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ORIGINAL RESEARCH PAPER

# Urban heat island classification through alternative normalized difference vegetation index

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**ABSTRACT**

**BACKGROUND AND OBJECTIVES:** Urban heat island is characterized by higher temperatures in urban areas compared to their surroundings. Vegetation, as measured by the normalized difference vegetation index, is essential for reducing urban heat island effects and impacting land surface temperature. The emergence of machine learning techniques, particularly the random forest approach, has led to improved precision in predicting land surface temperatures. This study explores alternative normalized difference vegetation index adjustments to understand their impact on urban heat island classification in Chiang Mai, Thailand. It investigates how changes to the normalized difference vegetation index can help to be part of practical urban planning measures, such as prioritizing vegetation type and location for cooling strategies in urban areas. Furthermore, the study intends to underscore the significance of vegetation as a viable solution for reducing the detrimental effects of urban heat islands while also promoting greater livability in urban environments.

**METHODS:** Satellite data from Sentinel-2 and Landsat 8 for 2016–2022 were used to develop a 20-meters grid resolution dataset, resulting in approximately 2 million points. Random Forest was employed to predict land surface temperature, followed by systematically adjusting normalized difference vegetation index values from-100 percent to +100 percent in 10 percent increments. Urban heat island was classified based on standard deviation thresholds. Results were examined and visually compared utilizing a geographic information system, which incorporated spatial variations and heat intensity patterns to gain deeper insights into the urban landscape.

**FINDINGS:** Adjusting normalized difference vegetation index values showed a nonlinear relationship with land surface temperature predictions, where certain thresholds caused unexpected decreases in Land Surface Temperature. The identification of urban heat island classifications highlighted various urban regions, each exhibiting unique heat intensity levels. The visual assessment revealed marked differences between the reference case and alternative scenarios, illustrating the responsiveness of land surface temperature to vegetation density. the results also emphasized the role of high normalized difference vegetation index values in cooling urban regions and reducing urban heat island intensity, while extreme reductions in vegetation led to potential misclassification of water bodies, creating anomalies in cooling patterns. The findings of this study highlight significant variables that contribute to the dynamics of urban heat islands, with a particular focus on alterations in vegetation. This information can serve as a valuable resource for future urban planning initiatives.

**CONCLUSION:** The study demonstrates the influence of normalized difference vegetation index on urban heat island classification and its potential in urban planning strategies. By showcasing nonlinear trends, the study further emphasizes the necessity of investigating vegetation dynamics in relation to land surface temperature predictions. The findings contribute to a deeper understanding of urban heat island effects and establish a groundwork for refining machine Learning models and urban planning frameworks. Future studies could expand to other urban areas, incorporate additional variables, and refine predictive algorithms for broader applications. This study will lay the groundwork for the advancement of future real-time monitoring tools that will enable proactive and sustainable solutions to urban heat island problems.

