirm the energy performance of any building is significantly influenced by the neighbourhood features (Mirzaei et al., 2015; Xu et al., 2022).

2.5.2 Micro-scale

This scale considers the interaction between a buildings and the neighbourhood morphological features as well as the prevalent climatic conditions (Mirzaei, 2015). Hence, the

models developed based on this scale would provide more details on how the building thermodynamically interacts, and what would be the thermal variables prevalent in a given location based on a research focus (Rotach & Calanca, 2003). In terms of the number of buildings that makes up a microclimate, (Oraiopoulos & Howard, 2022) proposed a number of up to 1,000 buildings. The benefits and drawbacks of the models associated with this scale have been outlined in section 2.4.1 of this thesis report.

2.5.3 City-scale

This scale examines the interaction between the large scales land-use-zones and the prevalent climatic condition in an area (Arnfield, 2003). City scale models mostly use indices to represent all or most of the urban surface parameters as a means of simplifying the process of urban parameter retrieval in a large scale (Polydoros & Cartalis, 2015b). City scale UHI models is seen to be proficient in investigating the impact of urban trends such as urban growth pattern (Y. Rao, Dai, Dai, & He, 2021) on the prevalent climatic condition. A major drawback to this scale has been the difficulty associated with accessing high-resolution urban morphology data for a city scale UHI analysis (Mirzaei, 2015).

2.6 Methods of UHI investigation

2.6.1 Experimental modelling approaches

Experimental approaches majorly include the collection of data through field survey of an actual case or the observation of a prototype model of a real case to investigate the formation as well as causes and effects of the UHI (Arnfield, 2003). This method has proven beneficial in micro scale investigation of thermal characteristics of individual morphology features, e.g., park existences, street canyon orientation, etc. with respect to the UHI formation and intensity. For example, (Rahman, Moser, Rötzer, & Pauleit, 2017) used the field survey approach to compare the impact of two different urban canyon and vegetation ration on the outdoor thermal comfort; the study demonstrated the cooling benefits of urban trees planted in open green squares compared to closed and paved squares canyons. (Kanda et al., 2005) also used prototype building array model to investigate the impact of the geometry on the energy balance

in a street canyon. (Uehara, Murakami, Oikawa, & Wakamatsu, 2000) investigated the effects of atmospheric stability on the flow field in a street canyon by testing a prototype case in a stratified wind tunnel.

The experimental approach is widely adopted as a means of validation data necessary for the UHI numerical models. (Allegrini, Dorer, & Carmeliet, 2014) conducted an experimental study where a wind tunnel was used to simulate buoyant flow fields in an urban street canyon. The result was used to validate the result from a computational fluid dynamics (CFD) model. The experimental approaches are also effective in most cases for establishing the boundary conditions, which are essential for conducting numerical simulations of the same case e.g., (De & Mukherjee, 2017).

Despite the addressed benefits of the experimental approach in the UHI investigation, this method is considered costly and time-consuming when multiple morphological features are taken into the account. Furthermore, investigating the temporal-spatial impact of morphological alterations on a microclimate is highly challenging to achieve with this method (Mirzaei & Haghighat, 2010).

2.6.2 Numerical modelling approaches

These methods are developed on the basis of mathematical equations often consisting of conservation equations of mass, momentum and energy, which are solved to describe the airflow and heat transfer in microclimates. The use of numerical models in the study of UHI is quite popular for a number of advantages. Unlike experimental methods, numerical models can deal with multiple atmospheric processes and urban design variables at the same time (John, 2003); also, the numerical models provide the flexibility to investigate the impact of the prescribed mitigation strategy as variables can easily be altered (Rajagopalan, Lim, & Jamei, 2014; Sun et al., 2017). Furthermore, besides being computationally expensive methods, numerical approaches are considered to be reliable in providing detail values in microclimate studies (Aflaki et al., 2017; Mirzaei & Haghighat, 2010). The numerical models are considered under two most prominent categories, including energy balance models (Nakata-Osaki,

Souza, & Rodrigues, 2018; Oke, 1982) and computational fluid dynamics models (Alobaydi, Bakarman, & Obeidat, 2016). In either cases, the major drawback still remains the high computer cost associated with the real-time and real-size modelling of a city. Hence, major assumptions have to be made as regards to the building shape as illustrated in Figure 2.2 as well as other urban features, and material thermal properties (Nazarian, Fan, Sin, Norford, & Kleissl, 2017).

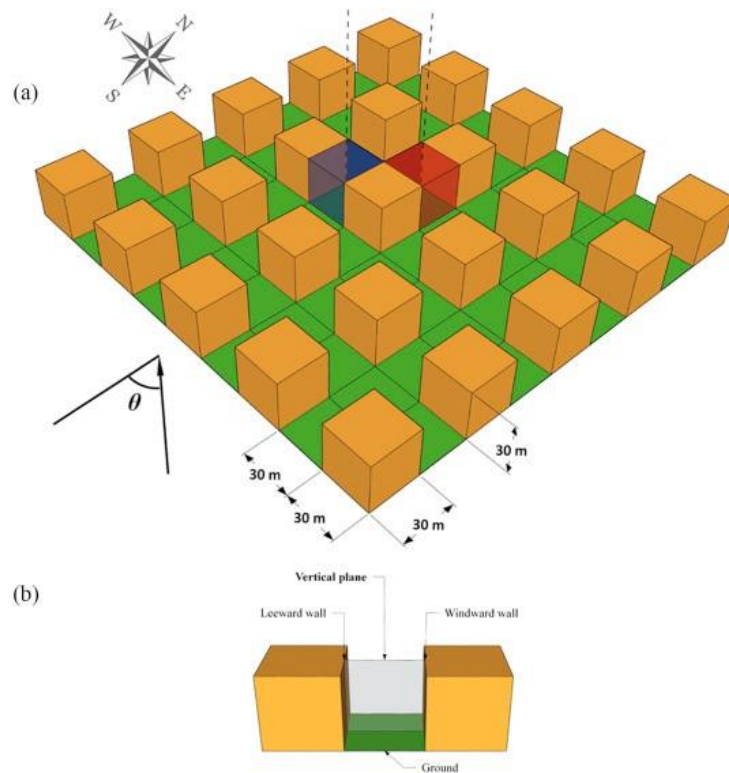


Figure 2.2 Schematic of (a) simplified 5 × 5 building arrays and (b) vertical plane of a street canyon (G. Chen, Rong, & Zhang, 2020).

2.6.3 Thermal Remote Sensing modelling approaches

Ever since the first remote-sensing studies on the urban surface temperature such as the one conducted by (P. K. Rao, 1972), the use of satellite or other airborne remote sensing approaches in the study of urban heat island has been widely used by scientist, seeking to explore the urban heat island distribution in a large scale as this is necessary in acquiring morphological information for large spatial extents (Gaitani, Burud, Thiis, & Santamouris, 2017; H. Li et al., 2018; Meng et al., 2018; Streutker, 2003). Some widely used approaches in

remote sensing UHI studies include remote sensed derived urban morphology parameters, and multi-spatio temporal satellite data.

Remote sensed derived urban morphology parameters

In this approach, spatial resolution images obtained from satellite or airborne remote-sensing is used to assess the thermal behaviour of urban surfaces by correlating several indices and surface characteristics to the land surface temperature (LST) as one of the main indicators for the UHI (X. Zhang, Estoque, & Murayama, 2017). A number of indices has since been developed to represent several morphological features from a Landsat image, which are explained in the below paragraph.

Urban main built up areas (UMBAs) and impervious surface distribution density (ISDD) were mainly used to better differentiate suburban boundaries and to ensure the integrity of land cover types (Meng et al., 2018). (He, Shi, Xie, & Zhao, 2010) also proposed built-up index (BU) to simplify and to improve the mapping accuracy of built-up areas in thematic mapper images over the conventional mapping index of built-up index (NDBI). Urban thermal field variance index (UTFVI) derived from Land Surface Temperature was adopted by (Ahmed, 2018; Singh, Kikon, & Verma, 2017) to improve characterization of urban heat island. A soil-adjusted vegetation index (SAVI) was firstly introduced by (Huete, 1988) as an efficient index in describing a dynamic soil-vegetation system from remotely sensed data. Moreover, (X.-L. Chen, Zhao, Li, & Yin, 2006) used normalized difference bareness index (NDBal) and normalized difference water index (NDWI) to enhance the mapping accuracy of barren land areas and water bodies, respectively, from remotely sensed data. (Son, Chen, Chen, Thanh, & Vuong, 2017) also developed a new index known as normalized difference composite index (NDCI), which was effective in the automatic extraction of impervious surface areas (IS) from Landsat images. Furthermore, (Zha et al., 2003), in their study on the practicality of using NDBI in automatically mapping urban areas from TM imagery, demonstrated that NDBI was a quicker and more accurate index in mapping built-up areas compared to the maximum likelihood classification method. (Adeyeri, Akinsanola, & Ishola, 2017) found that normalized

difference vegetation index 705 (NDVI705) is very efficient in exploring the sensitivity of the vegetation red edge while modified soil adjusted vegetation index 2 (MSAVI2) is efficient in calculating a more reliable soil brightness correction factor in regions with uncovered soil surface. They have also defined and utilized ratio vegetation index (RVI) to improve on the existing NDVI in the area of accurate characterization of thick vegetation from sparse vegetation. It should be noted that despite of many developed indices and their advantages in understanding spatial morphological characteristics of a city, these indices are barely developed to scrutinize the vertical characteristics of a city area.

Multi spatio-temporal satellite data

The availability of free historical Landsat data since the 1970s has made it a widely adopted approach for long-term monitoring of urbanization effects on the UHI intensity. This primarily involves the comparison of spatial images, usually of different time periods, to determine the trend of UHI intensity across the period considered.

This approach was adopted by (Ahmed, 2018) to compare the UHI intensity in Suez Governorate from 1988 to 2014 using LST AND Land use cover as indicators. A multi-temporal satellite data study by (J.-j. Li, Wang, Wang, Ma, & Zhang, 2009) investigated trend of the UHI intensity in the Shanghai metropolitan area during 1997- 2004 using satellite images representative of the two dates while the LST was used as the indicator of UHI. The study found the change in Land Use Land Cover (LULC) due to the rapid urbanization of the area to be the major driver of the increasing UHI trend from 1997 - 2004. Another study was conducted by (Son et al., 2017) on assessment of urbanization and Urban Heat Islands in Ho Chi Minh City, Vietnam, and compared Landsat images for the periods 1996 – 2007 – 2016. Using LST as the UHI indicator, the study concluded that the rising trend in the UHI intensity had been heavily influenced by the effect of urbanization. The thematic images showing the impact of rising urbanization trend on the LST is shown in Figure 2.3. (Kikon, Singh, Singh, & Vyas, 2016) also assessed the temporal changes in Noida, India, from the year 2000 to 2013 using their spatial images obtained by the remote sensing technique. The study concluded

that the increased temporal pattern in the UHI was mainly due to the urbanization effects, resulting in increased impervious surfaces over the period investigated. However, results from this approach are seen to be misleading as they directly compare the at-satellite brightness temperature between different time period to indicate the UHI intensity without accounting for the impact of the variable climatic and atmospheric conditions around the dates represented on the retrieved radiance temperature. Hence, there is a need to integrate the impact of climate along with the morphological aspects majorly being considered in order to achieve a more accurate explanation for the varying temporal pattern in the UHI for a given area.

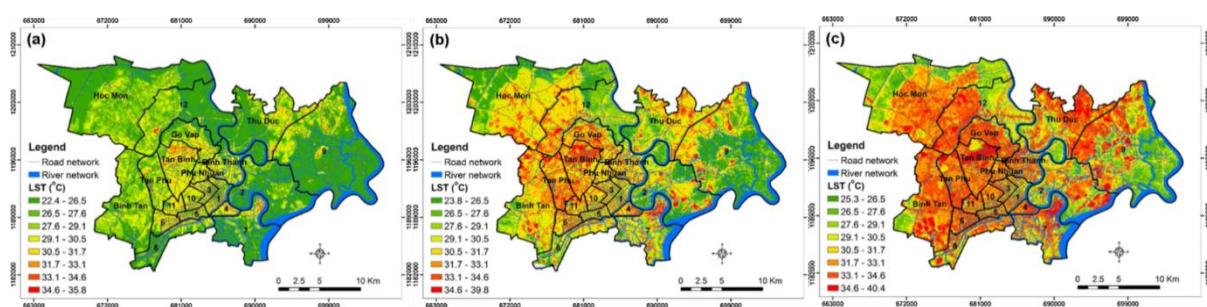


Figure 2.3 Increasing UHI temporal pattern observed between (a) 1996, (b) 2007, and (c) 2016, using LST retrieved from Landsat as UHI indicator (Son et al., 2017).

2.7 Chapter summary

The literature review section, firstly focused on defining UHI. Different types of UHI were also explained within the context of their occurrence. The causes of UHI were equally explored and key drivers of the phenomena were identified and discussed. Then, the impact of UHI across different levels of the urban climate was evaluated. The literature review also explained the various scales associated with the UHI studies, highlighting their strengths and limitations in each case. Then the different methods, and the justification for developing and improving conventional models for UHI predictions was examined. Finally, the different methods of studying UHI, including experimental, numerical model, and thermal remote sensing were critically reviewed. Despite the enormous work done to improve the understanding of the UHI formation and mitigating strategies, the literature review showed that more studies are

necessary to be conducted to broaden understanding of the driving factors of UHI, and to integrate them into improve the learning process of UHI predictive models and therefore, achieving more accurate predictive models.

Chapter 3

Definition of two novel elevation parameter to improve the prediction of urban heat island

3.1 Introduction

This section of the thesis firstly provides a background to the work done so far by other researchers in the view of integrating urban elevation aspects to UHI study. Then the identified gap associated with the current research is established as a justification for the definition of the two new elevation parameters. Lastly the procedure for retrieving each of these parameters are outlined.

3.2 Indices to investigate urban heat island

The limitation of the passive aerial/satellite remote sensing techniques in providing elevation information, has been broadly addressed as a major drawback associated with the thermal remote sensing method used in the UHI studies (Mirzaei, 2015; Parsaee, Joybari, Mirzaei, & Haghighat, 2019). In order to breach this gap, many studies have been focused on exploring the extent to which the vertical components of a city contribute to the UHI intensity and formation. Some of these studies are outlined in Table 3.1. Although, the use of isolated vertical urban morphology components to explain the UHI intensity (i.e., aspect ratio, sky view factor, floor area ratio, mean height, etc.) is quite popular, the overall contribution of other equally significant horizontal/vertical morphological components to the UHI formation are barely considered in literature.

Table 3.1 Researches on impact of vertical morphological aspects on UHI.