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## INTRODUCTION

Urban areas worldwide are experiencing rising temperatures relative to their suburban and rural counterparts, a phenomenon widely recognized as the urban heat island (UHI) effect. This phenomenon is mainly caused by urbanization, which transforms natural environments into impermeable surfaces like buildings, roads, and concrete. These materials absorb heat during the day and slowly release it over time, both day and night (Rajagopal *et al.*, 2023). Anthropogenic activities including industrial processes, vehicle exhaust, and air conditioning usage, exacerbate the UHI effect by introducing additional heat into urban areas (Singh and Sharston, 2023). The heat generated by these sources plays a significant role in global warming and affects urban surfaces, leading to heightened UHI effects in areas with dense construction. As cities expand, understanding and mitigating these interactions becomes important for urban researchers (Ulpiani, 2021). With the background of global climatic change, the UHI effect has become an urgent concern for city planners and environmental managers in recent years. The growth of urban areas necessitates effective thermal environment management to promote sustainability, safeguard public health, and elevate the quality of life for residents. Continuous expansion increases urban density, entailing higher building and human activity concentrations, which could trap and accumulate heat within city areas (Shi *et al.*, 2023). In regions with a tropical climate, such as Chiang Mai, the influence of UHI is heightened due to seasonal shifts in weather patterns, alongside the already high ambient temperatures. These changes cause localized heat discomfort and heat stress, particularly in areas with limited vegetation and high water table (Rinchumphu *et al*., 2024). UHI has adverse health effects on residents in the area, such as increased risk of cardiovascular disease, heatstroke, and premature death (Athokpam *et al.*, 2024). This buildup of heat in city environments contributes to higher average temperatures, thereby increasing the necessity for cooling systems to mitigate indoor heat. Elevated temperatures in urban areas are associated with increased energy consumption, particularly for air conditioning systems. When outside temperatures rise due to the UHI effect, buildings require more energy to maintain comfortable indoor environments (López-Guerrero *et al.*, 2024). As the demand for cooling rises, energy consumption and costs also increase, resulting in greater greenhouse gas emissions. This situation worsens the UHI effect, as the heat generated by air conditioning units contributes to higher outdoor temperature. This feedback loop creates a cycle where rising outdoor temperatures increase cooling demands, increasing urban heat levels (Chen and You, 2020). Consequently, susceptible populations, such as senior citizens and low-income households, experience elevated health risks stemming from direct heat exposure and the financial challenges associated with heightened energy costs. These weaknesses highlight the need to target cooling solutions, prioritizing areas where socioeconomic factors limit adaptability. This issue has led to increased efforts to monitor and mitigate UHI effects as part of broader urban sustainability and climate resilience strategies. An essential technique for tracking UHI is the examination of land surface temperature (LST) data, accessible through aerial and satellite imagery (Xu *et al.*, 2023). LST data effectively tracks temperature variations across different land surfaces, offering a valuable perspective on the distribution and intensity of UHI effects (Almeida *et al.*, 2021). However, while LST data have proven to be suitable for broad-scale analysis, they often lack the spatial resolution required for finer-scale urban planning. By leveraging thermal imaging, researchers and policymakers are able to detect “hotspots” in urban settings, which facilitates targeted actions to reduce heat in these areas. Potential interventions include enhancing green spaces, utilizing reflective building materials, and initiating urban greening initiatives (Wang *et al.*, 2016). The normalized difference vegetation index (NDVI) was reported as a threshold variable that implied its relationship with LST did not change until beyond a critical threshold, such as different levels of urbanization and different climatic zones. The findings of these studies underscored the multifaceted role that vegetation plays in reducing the UHI effect. Typically, greater vegetation cover leads to lower LST. Nevertheless, this cooling effect can weaken or change direction depending on the specific urban environment and a range of influencing factors (Ali *et al.*, 2024). This study focuses on Kayseri and Tuerkei based on the LST and UHI effects analysis. It showed a strong negative

correlation with UHI and NDVI, with a 20 percent (%) increase in NDVI. From there, the range for LSTs dropped from 21–51 degrees Celsius (°C) in 2013 to 18–40 °C in 2022 (Cetin *et al*., 2024). Integrating machine learning (ML) techniques in UHI research has further advanced the analysis of factors influencing LST and UHI patterns. Random forest (RF) and other ML models have been effectively utilized on large datasets, exposing complex interactions between urban elements, vegetation indices like NDVI, and the factors that contribute to temperature changes (Addas, 2023). ML techniques also hold significant potential for urban planning, allowing planners to make data-driven decisions regarding city layouts that consider UHI mitigation (Lin *et al*., 2023). However, the green infrastructure is functional in mitigating urban heating, and its performance heavily relies on climatic aspects, vegetation type, and aspects relating to how the city is set out. The use of predictive modeling for integration optimization is instrumental in advancing air quality, fostering biodiversity, and supporting social well-being, highlighting its vital importance in achieving sustainable urban development (Azmeer *et al*., 2024). By leveraging these methods, researchers and urban planners can better understand the elements that contribute to UHI intensity and predict future patterns under various urban development and climate scenarios, helping design urban layouts that reduce heat accumulation and improve overall urban livability. The current study aims to introduce a novel method for the systematic alteration of a wide spectrum of NDVI values, subsequently examining the resulting nonlinear impacts on the UHI intensity. Consequently, this holds particular importance in tropical cities, where the interplay of vegetation is vital for controlling extreme temperature fluctuations. This study focuses on a designated urban planning region in Chiang Mai Province, Thailand (Fig. 1), where the UHI effect is increasingly evident. The study area covers approximately 429 square kilometers ($km^2$) and is characterized by a tropical climate typical of a savanna biome. The region is marked