Author	Research	Cities	Methodology	Urban morphology studied
--------	----------	--------	-------------	--------------------------

(Nakata-Osaki, Souza and Rodrigues, 2018)	A GIS extension model to automatically calculate the UHI intensity based on urban geometry.		GIS	Aspect ratio
(Jihad & Tahiri, 2016)	Modelling the urban geometry influence on outdoor thermal comfort.	Morocco	Urban canopy model approach	Aspect ratio
(Priyadarsini, Hien, & Wai David, 2008)	Microclimatic modelling of the urban thermal environment to mitigate the UHI.	Singapore	CFD simulation	Aspect ratio
(De & Mukherjee, 2017)	Optimisation of street canyon orientation and aspect ratio in warm humid climate.	Rajarhat Newtown, India	CFD Simulation	Aspect ratio and building orientation
(Rahman et al., 2017)	Microclimatic differences and their influence on transpirational cooling of <i>Tilia cordata</i> in two contrasting street canyons.	Munich, Germany	Field Survey	Aspect ratio
(Memon, Leung, & Liu, 2010)	Effects of building aspect ratio and wind speed on air temperatures in urban-like street canyons.		CFD Simulation	Aspect ratio
(L. Zhang, Zhan, & Lan, 2018)	Effects of the tree distribution and species on outdoor environment conditions in a hot summer and cold winter zone.	Wuhan, China	CFD Simulation	Aspect ratio of trees (Tree distribution pattern)
(Sobstyl, Emig, Abdolhosseini Qomi, Ulm, & Pellenq, 2018)	Role of City Texture on the UHI at Night-time.		Field survey	Sky view factor
(Soltani & Sharifi, 2017)	Daily variation of urban heat island effect and its correlations to urban greenery.	Adelaide, South Australia	Field survey	Tree canopy
(Alobaydi et al., 2016)	The Impact of Urban Form Configuration on the Urban Heat Island.	Baghdad, Iraq	CFD Simulation	Street canyon

In this respect, a few numbers of studies have been developed to employ the use of indices and numerical factors to capture a wider range of components that constitute the vertical morphology of an urban climate. For instance, (Adolphe, 2001) developed a simplified spatial model based on a set of original morphological indexes, which are typical of the environmental performance of urban fabrics, including density, rugosity, sinuosity, occlusivity, compacity, contiguity, solar admittance, and mineralization. (Gan & Chen, 2016) further extended these morphological indices to develop a volume obstruction ratio to analyse the link between changing wind condition and block form variations. In another study by (Wei, Song, Wong, & Martin, 2016), they have proposed a set of parameters, including floor area ratio (FAR), building site coverage, layer (L), and open space ratio (OSP). They have further examined the impact of these parameters on urban microclimate, aiming to provide suitable ranges of parameters essential for the pedestrians' thermal comfort. (Huang & Wang, 2019) investigated the impact of 2D and 3D morphological features in several urban functional zones on the surface urban heat island indicated by the LST. The 3D morphological features for the study region were represented by shape coefficient (SC), mean height (MH), height variation (HV), normalized height variation (NHV), and sky view factor (SVF).

In summary, the drawback for these studies is related to their practicality in a large-scale associated with the data acquisition needed to develop the required indices. To overcome this limitation, (Ren, Cai, Li, Shi, & See, 2020) proposed the use of open source data for a rapid acquisition of the necessary vertical morphological data for the calculation of the parameters such as building height (De & Mukherjee, 2017), (SVF), frontal area density (FAD), and building volume density (BVD). (Equere et al., 2020) also proposed the use of GIS based 3D city engine combined with high-resolution 3D images from Google Earth to develop an elevation factor (EF) index to account for building and tree heights. Similarly, (Dirksen, Ronda, Theeuwes, & Pagani, 2019) adopted the use of high-resolution LiDAR data to retrieve the SVF to investigate its impact on the UHI for a study area of $70km^2$ in the Netherlands. Despite these advancements in the exploring of the vertical components of urban morphology

(especially with respect to its impact on the UHI), and achieved progresses in large-scale data acquisition, it suffices to say that the impact of topographical variations (Surface relief) are neglected as a generally flat ground is assumed in these studies. Although, (Lima Alves & Lopes, 2017) reported the significant impact of topographical variations to UHI, there is not enough done to clearly separate the vertical aspects into above ground and ground elevation, in order to assess their individual impact and better understand the driving factors of UHI intensity.

To improve the understanding of how the vertical spatial distribution impact the formation and intensity of UHI, this study has proposed two novel parameters namely elevation factor (EF), and the terrain factor (TF).

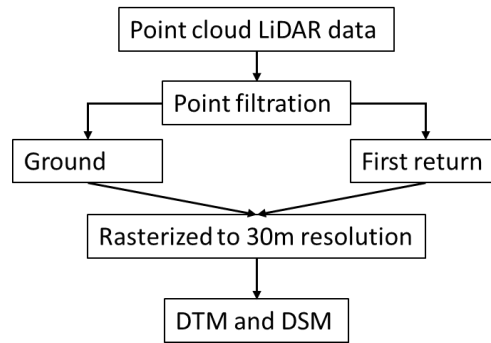


Figure 3.1 Algorithm showing the how point cloud LiDAR data is processed to derive DTM and DSM.

The derivation of these two elevation parameters is mainly point cloud based, Figure 3.1 shows the steps adopted to retrieve DTM and DSM from raw point cloud data using ArcGIS 10.4. The LiDAR point cloud data obtained from an open-source point cloud LiDAR database are firstly pre-classified. To create a DTM, the point cloud data is filtered to extract the only points from class 2, which corresponds to the ground returned points as shown in Table 3.1. The DSM is created by filtering the whole point cloud dataset to extract only points from the first return, which correspond to the highest feature in the landscape like a treetop or the top of a building. The filtered points are regularised to create a raster file to a resolution that corresponds with the satellite image resolution, using the Natural neighbour interpolation

method (Sibson, 1981). The resulting DTM is the elevation value of the bare ground excluding all super-structures while the DSM is the value of all above ground elevation features, including trees and building, a pictorial illustration difference between DTM and DSM is shown in Figure 3.2. More details on the rasterization of data is discussed in section 4.2.1 of this thesis.

Table 3.2 Point cloud LiDAR classification specification.

Returns	Correspondence
1 st	Highest feature in the landscape
Last	Forest canopy, ground cover, etc.
Single	may represent the earth's surface
All	All points returned
Point Classification	
1	Unassigned
2	Ground
3	Low vegetation
4	Medium vegetation
5	High vegetation
6	Building
7	Noise
9	Water
10	Rail
17	Bridge deck

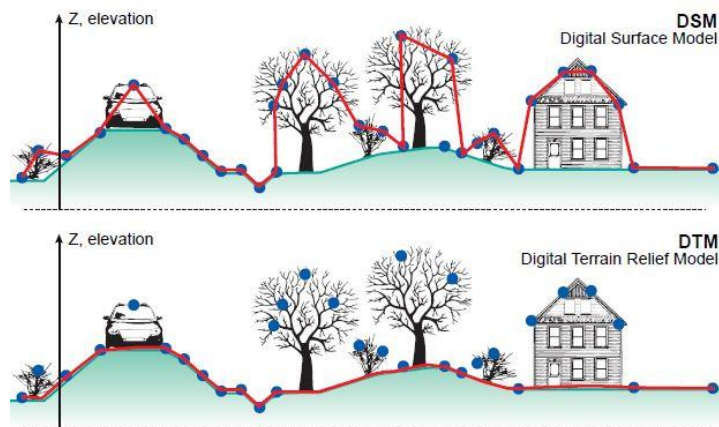


Figure 3.2 A pictorial illustration of the difference between a DTM and a DSM layer

(Cdema.org, 2022).

3.3 Elevation factor (EF)

EF will be the value of the DSM per pixel, which is the height value of all above ground elevation features, including trees and building, etc. in metres. The corresponding point cloud

data to the DSM can also be integrated to a rapid 3D city modeller software tool (Esri City engine), to produce a 3D model of a given city using the process described by ([Esri.com](https://www.esri.com), 2022). An example of the 3D city model produced for this study is shown in [Figure 3.3](#).

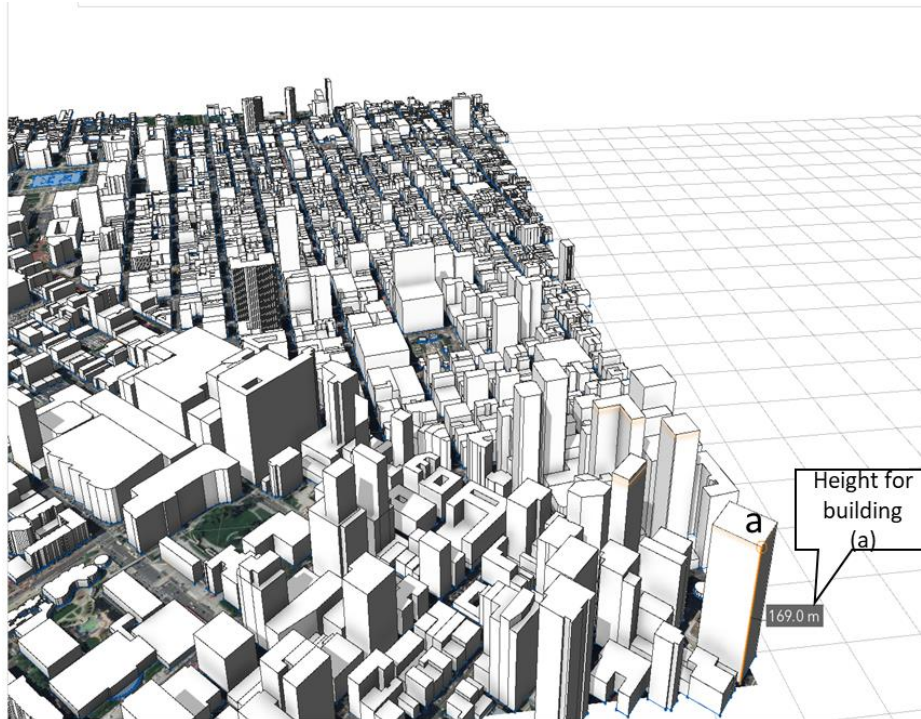


Figure 3.3 An example of a section of the 3D city model produced with esri 3D city engine by integrating LiDAR point cloud data corresponding to the DSM.

3.4 Terrain factor (TF)

TF is the value of the DTM for each pixel which will be the height value of the bare ground excluding all super-structures in meters. An example of terrain factor distribution map produced for this study area is shown in [Figure 3.4](#).

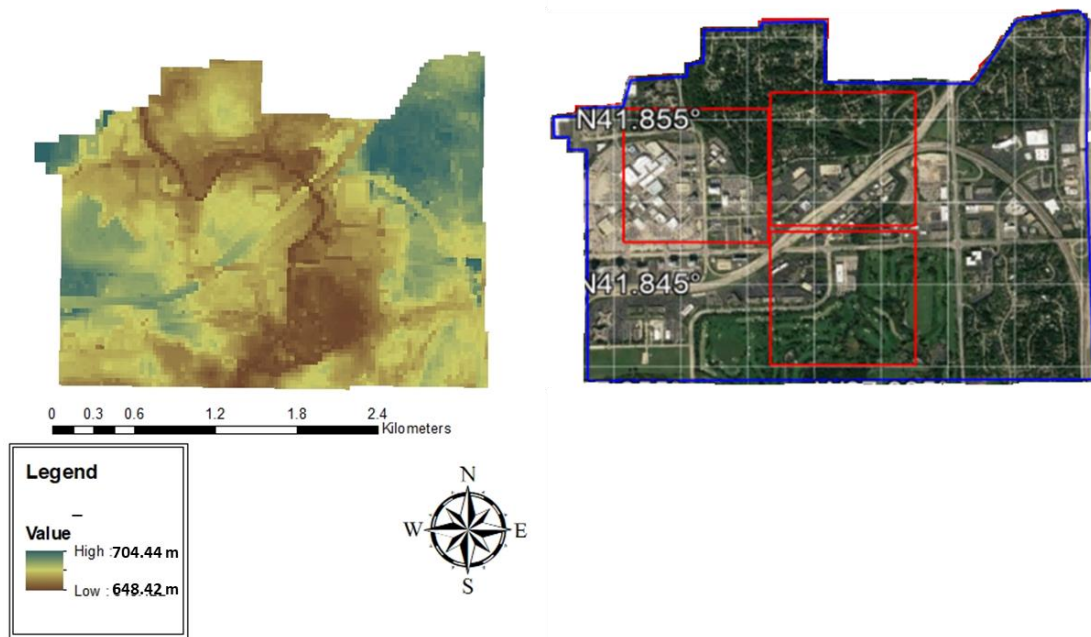


Figure 3.4 An example of the terrain factor distribution showing the topographical variation across a section of the study area.

3.5 Chapter summary

A detailed review of the current research focused on the integration of the elevation aspect of cities to UHI studies is firstly presented. From the reviewed literature the research gap associated with this aspect of UHI study is outlined to provide justification for the definition of these two novel parameters as they would help improve the understanding of how the vertical spatial distribution impact the formation and intensity of UHI. The procedure for retrieving the two novel parameters of EF and TF from the LiDAR point cloud data and associated steps for further processing the TF into raster files using Arc GIS 10.4, and processing the EF into a 3D models using esri city engine tool are equally explained along with illustrative diagrams and associated pictures.

Chapter 4

Methodology

4.1 Introduction

This section of the thesis describes the framework adopted in the development of the proposed model for improved accuracy in spatial UHI distribution predictions. Starting from the raw data collection stage, through the data processing stages and then lastly the actual model development details including the input parameters and the model configuration. All the software tool utilised at each stage of the model development are also highlighted in this section. The concluding section of this chapter outlines the formulas for the error measurement techniques used in testing the model predictive performance. [Figure 4.1](#) shows a schematic diagram illustration of model development framework.

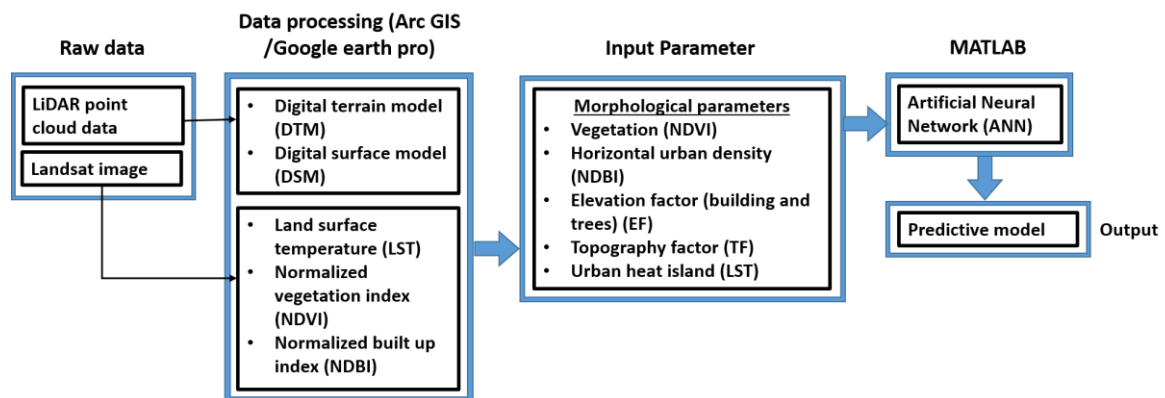


Figure 4.1 Schematic diagram illustrating the proposed model development framework.