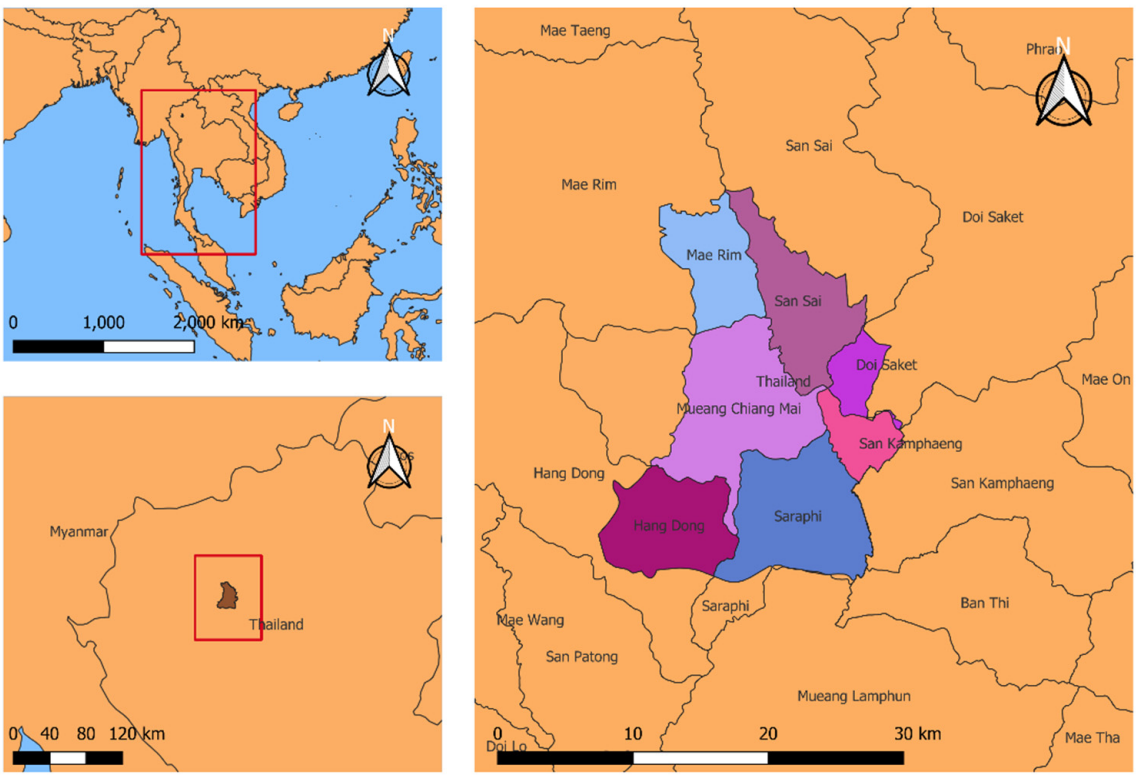


Fig. 1: Geographical location of the study area in Chiang Mai Province, Thailand

by three distinct seasonal phases: the dry season, the cool season, and the wet season, with each phase presenting unique climatic characteristics that impact the dynamics of UHI. Research on UHI effects in Chiang Mai is limited despite its rapid urbanization and unique climate, highlighting the need for further studies to inform sustainable urban planning. Chiang Mai's rapid urbanization and tropical climate make it an ideal location to examine UHI patterns and develop predictive models using satellite-derived LST data and ML techniques. The objective of this study is to investigate changes in LST, assess the role of vegetation cover through modifications in the NDVI, and implement machine learning techniques to refine UHI classification and urban planning methodologies. This study was conducted in Chiang Mai Province, Thailand, between 2016 and 2022, focusing on an urban planning region with significant UHI effects.

This study utilizes satellite data from Sentinel-2 and Landsat 8, collected between 2016 and 2022, to analyze temporal and spatial UHI patterns in Chiang Mai's rapidly urbanizing tropical environment. This study aims to assist urban planners and environmental policymakers in formulating strategies to alleviate the impacts of UHI, improve urban resilience, and design sustainable cities, particularly in Chiang Mai and other tropical cities globally.

## MATERIALS AND METHODS

*Remote sensing (RS)*

RS has become essential for observing and tracking environmental changes, especially concerning the UHI effect (Zeren *et al*., 2023). The utilization of satellite imagery allows for the acquisition and assessment of environmental data over vast areas. The quality of this data's resolution is influenced by the satellite's technical specifications. For instance, the Landsat 8 satellite, a widely used platform, can capture detailed images of the Earth's surface, including thermal data for assessing LST. This satellite has been applied in studies to compare LST between urban and rural regions (Cetin *et al.*, 2024). Furthermore, satellite imagery is instrumental in studying urban development, measuring the extent of urban sprawl, planning urban areas, and creating effective management approaches. While aerial photography and satellite data can be used in various research applications, these technologies also come with certain limitations, such as the restricted frequency of image captures per day and the inability to control the number of clouds (Errea *et al.*, 2023).