4.2 Raw data collection

The proposed model is developed based on two main streams of satellite datasets for the purpose of deriving both horizontal and vertical morphological parameters of the selected areas, including Landsat Image and point cloud LiDAR data.

4.2.1 Landsat images

The origin of Landsat images dates back to 1972, when The National Aeronautics and Space Administration (NASA) and the U.S. Geological Survey jointly launched the Landsat series of Earth Observation satellites for the purpose of continuously acquiring images of the Earth's land surface, and providing uninterrupted data to help land managers and policymakers make informed decisions about natural resources and the environment ([Landsat.usgs.gov](https://landsat.usgs.gov/), 2022b).

There has been many Landsat projects launched since inception including Landsat 1 up to Landsat 9. However, the model development process described in this thesis used images from Landsat 8 OLI_TIRS suit. The Landsat 8 satellite, was launched in February of 2013, and it collects images of the Earth with a 16-day repeat cycle, referenced to the Worldwide Reference System-2 ([Usgs.gov](https://usgs.gov/), 2022b). Landsat 8 OLI_TIRS suit was used because at the time of conducting this study it was the most recent Landsat project launched; as Landsat 9 was launched much later on the 27th of September 2021 ([Landsat.usgs.gov](https://landsat.usgs.gov/), 2022a). Furthermore, the Landsat 8 OLI_TIRS suit has two additional spectral bands over previous Landsat instruments which improves its accuracy relative to other Landsat projects ([Usgs.gov](https://usgs.gov/), 2022a). Landsat 8 OLI_TIRS suit images for any location can be assessed for free on The United States Geological Survey website. The properties of the spectral bands contained in Landsat 8 OLI_TIR suit is outlined in [Table 4.1](#).

Table 4.1 Spectral band properties for the Landsat 8 OLI_TIRS suit.

Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS)	Bands	Wavelength (micrometres)	Resolution (meters)
	Band 1 - Ultra Blue (coastal/aerosol)	0.435 - 0.451	30
	Band 2 - Blue	0.452 - 0.512	30
	Band 3 - Green	0.533 - 0.590	30
	Band 4 - Red	0.636 - 0.673	30
	Band 5 - Near Infrared (NIR)	0.851 - 0.879	30
	Band 6 - Shortwave Infrared (SWIR) 1	1.566 - 1.651	30

Band 7 - Shortwave Infrared (SWIR) 2	2.107 - 2.294	30
Band 8 - Panchromatic	0.503 - 0.676	15
Band 9 - Cirrus	1.363 - 1.384	30
Band 10 - Thermal Infrared (TIRS) 1	10.60 - 11.19	100 x (30)
Band 11 - Thermal Infrared (TIRS) 2	11.50 - 12.51	100 x (30)

4.2.2 Point cloud LiDAR data

Light Detection and Ranging (LiDAR) is a remote sensing technique used to perform an automated vertical measurement collection. This measurement technique uses ultraviolet, visible, or near-infrared light to gauge spatial relationships and shapes by measuring the time-of-flight between the emitted beam and the reflected pulse from the object ([Jiang et al., 2020](#)), a pictorial illustration of the LiDAR measurement technique is shown in [Figure 4.2](#). The processed and organised data LiDAR data from each measurement session becomes point cloud data.

The initial point clouds are large collections of 3D elevation points, which include x, y, and z, as illustrated in [Figure 4.3](#) and would normally include additional attributes such as GPS time stamps if available. Point cloud data is increasingly being used for automated 3D city modelling and other related studies in the built environment ([Niemeyer, Rottensteiner, & Soergel, 2014](#); [B. Yu, Liu, Wu, Hu, & Zhang, 2010](#)).

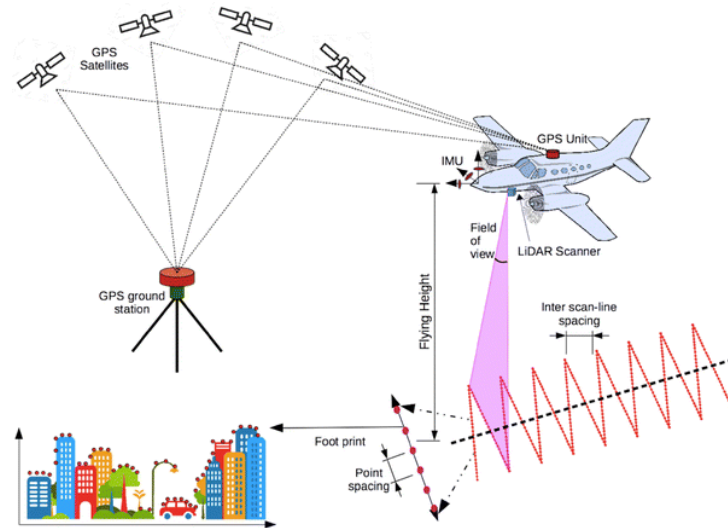


Figure 4.2 Pictorial illustration of the LiDAR measurement technique using a manned aircraft (Lohani & Ghosh, 2017).

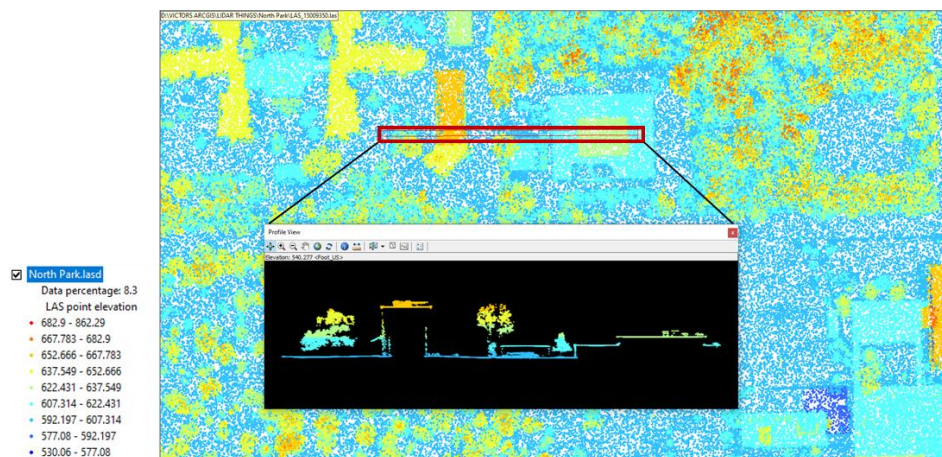


Figure 4.3 LiDAR point cloud data for a section of the study area shown in a height represented colour scheme, and an illustrative side elevation profile.

4.3 Data processing

The geo-processing of both Landsat images and Point cloud LiDAR data into horizontal and vertical morphological parameters was performed using ArcGIS 10.4. Google Earth-pro was used to create the digital map of each study area. Further explanations are provided in the following sections.

4.3.1 Data rasterization

In a simple term, a raster consists of a matrix of cells (or pixels) arranged into rows and columns (or a grid) where each cell contains a value representing information, such as temperature, height, etc. ([Desktop.arcgis.com, 2022](https://desktop.arcgis.com/en/arcgis/latest/concepts/raster-data.htm)). An illustration of the rasterised urban morphology parameters for a section of the study area is presented in [Figure 4.4](#).

The raw data of Landsat images and point cloud LiDAR data was firstly processed into raster format because of this formats ability to uniformly store points, lines, polygons, and surfaces for easy read by many software tools. The Landsat images available on the U.S. Geological Survey website are already processed into raster format with a cell size of 30 x 30m.

The point cloud LiDAR data are processed into raster files by using the nearest neighbour interpolation technique described by ([Sibson, 1981](#); [Zheng et al., 2021](#)) to assign values to each pixel. This process was conducted automatically using the ArcGIS 10.4. tool, following the steps described by ([Pro.arcgis.com, 2022](https://pro.arcgis.com/en/pro/10.4/concepts/raster-data.htm)).

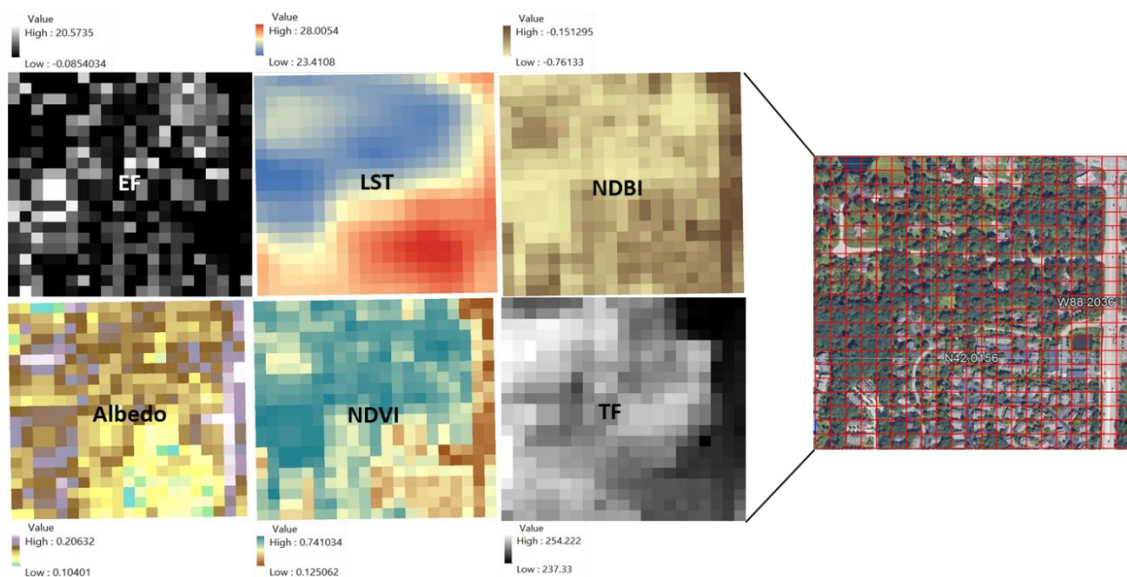


Figure 4.4 A pictorial illustration of all the morphological parameters used in this study in their raster format.

4.3.2 Landsat image processing

This section describes the framework adopted to retrieve the LST, NDVI, NDBI and the surface albedo from the Landsat image. All the processes described in this section was conducted using the ArcGIS 10.4. software tool.

a) Land surface temperature retrieval

The Split-Window algorithms was adopted as the geo-processing technique to retrieve the LST. As demonstrated in Figure 4.5, this algorithm has been widely adopted due to its high accuracy (Equere et al., 2020).

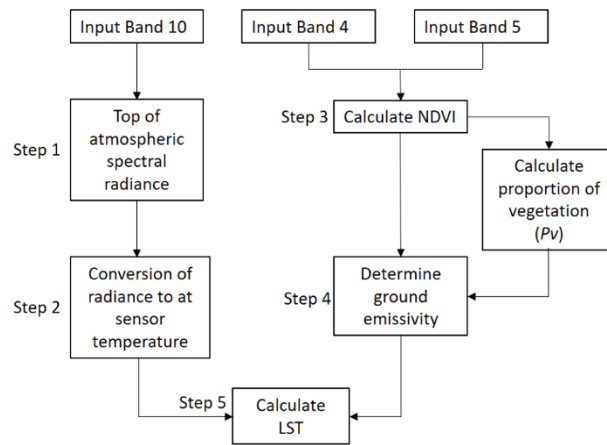


Figure 4.5 A schematic diagram showing the framework for retrieving LST from Landsat 8 OLI_TIRS suit.

Step 1 Top of Atmospheric (TOA) spectral radiance

The thermal Infrared band (Band 10), for the area should be first converted from the digital number, which is the satellite assigned pixel value to at sensor radiance using equation 4.1 (Kikon et al., 2016):

$$L_{\lambda} = M_L \times Q_{cal} + A_L \quad (4.1)$$

where L_{λ} is the at-sensor spectral radiance ($W \cdot m^{-2} \cdot sr^{-1} \cdot \mu m^{-1}$), M_L is the band specific multiplicative rescaling factor (0.0003342), Q_{cal} is the quantized calibrated values, which

corresponds to the Band applicable (Band 10), and A_L denotes the band specific additive rescaling factor (0.1).

Step 2 Conversion of Radiance to at-sensor temperature

The inverse of the Plank function is applied to the estimated radiance value to derive the temperature values (Kikon et al., 2016; W.-C. Wang, Zeng, & Karl, 1990) as below:

$$T_B = \frac{K_2}{\ln\left(\frac{K_1 \varepsilon}{L_\lambda}\right) + 1} - 273.15 \quad (4.2)$$

where T_B is the brightness temperature (in degrees), K_1 and K_2 are the coefficients determined by the effective wavelength of a satellite sensor (contained in the Meta data file), and ε is the spectral emissivity (typically assumed to be 0.95).

Step 3 NDVI

Calculating NDVI is essential in the LST derivation as the vegetation fraction (P_V) as well as the ground emissivity (ε_{OLI}) are extracted from NDVI; hence, NDVI is given as:

$$NDVI = \frac{NIR - R}{NIR + R} \quad (4.3)$$

where NIR is the Near Infrared (Band 5) and R is the Red (Band 4). In this study, ArcGIS 10.4 was used to obtain NDVI of the selected areas.

Step 4 Ground emissivity

The ground emissivity was calculated using the equation proposed by (Sobrino, Jiménez-Muñoz, & Paolini, 2004):

$$\varepsilon_{OLI} = 0.00149 \times P_V + 0.986481 \quad (4.4)$$

Here, the vegetation fraction is adapted from (Carlson & Ripley, 1997) as follows:

$$P_V = \left(\frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \right)^2 \quad (4.5)$$

where $NDVI_{min}$ is -0.98 and $NDVI_{max}$ is 0.83.

Step 5 LST Calculation

The land surface temperature was retrieved from the spectral bands using the equation from (Son et al., 2017):

$$T_S = \frac{T_B}{(1 + (\lambda \frac{T_B}{\rho}) \ln \varepsilon_{OLI})} \quad (4.6)$$

where T_S is the LST (in Celsius), λ is the wavelength of emitted radiance (10.9 μm for Landsat OLI), and ε_{OLI} is the ground emissivity. ρ is the atmospheric correction factor expressed by:

$$\rho = h \frac{c}{\sigma} \quad (4.7)$$

where σ is the Boltzmann's constant (1.38×10^{-23} J/K), h is the Planck's constant (6.626×10^{-34} Js), and c is the velocity of light (2.998×10^8 m/s).

b) Normalized Differential Built-up Index (NDBI)

The NDBI maps built up areas and barren ground are calculated from satellite images as it has been widely used for this purpose in several studies (He et al., 2010; Zha et al., 2003). The NDBI is calculated with the below equation:

$$NDBI = \frac{SWIR - NIR}{SWIR + NIR} \quad (4.8)$$

where $SWIR$ is shortwave infrared.

c) Surface albedo (α)

Surface albedo, which measures the fraction of the reflected shortwave radiation by a surface, can be derived from satellite images using the formula proposed by (Liang, 2001):

$$\alpha = \frac{0.356\alpha_2 + 0.130\alpha_4 + 0.373\alpha_5 + 0.085\alpha_6 + 0.072\alpha_7 - 0.0018}{1.016} \quad (4.9)$$

where α_i ($i = 2, 4, 5, 6, 7$) is the band numbers from Landsat 8 OLI_TIRS suit.

4.4 Model development

This section describes the process of building a model to predict UHI spatial with improved accuracy, using the urban morphological parameters including NDVI, NDBI, surface albedo, EF, and TF, with LST as the target parameter. For this purpose, an artificial neural network model was developed to assess the model performance after integrating TF to the model training exercise. The steps described include, the parameters correlation test, factor characterization, ANN development, and the model evaluation.

4.4.1 Parameter correlation testing

To avoid overfitting of the model, a correlation analysis is conducted on all parameters to ensure significant correlations with the target parameter of LST, before inclusion of them in the training process. The Pearson correlation coefficient for each parameter was calculated using the formula expressed in equation 4.10.

$$r = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}} \quad (4.10)$$

Where r = correlation coefficient, x_i = values of the x-variable in a sample, $\bar{x}$ = mean of the values of the x-variable, y_i = values of the y-variable in a sample, and $\bar{y}$ = mean of the values of the y-variable. The resulting value from a Pearson correlation coefficient calculation is normally between -1 and 1 where 1 indicates a strong positive relationship and -1 indicates a string negative relationship, while a resulting 0 would mean no relationship at all between the two parameters considered (Schober, Boer, & Schwarte, 2018).

4.4.2 ANN Model development

ANN is a modelling technique that mimics the human nervous system of learning by example to learn from representative data in order to describes a physical phenomenon or a decision process (Sadiq, Rodriguez, & Mian, 2019). A typical architecture showing lines connecting neurons is shown in Figure 4.6. Each connection is associated with a numeric number called weight. The output h_i of neuron i in the hidden layer is expressed as:

$$h_i = \sigma(\sum_{j=1}^N V_{ij}x_j + T_i^{hid}) \quad (4.11)$$

where $\sigma()$ is the activation (or transfer) function, N is the number of input neurons, V_{ij} is the weights, x_j is the inputs to the neurons, and T_i^{hid} is the threshold terms of the hidden neurons. The activation function introduces nonlinearity into the neural network, and also minimizes the effect of divergent neurons on the neural network (S.-C. Wang, 2003).

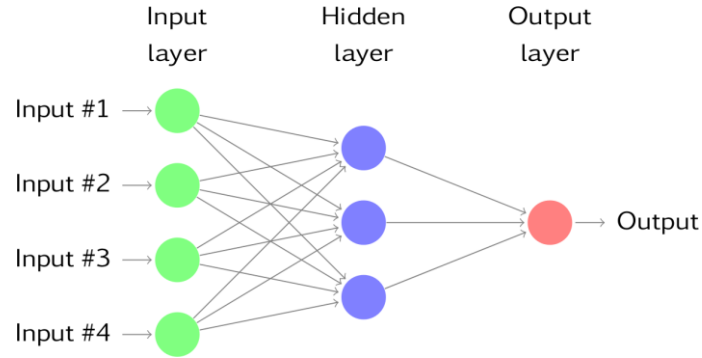


Figure 4.6 A representative diagram of a typical ANN architecture all the components of the network.

For the purpose of this study a Multilayer perceptron (MLP) feedforward neural network (FFNN) including one input layer, one hidden layer with three hidden neurons, and an output layer. In FFNN the information is transmitted only in one direction, and involves data entry from the input nodes and passes through the hidden layer until it gets to the output layer (Abiodun et al., 2018). Even though all the layers connect to each other, these connections are not all equal because each connection can have a different weight or strength depending on the amount of the knowledge of the network (Hagan & Menhaj, 1994).

The ANN was chosen because of the significant advantages it has relative statistical models including the fact that In ANN models there are no assumptions about data properties or data distribution. Hence, ANNs are more useful in practical application. Furthermore, in comparison to other machine learning techniques the ANN is considered to be very flexible and more fault tolerant, with a better ability to handle incomplete data and noise (Abiodun et al., 2018). However, a major drawback to the use of ANN is that its solution finding is based on a black box approach, which means it is difficult to figure out how that solution was attained (Tu, 1996).

Hence, does not offer the opportunity to explore the physical mechanisms whereby various environmental factors affect the formation of UHIs.

The model development procedure was executed on MATLAB R2018a, using the ANN tool box available. The raster images were then fed into the bespoke code developed in MATLAB to read the value at each pixel using the grayscale image pixel value extraction procedure provided by ([Mathworks.com](https://www.mathworks.com), 2014).

4.4.3 Factor characterization

A factor characterization is conducted to determine the most influential morphological parameters that explains the variance in LST distribution. For this purpose the Pareto chart of the standardized effects was used, this plot allows for detection of the factor and interaction effects among individual factors that are most significant to the process or design optimisation study. A typical Pareto chart plot displays the absolute values of the each effect, and draws a reference line on the chart, such that any effect that extends past this reference line is potentially important ([Antony, 2014](#)). The Pareto chart was constructed using the Minitab software tool.

4.4.4 Model evaluation

When testing the performance of any forecasting model, the prediction values it produces must be evaluated by calculating suitable error metrics. An error metric technique compares the trained model predictions with the actual (observed) data from the testing data set ([Botchkarev, 2018](#)). This provides an objective way of quantifying the performance of a model and also quantitatively compare different models([Makridakis, Spiliotis, & Assimakopoulos, 2018](#)). This study adopted the following error metrics including root mean square error (RMSE), mean actual error (MAE), normalized mean bias (NMB), and normalized mean error (NME) to test the model performance in this study. The description of each error metrics including their formula is described as follows.

a) Error

The formula for error calculation in this study is expressed the below equation:

$$error = (y_i - \hat{y}_i) \quad (4.12)$$

where y_i is the predicted LST value and $\hat{y}_i$ is the actual LST value.

b) Root mean square error

RMSE is a measure of how spread out these residuals are. In other words, it tells the data concentration around the line of best fit (Neill & Hashemi, 2018). The formula for calculating root mean square error is also expressed as:

$$RMSE = \sqrt{\frac{1}{N} \sum (y_i - \hat{y}_i)^2} \quad (4.12)$$

where N is the number of pixels, and y_i is the predicted LST value and $\hat{y}_i$ is the actual LST value.

c) Mean absolute error

The mean absolute error gives the average magnitude of forecast errors and is calculated as:

$$MAE = \frac{1}{N} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (4.13)$$

where y_i is the predicted LST value and $\hat{y}_i$ is the actual LST value, and N is the number of pixels.

d) Normalized mean bias

Normalized mean bias error (NMB) captures the average bias in the prediction and is calculated as:

$$NMB = \sum_{i=1}^n \left(\frac{y_i - \hat{y}_i}{\hat{y}_i} \right) \quad (4.14)$$

where y_i is the predicted LST value and $\hat{y}_i$ is the actual LST value.

e) Normalized mean error

Normalized mean error has a reputation of preventing excessive influence of outliers in a model proficiency test results ([Hogan, 2022](#)). The formula for calculating NME is expressed as:

$$NME = \sum_{i=1}^n \left(\frac{|y_i - \hat{y}_i|}{(\hat{y}_i)} \right) \quad (4.15)$$

where y_i is the predicted LST value and $\hat{y}_i$ is the actual LST value.

4.5 Chapter summary

This section of the thesis describes the framework adopted in the development of the proposed model for improved accuracy in spatial UHI distribution predictions. Starting from the raw data collection stage from the two main data sources of Landsat data and LiDAR point cloud data. The section also described the data processing stages applied to the raw data to produce the required morphology parameters of (NDVI, NDBI, Albedo, EF, and TF). Then lastly the actual model development details including the input parameters and the ANN model configuration is also described including all the software tool utilised at each stage of the model development. Then the error metrics used for the model performance evaluation are highlighted.

Chapter 5

Case study areas

5.1 Introduction

This section of the thesis describes in detail the case study areas where the morphological parameters used to develop the proposed model were derived. These areas were equally used as testing sites for the developed model. The justification for their selection, and detailed description of each morphological parameter retrieved, including the retrieval process, is also presented. Lastly, the exact number of pixels used for model training, testing and validation for each area are presented.

This study seeks to improve the prediction of the UHI by the integration of the impact of elevation aspect of the city to the model learning process. Two novel elevation parameters which are TF to represent the topographical variations, and EF to represent the above ground elevation features. These new parameters are integrated with other morphological parameters, including NDVI, NDBI, and Albedo to develop a UHI predictive model. For this purpose, two areas representative of high topographic and low topographic variations (relatively flat) are selected as case studies from Illinois, USA where LiDAR data are available. Oak Brook village located in Du Page County is the representative of high topographic variations and North Park, Chicago city is the representative of a relatively low topographic variation. The selected areas are processed to derive the vertical parameters of elevation and terrain factors. Landsat images and Google Earth were also used to retrieve the horizontal morphological parameters for the investigated area. An artificial neural network was then developed to train the vertical and horizontal morphological parameters together to predict the surface UHI.

5.2 Study areas in Illinois

Two study areas are selected from the state of Illinois, United States of America namely, North Park and Oak Brook. In the first instance Illinois is selected because of the detailed topographic data available. North Park is one of the 77 neighbourhoods in Chicago, Illinois, with a population of 18,914. North Park is in Cook County, and it's a mix of urban and suburban communities ([Niche.com](https://www.niche.com), 2020). North Park is under the Chicago climate, which is classed as hot-summer humid continental (Koppen:Dfa) with all four seasons of winter, summer, spring, and fall. The annual precipitation is evenly distributed, with the driest months being January and February, and the wettest months being July and August. The major influence on Chicago's weather across all seasons is the Lake Michigan nearby.

Oak Brook is a village in Du Page County, one of the 102 counties in the state of Illinois. It has a population of 8,108. It has a total area of 21.44 km², of which 96.03% is land and 3.97% is water ([U.S.CensusBureau](https://www.census.gov), 2020). Oak Brook is located about 19 miles (31 km) west of the Chicago Loop (downtown Chicago) and is served by a network of major federal, state, and county roads, including the Tri-State Toll way (Interstate 294), the Ronald Reagan Memorial Toll way (Interstate 88), and the Eisenhower Expressway (Interstate 290) ([OakBrook.org](https://oakbrook.org), 2020). The average annual rainfall and snow are 39 and 31 inches, respectively. On average, there are 188 sunny days per year in Oak Brook. July is the hottest month for Oak Brook with an average high temperature of 28.83°C, which ranks it as cooler than most places in Illinois. January is the snowiest month in Oak Brook with 10.2 inches of snow while six months of the year have significant snowfall. July is the most humid month though humidity is low for most of the year([Bestplaces.net](https://www.bestplaces.net), 2020). The geographical maps of North Park and Du Page County, showing their positions in the state of Illinois, is shown in [Figure 5.1](#).

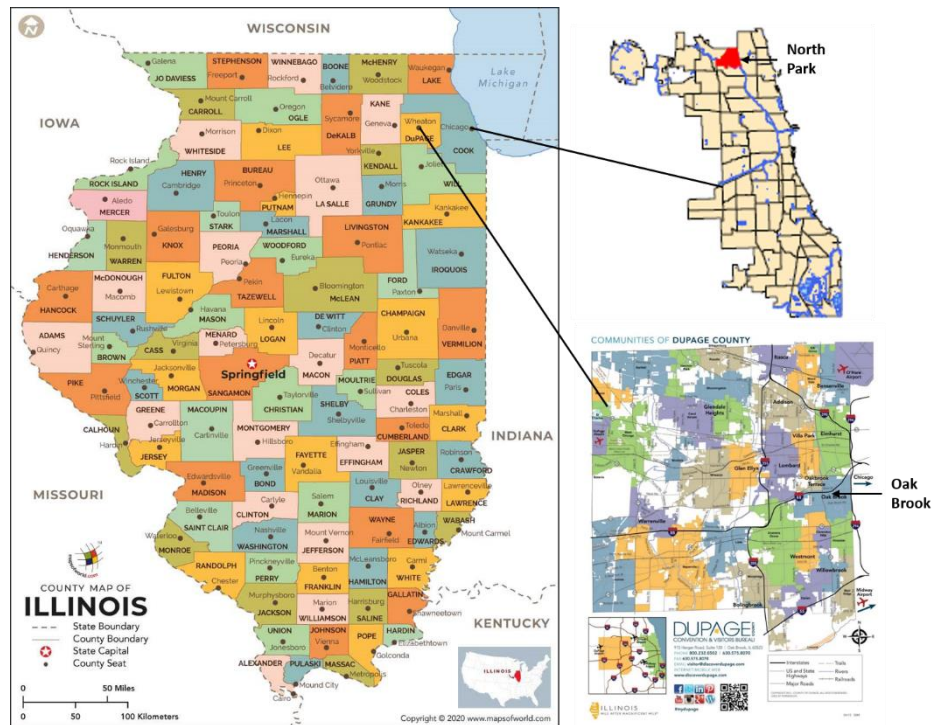


Figure 5.1 Geographical maps of the case study areas of North Park and Oak Brook in the State of Illinois.

5.2.1 Illinois study area data

To investigate the impact of terrain variation in the UHI intensity formation, the topographical map for the whole state of Illinois was obtained from the Illinois Height Modernization (ILHMP) available at LiDAR Data online database ([IllinoisStateGeologicalSurvey, 2015](#)). The coefficient of variance in the spatial distribution of the terrain factor across each of the selected case study areas is used to represent the level of topographic variation in the area. North Park was selected to represent areas with low topographical variance, with a coefficient of variance of 0.82, while Oak Brook village was selected for its predominant topographical variance with a coefficient of variance of 3.94; the topographical map for the state of Illinois and the terrain variance of North Park and Oak Brook village are shown in [Figure 5.2](#). Areas A, B, and C each of $810,000m^2$ from North Park, as shown in [Figure 5.3](#), were selected for the model training. The developed model will be then used to predict LST for the areas, which were not included in the training process. Due to the size and sparse distribution of land use activities in Oak Brook, an area Oak 1 outlined in blue in [Figure 5.3](#) was selected for the study as it has

sufficient mix of land use activity, hence, can capture the impact of other morphological parameters considered in this study, including NDVI, NDBI, EF and Albedo. Areas A, B and C also of $810,000m^2$ from Oak1 case study area, were selected for the model training while the developed model would be used to predict the LST of the area Oak1 outlined in Figure 5.3. Furthermore, a test row is selected as shown in Figure 5.3 to further test the model performance.