*Variables involved in UHI studies*

LST data effectively tracks temperature variations across different land surfaces, offering a valuable perspective on the distribution and intensity of UHI effects. Prior studies into the UHI phenomenon have pointed out various essential factors that play a critical role in affecting land surface temperature LST. Key factors include aspect, surface roughness, slope, normalized difference built-up index (NDBI), normalized difference water index (NDWI), and NDVI (Sameh *et al.*, 2022). These variables are represented in Fig. 2.

Aspect refers to the directional orientation of a slope, significantly impacting the level of solar radiation that an area is exposed to. Areas with differing orientations are subject to varying degrees of sunlight exposure, which consequently influences LST in urban environments (Peng *et al.*, 2020). Roughness represents a surface's instability, signifying elevation changes across a terrain. This variable has the potential to influence wind movement, subsequently affecting how heat is distributed. Areas within cities that exhibit increased surface roughness are likely to retain higher levels of heat (Sen and Roesler, 2020). The terrain's slope, or gradient, can influence the movement of air and water, impacting the local climate. In urban areas with varying inclinations, slope is a key factor in shaping how heat is absorbed and distributed (Liu *et al*., 2021). The NDBI measures the concentration of built structures in urban areas. Elevated NDBI values are associated with regions of higher density, typically marked by numerous buildings and road networks (Suharyadi *et al*., 2022). A higher NDBI correlates with an increased area of concrete surfaces. Due to its substantial thermal mass and low albedo, concrete's dense structure effectively retains solar energy throughout the day (Mahata *et al*., 2024). NDWI measures the presence of water within a specific area. In UHI studies, it is applied to evaluate the cooling influence of water bodies and moist surfaces, which can help alleviate heat in urban settings. A study performed in Chiang Mai Province

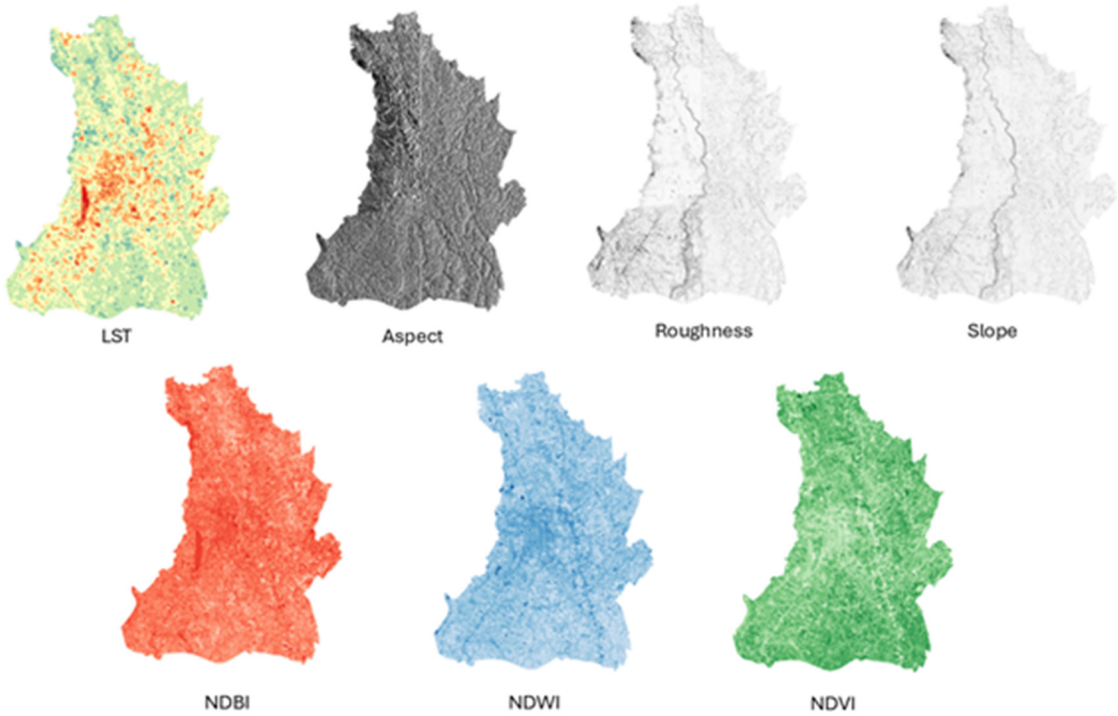


Fig. 2: presents a map highlighting their importance to UHI in Chiang Mai Province