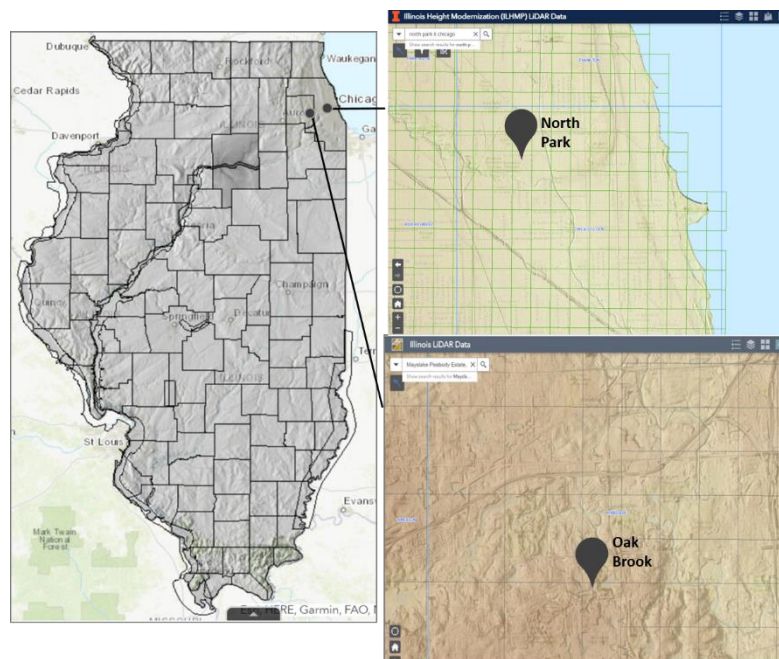


Figure 5.2 Topographical map of Illinois, including the terrain variance of North Park and Oak Brook and the selected study area.

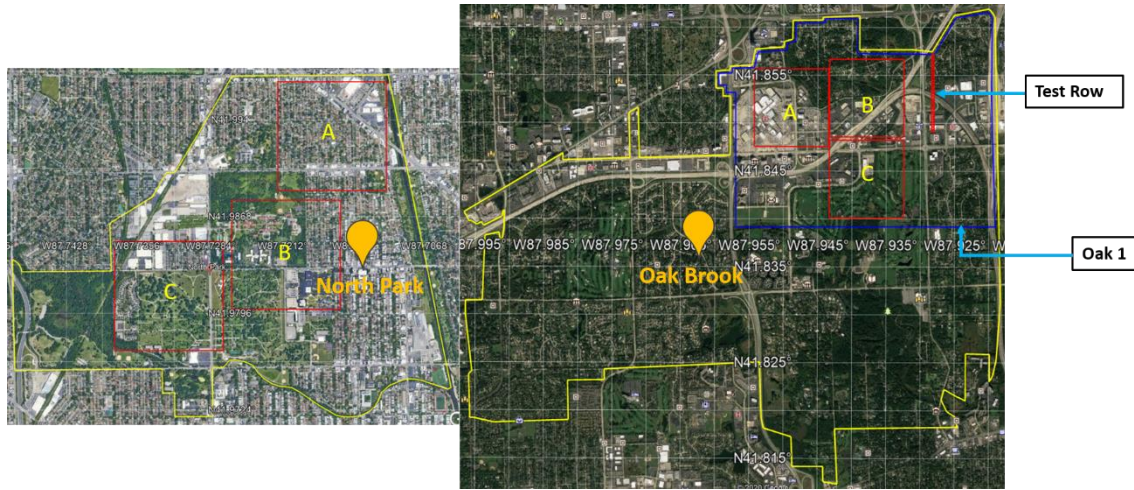


Figure 5.3 Bird's-eye view of the study areas; North Park and Oak Brook village, including the training areas and the test row.

5.3 Morphological data retrieval and processing

This section describes the morphological parameters retrieved from the both the Landsat images and the LiDAR point cloud data, including all associated pictorial illustrations.

5.3.1 Landsat image

The Landsat images were derived from Landsat 8 OLI_TIRS suit for the state of Illinois, U.S.A. acquired the 21st July 2014, at 16:34:12 from ([United States Geological Survey](#)). This date was selected to match the acquisition period of the available LiDAR data. The satellite data was downloaded already georeferenced, and BOA (bottom of atmospheric) calibrated. Then after, the required morphological parameters were derived, including LST, NDVI, surface albedo, and NDBI for the selected areas as described in [chapter 4](#) of this thesis. The images of the Landsat image based derived parameters for both Oak Brook and North Park areas of Illinois is shown in [Figure 5.4](#) and [Figure 5.5](#) respectively.

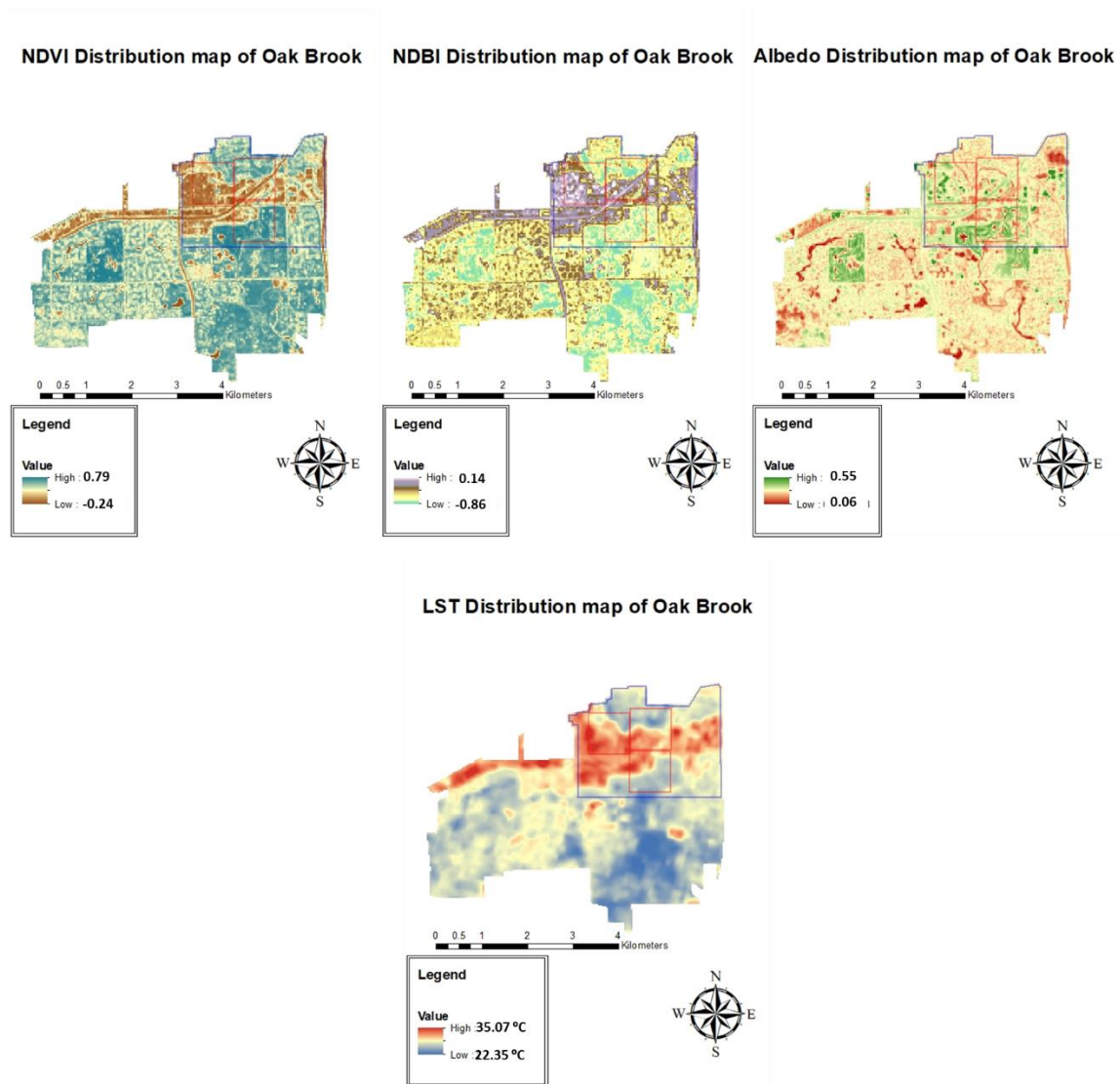


Figure 5.4 A pictorial illustration of the distribution of each Landsat derived morphological parameter across Oak Brook town.

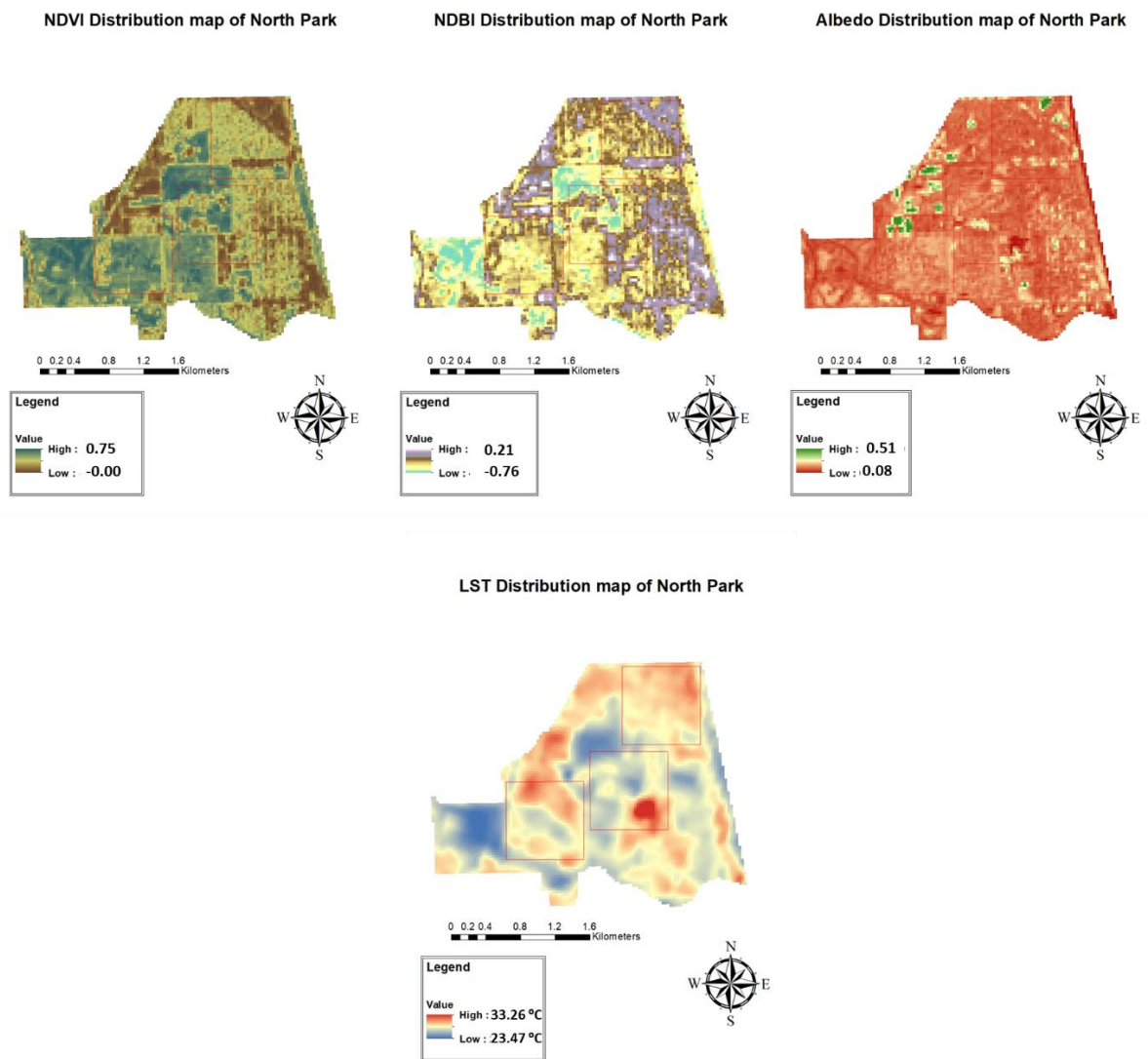


Figure 5.5 A pictorial illustration of the distribution of each Landsat derived morphological parameter across North Park town.

5.3.2 LiDAR point cloud data

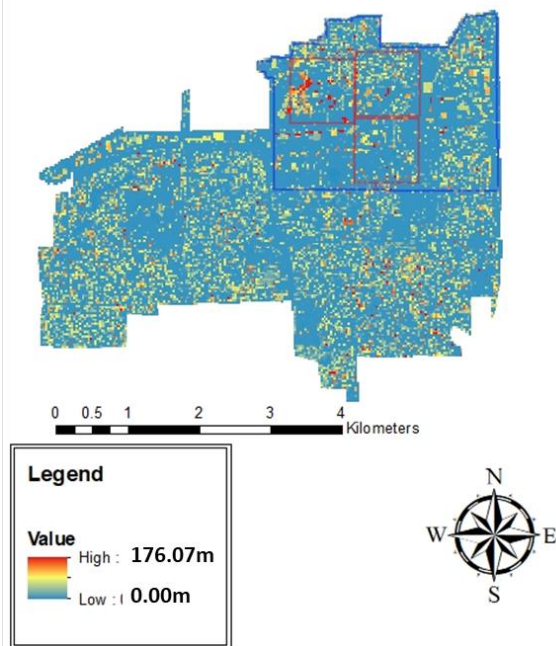
The LiDAR data was obtained from Illinois Height Modernization Project (ILHMP) website as the technical details are shown in [Table 5.1](#). The vertical accuracy for the LiDAR dataset was assessed against ground check points (GCP) distributed throughout the study area, which met the requirement of RMSE less than 9.25 cm and of fundamental vertical accuracy (FVA) less than 18.13 cm. LiDAR data were utilized to generate the digital surface model (DSM) and the digital terrain model (DTM) of the investigated areas. The images of the LiDAR point cloud

data based derived parameters for both Oak Brook and North Park areas of Illinois is shown in [Figure 5.6](#) and [Figure 5.7](#) respectively.

Table 5.1 Technical details of the LiDAR point cloud data for the state of Illinois.

Product	These LIDAR data are processed Classified LAS 1.4 files
Geographic extent	Du Page county, Illinois has covered an area of approximately 466 square miles
Acquisition	The data was developed based on a horizontal projection/datum of NAD83 (2011), State Plane, U.S Survey Feet and vertical datum of NAVD88 (GEOID12B)
Ground conditions	Lidar was collected July 2014 while no snow was on the ground and rivers were at or below normal levels
Data examination scale	1:3000
Collection rate	4 points per meter
Average point spacing	0.5 meters
Average point density	6.64 pulses per square meter
Flying height (Above ground)	3,1396 meters
Ground speed	150 knots
Field of view (FOV)	40 degrees
Scan rate setting	42 Hz
Laser pulse rate	194

EF Distribution map of Oak Brook



TF Distribution map of Oak Brook

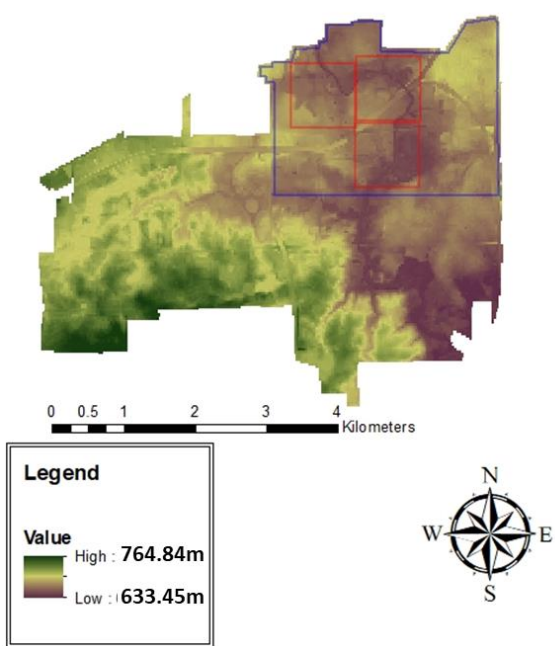


Figure 5.6 A pictorial illustration of the distribution of each LiDAR point cloud derived morphological parameter across Oak Brook town.

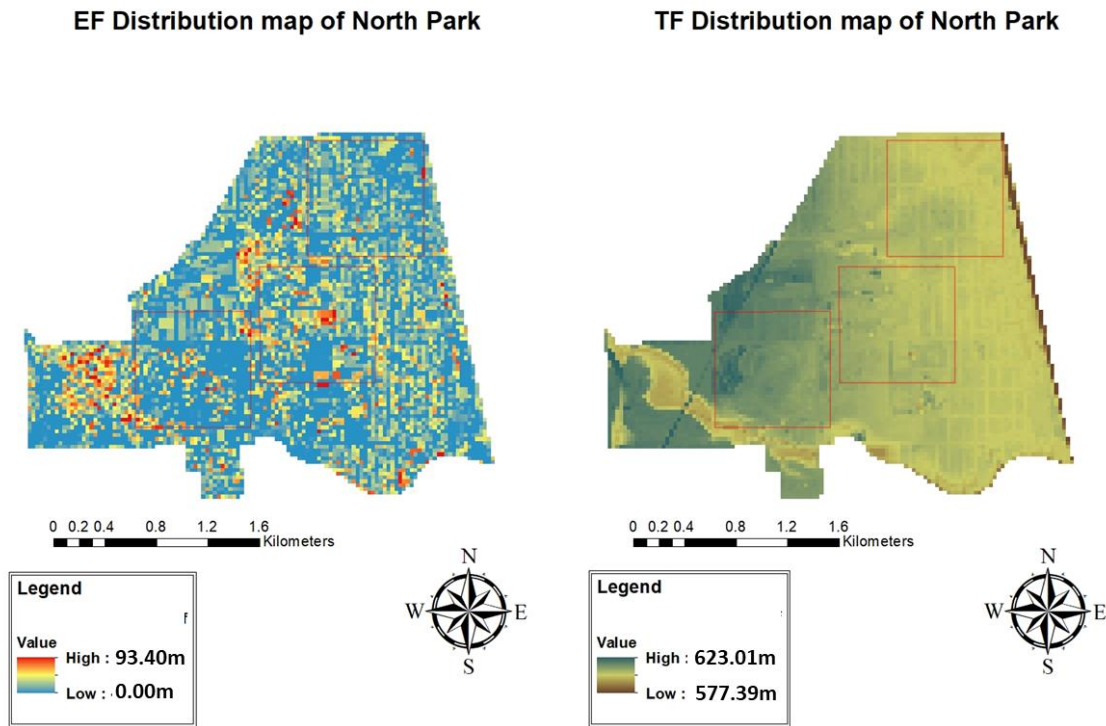


Figure 5.7 A pictorial illustration of the distribution of each LiDAR point cloud derived morphological parameter across North Park town.

5.4 Model input data

The input data for the ANN model included NDVI, NDBI, Albedo, TF, and EF while the LST of the selected area was set as the network target. The input datasets were randomly divided up for training, validation, and testing stages, in both case study areas 2019 pixels were used for training and two sets of 432 pixels for validation and testing, respectively.

5.5 Chapter summary

This chapter firstly describes each study area of Oak Brook and North Park in Illinois State U.S.A, including its geographical location on the map and also presents all the morphological information and data. The coefficient of variance in the spatial distribution of the terrain factor across each of the selected case study areas is used to represent the level of topographic variation in the area. Based on their respective topographical variation characteristics, North

Park was selected to represent areas with low topographical variance, while Oak Brook village was selected for its predominant topographical variance. Then a clear description of all the parameters retrieved from these areas, which was later used as input parameters in the model development procedure was presented in pictorial illustration. The parameters retrieved from each of the areas were grouped into Landsat derived parameters (i.e. LST, NDVI, and NDBI) and LiDAR point cloud derived parameters (i.e. EF and TF). Then the exact size of the data inputted into the machine learning network for training, testing and validation is highlighted.

Chapter 6

Results and discussion

6.1 Introduction

In this section of the thesis, the results of the Pearson correlation test conducted between the LST and each morphological parameter (i.e., NDVI, NDBI, EF, TF, and Albedo) is firstly reported and discussed. Then, the predictive performance of the model developed by training the significantly correlated parameters is evaluated to show the improved prediction accuracy of the model trained with the terrain factor in relation to the model trained without the terrain factor. Then, the factor characterization performed to determine which morphological individual, or group of parameters have the most effect on the LST intensity for each area is reported and discussed. Lastly, the chapter discusses the results of the model validation, which involved testing the developed model on areas not previously used for the training.

6.2 Parameter correlation testing

To avoid overfitting of the model, a correlation analysis is conducted on all parameters to ensure significant correlations with the target parameter of LST, before inclusion of them in the training process. Using Pearson correlation method, the correlation coefficients as shown in [Figure 6.1](#) are calculated. For Oak Brook study area, the surface albedo has no significant correlation with the LST in that study area. Hence, the parameters used for the model training in Oak Brook include TF, EF, NDVI and NDBI. Furthermore, the correlation analysis also shows NDBI to be the most significantly correlated parameter with the LST in this area. Also, TF is seen to have a higher correlation with LST in this area than the urban superstructures represented by EF. This further justifies the selection of TF as a training parameter.

For North Park study area, all the five morphological parameters, including surface albedo, TF, EF, NDVI, and NDBI, proposed for the model training have significant correlation with the LST of the area. However, NDVI is seen to have the highest correlation with the LST, and TF

is the least correlated. This is because North Park has a relatively flat terrain, which implies that the negligible variations in the topography would not have as much impact on the LST in relation to Oak brook study area.

	<i>TF</i>	<i>EF</i>	<i>Albedo</i>	<i>NDVI</i>	<i>NDBI</i>	<i>LST</i>	
LST	0.75	0.07	-0.01	-0.83	0.84	1	a

	<i>TF</i>	<i>EF</i>	<i>Albedo</i>	<i>NDVI</i>	<i>NDBI</i>	<i>LST</i>	
LST	-0.11	-0.17	0.15	-0.61	0.5	1	b

Figure 6.1 Pearson correlation coefficient values indicating the correlation strength of each morphological parameters with the LST in a) Oak Brook, and b) North Park study areas.

6.3 Model performance

The error histogram plot for both ANN models trained with TF and without TF for Oak Brook study area, as shown in [Figure 6.2](#) can be found to be almost normally distributed with majority of the errors per pixel falling with ± 1 ; this implies on a good predictive capacity of both models. Also, the residual plots for the training, validation and testing of both models are quite close to the line of best fit at 45° angle, which demonstrate a significant correlation between the target parameter (LST) and the morphological parameters.

However, [Figure 6.2](#) and [Figure 6.3](#) show the impact of integration of the proposed morphological parameter TF, which accounts for the surface elevation and relief of an area, to train a predictive ANN model. Compared to the base model trained with morphological on-surface elevation feature (e.g., EF). The ANN model trained with TF has a higher predictive accuracy as its RMSE for the training, validation and testing processes are 0.90, 0.92 and 0.90 °C, respectively. These values are relatively lower than the RMSE from the model trained without the proposed factor TF as the values are found as 1.26, 1.29 and 1.20 °C, respectively. The implication is that the integration of TF to the training process expanded the learning scope of the model to cover the impact of surface elevation changes, which is understood

from the correlation analysis in Figure 6.1 as a significant morphological factor in the considered study area.

Also, it can be seen that integration of the TF results in a significant improvement in the coefficient of determination R^2 for the overall model in Oak Brook study area from 0.74 to 0.81. Since the coefficient of determination R^2 indicates a model's ability to explain the variability in the dependent parameter, this significant improvement in R^2 demonstrates that TF significantly impacts on the UHI intensity and formation in the studied area as the new model can explain up to 81% of the variance in LST of the area.

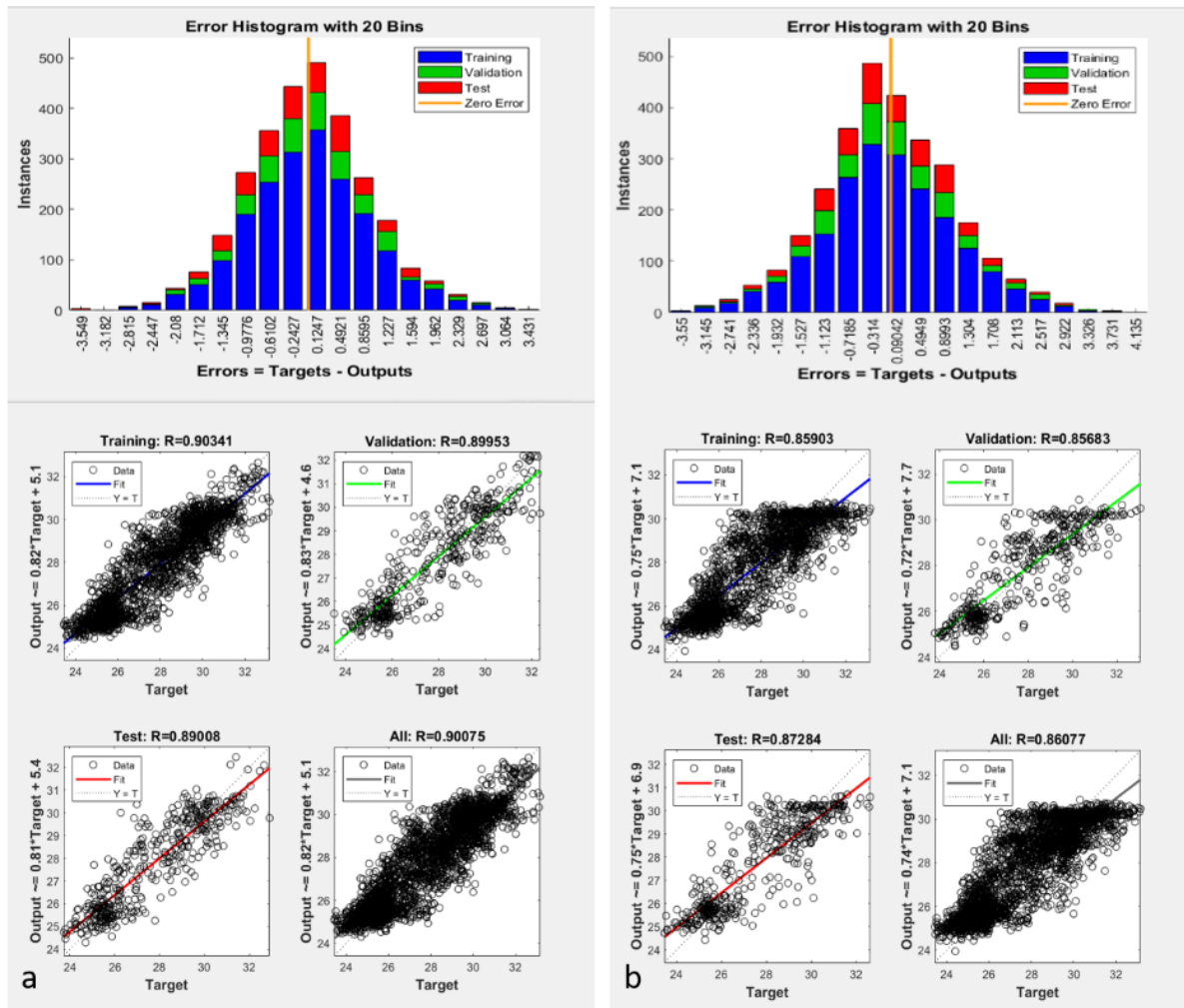


Figure 6.2 Model performance results, error distribution, and residual plots of ANN model for Oak Brook study area (a) with TF, and (b) without TF.

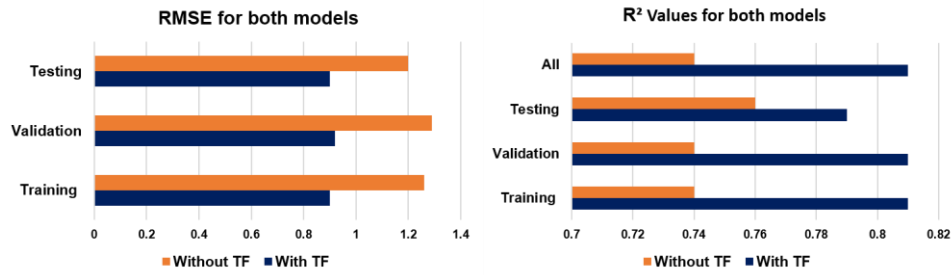


Figure 6.3 RMSE and R^2 comparison of both models for Oak Brook study area.

The model performance results for North Park study area are shown in Figure 6.4 and Figure 6.5. It can be seen that the R^2 which is the ability of the model to explain the variance in the LST for this area is relatively lower than the R^2 values from the model trained with the Oak Brook study area. This is because North Park is located in the heart of Chicago city. A typical urbanized city like Chicago, would be characterised, by high population, increased emission levels due to transportation and other industrial activities, and a more diverse nature of human activities. All of these can impact on the LST beyond the selected parameters used for the training process. Therefore, a relatively low R^2 indicates that the best model can only explain up to 54% of the variance in the LST for this area.

Furthermore, it can be seen from Figure 6.4 and Figure 6.5 that unlike Oak Brook study area, the model without TF have slightly better R^2 values for the training, validation and testing procedures with the values of 0.50, 0.53, and 0.55, respectively. While these values were respectively 0.5, 0.47, and 0.47 for the model trained with TF. Nonetheless, no significant changes can be seen in the RMSE values for both models because, the integration of TF to the model have shown not a significant improvement in the learning scope of the model. Since this area is relatively flat, it is unlikely that a marginal variation in the elevation to impact on the LST.

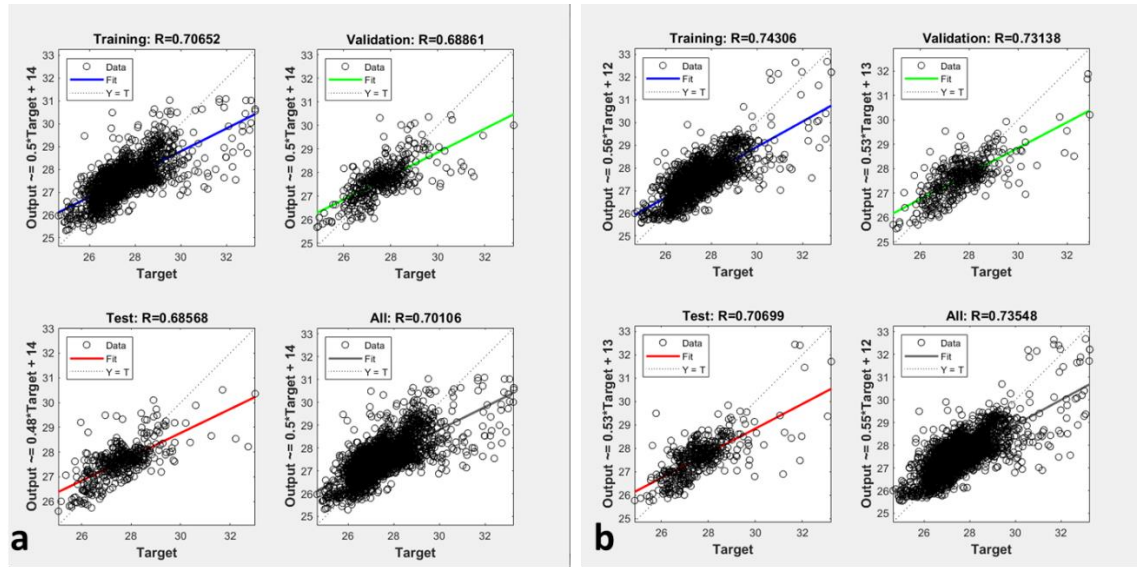


Figure 6.4 Model performance results showing residual plots of ANN for North Park study area (a) with TF, and (b) without TF.

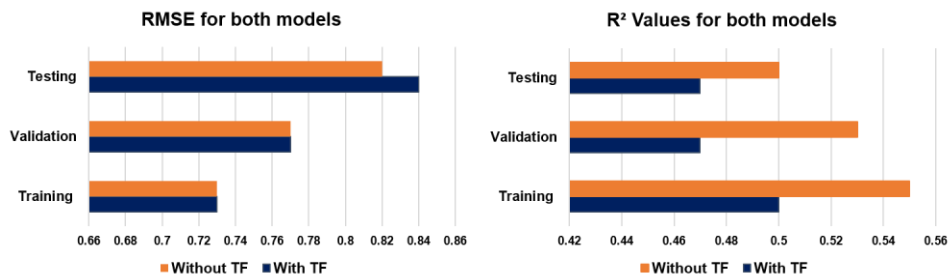


Figure 6.5 RMSE and R^2 comparison of both models for North Park study area.

6.4 Factor characterization

A factor characterization is conducted to determine the most influential morphological parameters that explains the variance in LST for the two study areas of North Park and Oak Brook. From Figure 6.6 the most influential parameters for Oak Brook are a combination of NDBI and NDVI represented by CD. This finding agrees with the results of the correlation test previously reported in Section 6.2, where these two parameters had the most significant correlation with the area LST. Furthermore, this implies that these two parameters collectively have the capacity to explain nearly every variance in the LST distribution for the considered area Oak1 (see Section 5.2.1). NDBI and NDVI are indices for built up areas (Urbanised) and vegetation spread in the area respectively. Hence, their ranking as the principal influential parameters reveals the important of vegetation in mitigating the UHI.

Also, as depicted in [Figure 6.6](#), the significant influence of the NDBI is represented by C as an independent morphological parameter related to the LST formation and intensity. The NDBI accounts for the urbanization effect, which mostly includes replacement of the natural land with artificial materials. Hence, it suffices to say that urbanization activities are the principal morphological factors of the UHI in such urban climates.

From the factor characterisation chart in [Figure 6.6](#), the proposed parameter of TF is denoted by A, which is ranked as the 3rd most influential parameter. TF is the only parameter after NDBI with the capacity to independently explain to a significant extent the variance in LST distribution in the study area of Oak Brook. This further demonstrates the significant role that the surface elevation plays in the UHI formation and intensity for this area. Thus, the inclusion of this parameter seems to be an essential causative factor to train the model. It is important to mention that only NDBI and TF can independently explain the LST variance according to the Pareto chart of the standardized effects while not even NDVI, with a relatively higher significant correlation to LST than TF, can independently explain the variance in LST for this study area.

ABC (TF, EF and NDBI) ranked as the 4th most influential parameters combined in LST variation explanation as seen in [Figure 6.6](#). EF accounts for the urban elevation features above the ground such as buildings, trees, etc. These features play a vital role either in the UHI mitigation as in the shading effect caused by shadows from vertical features, as the thermal mass effect, and as an obstruction against wind flow and latent heat exchanges. Hence, its inclusion to the model is essential as it is understood as a significant causative factor. Furthermore, there seems to be a link between these three parameters as the more urbanized areas would ideally have more on surface elevation features such as buildings, utility poles, etc. In other words, more buildings and infrastructures would be ideally built on more relatively flat surfaces, so the UHI is expected to be more intensified around a more flat surface in most of the occasions.

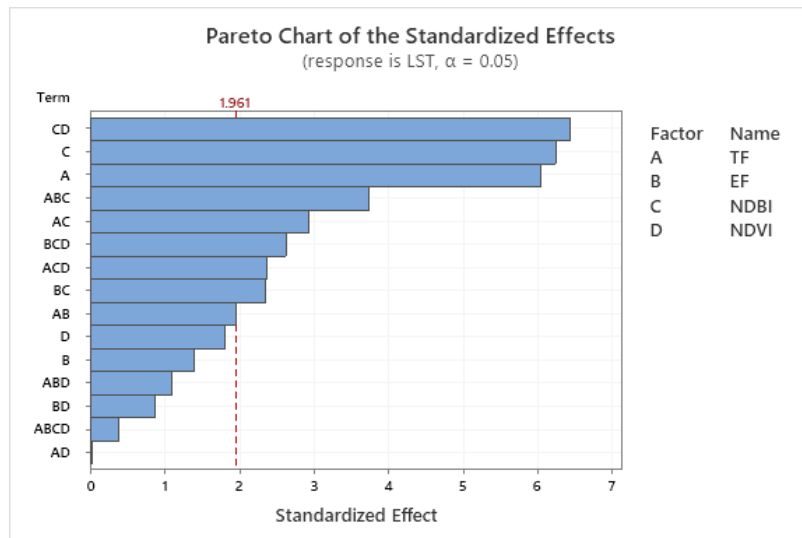


Figure 6.6 Pareto chart of the standardized effects for Oak Brook study area.

The results for the factor characterization for North Park is shown in Figure 6.7. Where the most influential parameter with the ability to independently explain the variance in LST for this area is NDVI, which is denoted by E. This outcome agrees with the result of the correlation analysis in section 6.2, where the NDVI also had the highest correlation value to the LST distribution in this study area. North Park and its surrounding towns are mostly urbanised, which implies that most natural surfaces have been replaced with artificial ones. It is evident for natural surfaces, such as open areas of grass, trees, water bodies, etc., which NDVI represents its significant impact on the LST distribution.

Also, Figure 6.7 shows that surface albedo and TF, denoted by BD, are collectively ranked as the second influential parameter for this area. In a typical city with increased artificial surfaces, it suffice to mention that surface albedo is a significant parameter in the UHI intensity in this study area, unlike in Oak Brook study where the surface albedo was not significantly correlated with the LST. Furthermore, since the UHI effect is intensified by trapped solar rays, flat surfaces tend to reflect more solar radiation back into the atmosphere due to their higher view factors in comparison with surface with higher elevations.

The third influential parameter for North Park is a combination of EF and NDVI indicated by A and E. Since North Park is a more urbanized area in terms of surface features, which is more

impacted by the shading effect caused by vertical features, the thermal mass absorption, and obstruction of wind flow and latent heat exchanges. All of these effects can intensify the UHI in this area. The significant impact of NDVI, which accounts for vegetation and natural surfaces has already been described in the previous section.

Furthermore, it can be seen from [Figure 6.7](#) that TF is ranked as the forth influential parameter for this area. This further proves that an area's topographic variation still remains essential in the explanation of the UHI formation and intensity.

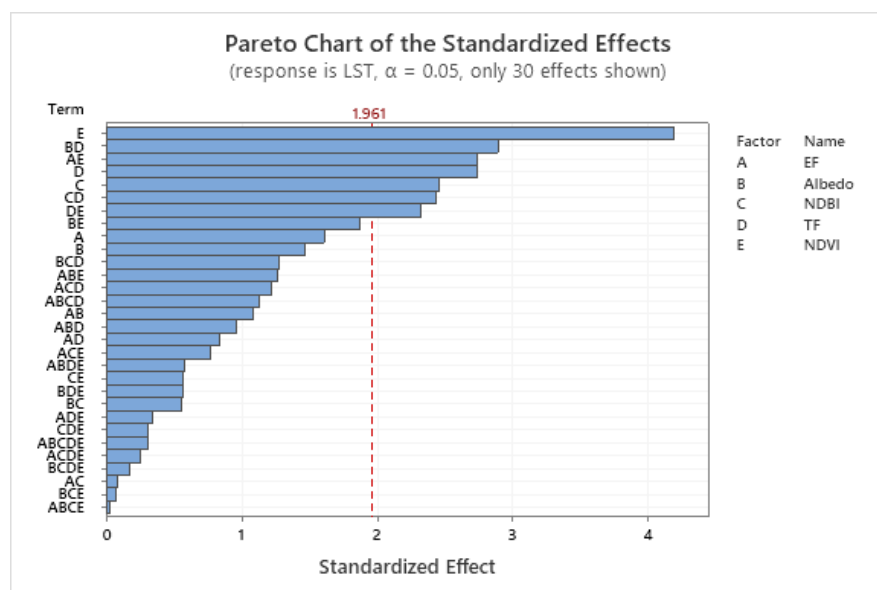


Figure 6.7 Pareto chart of the standardized effects for North Park study area.

6.5 Model validation

The essence of the model validation is to assess the accuracy of the LST predictive models in relation to the impact of adding the topographical variation to the training process. To conduct this validation, the developed models with TF and without TF is used to predict the LST for a section of the city named Oak 1 in [Figure 5.3](#). Substantial topographical variations can be observed in this area compared to the North Park study area. Also, to further understand the impact of TF in the LST prediction, the models are used to predict the LST for a row of 30 pixels, which are not previously included in the training process.

6.5.1 Oak 1

Figure 6.8 shows the morphological parameters used in the training and developing the predictive models. According to the correlation analysis, NDBI has a strong positive correlation with LST, hence, the highest LST points are distributed along the areas with high NDBI values, representing intense impervious surfaces or built up areas. Similarly, NDVI, which has a strong negative correlation with LST, is seen to impact the LST distribution as LST intensity can be observed in areas with low NDVI, which represents vegetation. The impact of the positive correlation of TF with LST can also be observed in most parts of Oak 1 as the LST tend to be intensified on areas with higher terrain elevations as observed in Figure 6.9. The impact of the on-surface elevation features represented by EF, which has a relatively low positive correlation with LST, can be seen to follow a similar trend as the NDBI with LST intensity in points of high EF.

From Figure 6.9, the predictive performance of both models is compared to the satellite measured LST distribution of Oak1 area. The model trained with TF is seen to perform better at highlighting the LST hot spots that match with the measured LST distribution map compared to the model trained without the proposed factor TF. Towards the left side of the TF map shown in Figure 6.8, where there seems to be significant variance in the surface elevation, the model trained with TF is seen to highlight the LST distribution to match the measured LST even better than the model trained without TF. This is indicating how integrating TF to the learning process improves the models' understanding related to the impact of varying terrain.

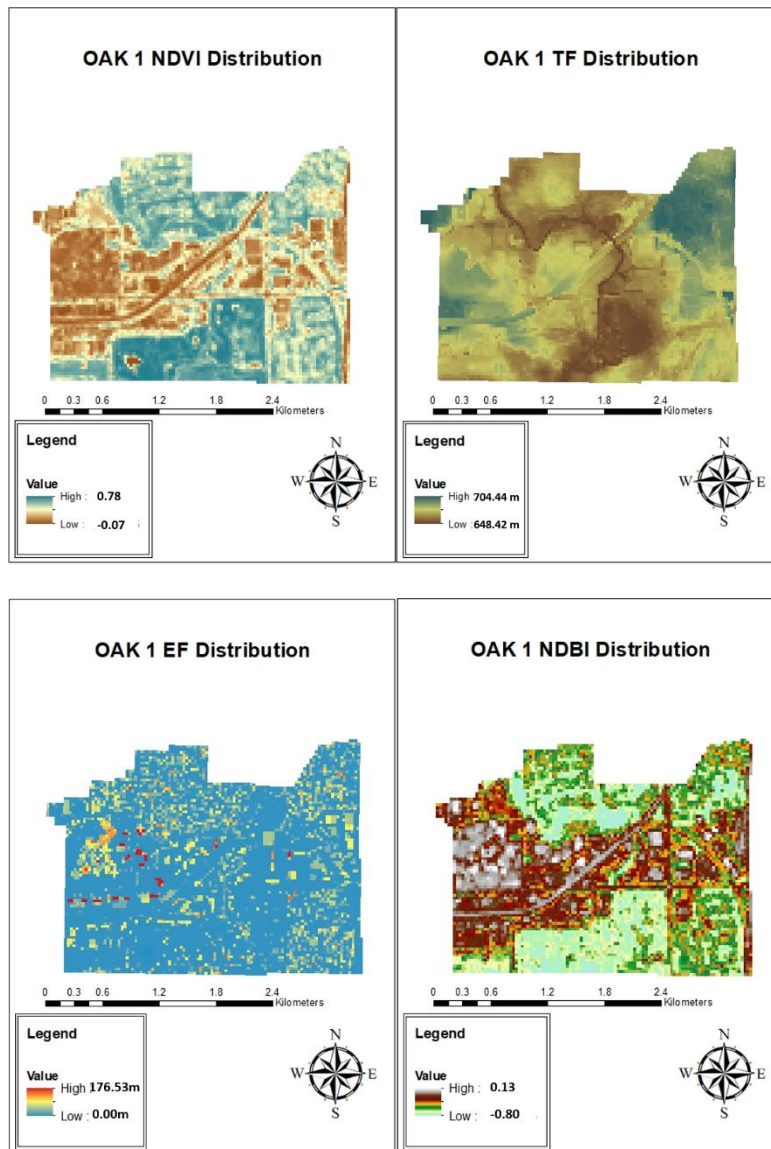


Figure 6.8 A pictorial illustration of the distribution of each morphological parameters Oak1 area.

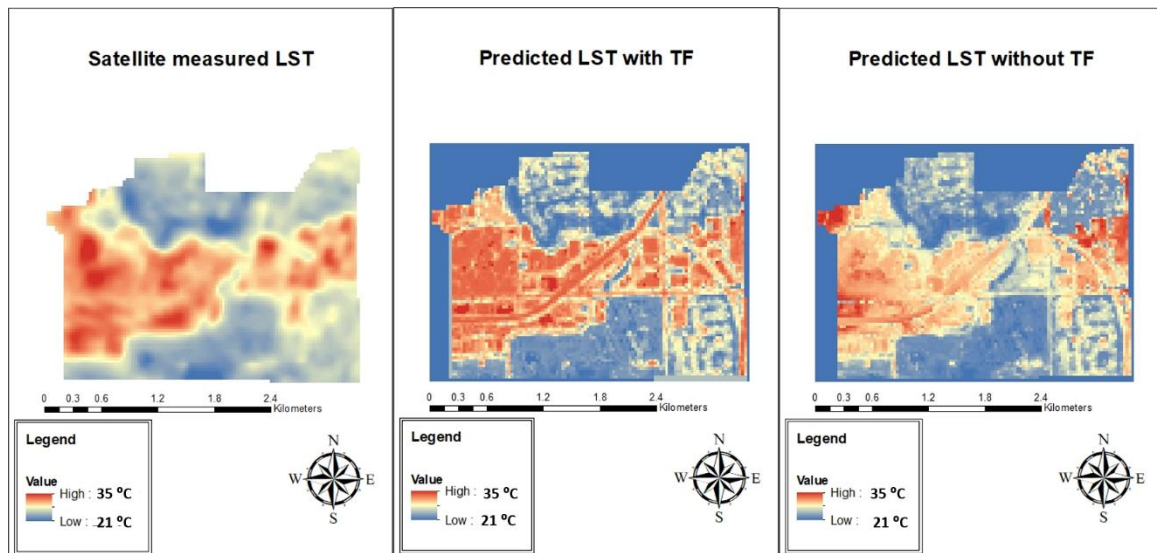


Figure 6.9 Comparison maps for the measured and predicted LST of Oak1 area.

6.5.2 Test Row

To further understand the predictive performance of both models and examine the prevailing factors that result in the variance between measured and predicted LST, the test row is evaluated in this section. From Figure 6.10, a major observation is that the ground surface is not flat, contrary to the assumption by numerous studies in exploring urban elevation parameters, which often neglect the impact of varying surface elevations. Also, it can be seen that the TF profile follows a descending pattern aligned with the surface elevation from left to right.

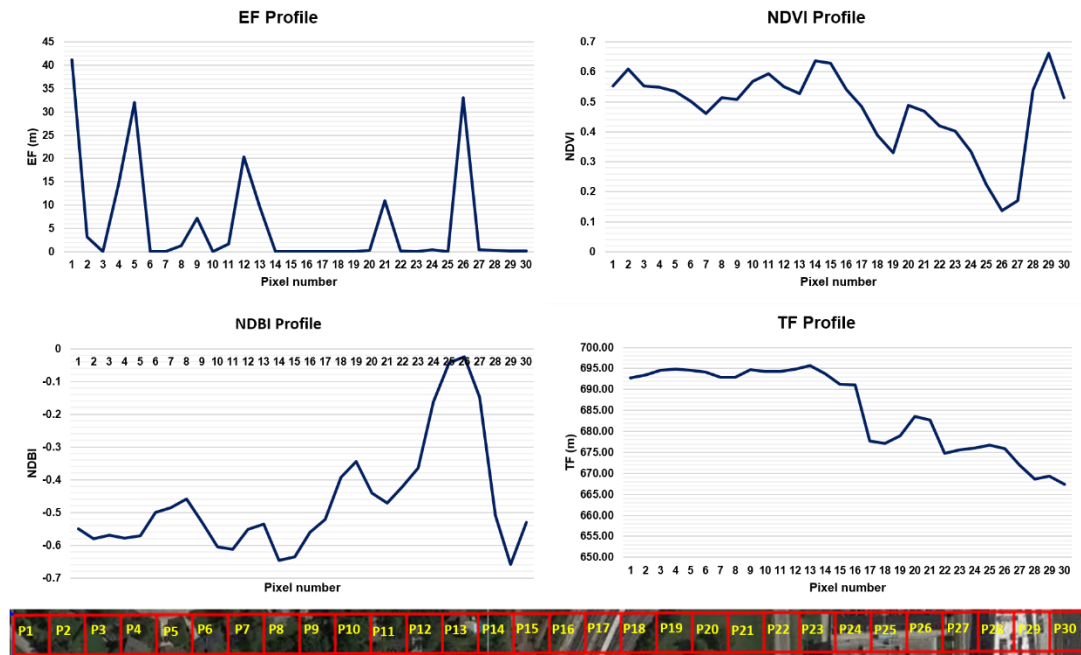


Figure 6.10 Test row parameter profile and bird-eye view of each pixel.

The predictive performance of both models in the LST prediction for the test row is firstly analysed with the absolute error box plot shown in Figure 6.11. The model trained with TF is seen to perform better in overall than the model trained without TF. The error distribution shows that over 75% of the error from the LST predicted by the model trained with the proposed parameter TF lies with 0 and 1°C, which is relatively better than the error distribution for LST predicted for the model excluding TF while over 75% of the error lie between 0.2 and 1.8°C. Also, nearly 100% of the error of the TF trained model is seen to lie within 0 and 1.8°C while the predictions from the model trained without TF has 25% of its error distributed within 1.8 and 2.2°C. Furthermore, the median for the error distribution of both models, indicated by the thick horizontal middle line in each box plot, renders a significantly lower median for the TF trained model predictions than the model trained without TF.

In summary, the model trained with TF demonstrates a higher predictive accuracy than the model trained without TF. However, there are a few cases as outliers observed from the box plot in Figure 6.11. The outliers occur in pixels 15, 28, 29 and 30 from the TF trained model and pixel 29 from the model trained without TF, where major outliers are indicated by asterisk

and minor outliers with circular dots. It is worth mentioning that (see [Figure 6.11](#)) the LST predicted by the model trained without TF for pixels of 15, 28, 29 and 30 are more accurate than those from the model trained with TF. This is because NDBI and NDVI (see [Figure 6.10](#)) play a more dominant role at these pixels as significant changes can be observed at the value points around these pixels while the surface elevation situation at these points are seemingly flat (unchanging). Hence, the TF trained models perform not accurate in these pixels compared to the model trained without TF as the effect of TF is negligible. Furthermore, the TF profile shows that the pixels 15, 28, 29 and 30 are positioned relatively lower than preceding pixels from the left side with a significant height difference in each case. Also, it can be seen that these pixels have no on-surface feature on them as shown by the EF profile in [Figure 6.10](#). There is a high possibility of shadow or leeward effect generated from either nearby on-surface elevation features represented by EF, or nearby higher surface elevation indicated by higher TF values, obscuring the accurate reading of the LST by the satellite. Hence, the minor and sever cases of outliers can be observed in LST prediction in both models. In summary, this disparity in the LST values indicates the impact of considering fewer factors in the explanation of the LST variance. Hence, the scope of the morphological parameters should be broadened to include more topological as well as climatic factors to improve the LST prediction of the cities.

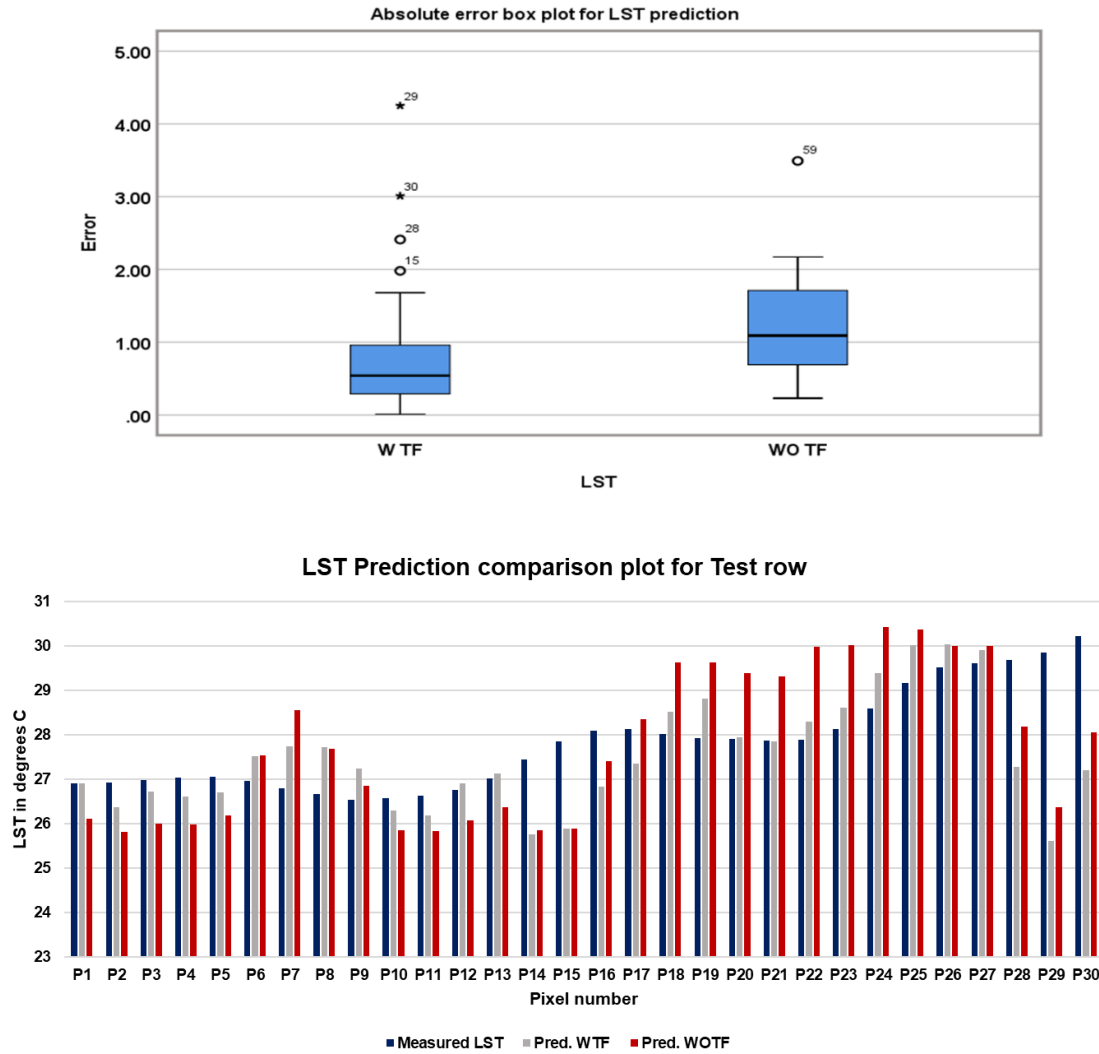


Figure 6.11 Error distribution box plot and predicted LST comparison plot for test row.

To further analyse the performance of each model, the variance between the predicted LST and satellite measured LST for the test row is evaluated by the defined error metrics in equation 4.13, 4.14, and 4.15 in section 4.4 of this thesis. From Table 6.1, it can be seen that the RMSE gives a relatively high weight to large errors, because the errors are squared before they are averaged. This means that RMSE is able to the variance associated with the frequency distribution of error magnitudes, making it most suitable in highlighting large errors compared to the other presented metrics. Furthermore, it can still be observed from most of the metrics that the model with TF shows a higher accuracy.

Table 6.1 Error metrics results used to compare the model performance between the model trained with/without TF models.

Error metric	LST w/TF	LST wo/TF
RMSE	0.93	1.11
MAE	0.87	1.24
NMB	-0.01	0.00
NME	0.03	0.04

RMSE = Root mean Square Error, MAE = Mean Actual Error, NMB = Normalized Mean Bias, NME = Normalized Mean Error.

Chapter 7

Conclusion and Recommendations

7.1 Introduction

The overall aim of this thesis is to explore the extent of impact the elevation aspect of cities have on the UHI formation and intensity, as well as to develop a model with improved UHI spatial distribution prediction capacity. Two aspects of the urban elevation are explored, namely (1) the on-surface urban features and (2) the topographical features of the city.

7.2 Conclusion

To establish the relevance of the two novel urban elevation parameters defined in this study the Pearson correlation test was firstly conducted to determine the correlation strength of the proposed elevation parameters (i.e EF and TF) with the LST. The correlation strength of other morphological parameters used for the model training were also tested to determine fitness to be included in the ANN model training exercise. For Oak Brook study area, the Pearson correlation coefficient results showed that NDBI, NDVI, TF and EF were significantly correlated with the LST with NDBI as the most significantly correlated factor and EF with the least significantly correlated one. For North Park study area, five parameters used for the training process, including NDBI, NDVI, EF, TF, and surface albedo, with NDVI as the highest correlated factor with LST and TF as the least correlated one. It can be concluded that the surface elevation represented by the TF impacts more on the UHI than on-surface features represented by EF for areas with significant topographical variations. Nonetheless, in areas with low topographical variations, the TF has less impact on the UHI.

To further explore the impact of the terrain factor, an ANN model is trained to predict the spatial distribution of the UHI in two areas representative of low and high topographical variations, using conventional remote sensing method based on derived morphological parameters with integration of a newly proposed morphological parameter, known as terrain factor (TF). TF

accounts for the topological factors, including surface elevation and relief. The performance of the predictive model is seen to be significantly improved in the LST prediction for the area representative of a high topographic terrain, as its RMSE in the model training validation and testing decreased from 1.26, 1.29, and 1.20 to 0.90, 0.92, and 0.90, respectively, and its overall R^2 increases from 0.74 to 0.81 compared to the model, excluding TF. However, the inclusion of TF to the model training did not result in a significant improvement in the LST prediction in the area representative of a low topographical variation (relatively flat). Hence, it can be concluded that TF is an essential factor to explain the UHI formation and intensity in areas with high topographical variations.

Also, the Pareto chart of the standardized effects was used to further emphasises on the significance of the proposed parameter TF as its ranked 3rd most influential independent parameters in Oak Brook study area and 4th in North Park study area, according to the Pareto chart of the standardized effects. This implies that the vertical morphological parameters' impacts on the UHI are not limited to on-surface features.

As another conclusion from this study, it is observed that the ANN model developed with the proposed TF performs better in the LST prediction in areas with complex surface elevation than those with a relatively flat one. In the contrary, the model trained without the TF does not show an advantage in areas with a relatively flat surface terrain.

7.3 Recommendation for future research

The improvement in the predictive performance of the proposed model developed with the newly define urban elevation parameters demonstrates potential of developing a robust predictive model for spatial distribution with high accuracy, through the broadening the scope of the parameters selected for model training. Also, this study shows the significant of the elevation aspects of cities in explaining UHI spatial distribution. Hence, future work is recommended to explore extensively other parameters associated with urban elevation aspects, beyond those covered by this study, for example, terrain slope and terrain angle.

Furthermore, the scope of this study was limited to improving the prediction of spatial distribution of UHI in cities. Hence, further work is recommended to expand the scope of UHI prediction cities to temporal, so as to track the rising trend of UHI over a period, and better understand the associated factors responsible for the trend.

Future studies should include the impact of atmospheric and climatic factors that influence the LST on a given pixel.

7.4 Application of developed model

Based on the results presented, the developed model excelled significantly in predicting LST for areas with high topographic variations. Hence, making it a suitable tool for accurate LST prediction in areas of high topographic variations. Achieving accuracy in LST prediction is important since LST has been widely adopted to indicate UHI.

The LST provides a means of mapping UHI and also a means for policy makers, researchers, and town planners to evaluate the efficiency of their proposed urban intervention strategy to control UHI effect in any given area. Also LST can be used as boundary conditions in Building Energy Modelling simulation cases where outdoor surface temperature data is not available.

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