has explored the temperature-regulating effects of parks, demonstrating their extensive impact on the regional climate (Nantarat *et al.*, 2021)**.** The NDVI is a widely utilized metric in RS research to assess vegetation abundance and density (Sadeh *et al.*, 2021). The index is formulated from the variation observed between the near-infrared (NIR) and red bands of the electromagnetic spectrum, which are captured by satellite imagery. Greater vegetation density can lead to a notable decrease in LST through various cooling mechanisms: plants provide shade, diminish direct solar radiation, and promote transpiration. These mechanisms function in unison to decrease the temperature of the ambient atmosphere (Singh *et al.*, 2024). The NDVI index is developed based on the difference between NIR and red electromagnetic spectrum bands captured by satellites. To ensure that the data in this study was high in quality and relevant, three variables were extracted: NDVI, NDBI, and roughness. Drawing from earlier studies on urban climate, the variables have been chosen according to their respective importance. NDVI gives detailed information about vegetation cover with cooling effects, while the NDBI shows heavy urban density and impervious surfaces that hugely contribute to UHI intensity. Roughness, which is based on elevation data, was incorporated into this category to determine its role in influencing the movement of flow and the distribution of heat (Faisal *et al.*, 2021). The given research focuses on the physical and land-cover-related variables, but humidity, albedo, or even socioeconomic conditions may be crucial in the dynamics of UHI. Humidity impacts thermal comfort and heat retention, while albedo refers to the reflectivity at the urban surface, controlling the surface's ability to absorb or reflect solar radiation. Factors such as population density and income levels, which are often categorized as socioeconomic, generally relate to land utilization and the allocation of green areas, consequently affecting the intensity of UHI in an indirect manner (Pena Acosta *et al.*, 2023).

Table 1 shows the NDVI, which ranges from -1 to +1, and indicates how different surfaces are covered. It's

Table 1: NDVI value range description (Atun *et al.*, 2020)

| NDVI value range | Land cover type |
|---|---|
| High (0.5 to 1.0) | Dense and healthy vegetation |
| Moderate (0.3 to 0.5) | Sparse vegetation or lower-density vegetation |
| Low (0 to 0.3) | Barren land, urban areas, or minimal vegetation |
| Negative (-1 to 0) | Non-vegetative surfaces (water bodies, snow, clouds, bare soil) |

divided into four categories. The first classification, High NDVI, refers to locations abundant in lush and thriving vegetation, such as woodlands, orchards, agricultural fields, and community parks. The UHI effect is an important mitigation area in these areas, as they reduce the LST significantly by shading and evapotranspiration. Regions characterized by elevated NDVI values are typically associated with cooler climates and superior air quality. This phenomenon offers numerous advantages for the environment. The second category, Moderate NDVI, describes places with sparse vegetation or fewer plants. It might include grasslands, bushes, and certain urban areas that have some greenery. While these regions can help lower LST, their effect is less intense than in areas with high NDVI. Areas characterized by moderate NDVI typically serve as transitional zones where vegetation is sparse, but its cooling influence remains significant. These regions play a moderate role in mitigating urban heat stress and present opportunities for enhancement through focused greening efforts. The next category, Low NDVI, relates to urban spaces or areas with minimal plant cover. Low NDVI is associated with surfaces that don't allow water to pass through, which tends to absorb and retain heat. It leads to higher LST and contributes to the UHI effect. The low NDVI zones in cities often become hotspots of thermal stress, evidencing the need for increased vegetation or cooling technologies, like reflective surfaces or urban green roofs. The concluding category is Negative NDVI, signifying areas that lack vegetation, including bodies of water, snow, clouds, or exposed soil. These regions can particularly contribute to cooler areas because of the evaporation of water. NDVI is essential for studying how much vegetation is present. Cities with higher NDVI usually have less severe UHI effects (Singh *et al*., 2024). Through the examination of NDVI distribution, urban planners can pinpoint locations that are deficient in plant life and concentrate their efforts on enhancing green spaces in those regions (Tahooni *et al.*, 2023). Changes in NDVI can also impact UHI levels in cities.

*Overview ML*

Data preparation in quantum geographic information system (QGIS), a dataset was developed using QGIS to investigate the UHI effect and the impact of vegetation changes on urban heat (Isinkaralar, 2024). This dataset utilizes satellite images from Sentinel-2 and Landsat 8, covering 2016 to 2022. Representative locations within the study area were selected using a method of random point sampling. NDVI, NDBI, aspect, roughness, and LST data were collected and saved in comma separated value (CSV) format at each sampling point. This strategy precisely reflects the range of land cover types and their related thermal properties found in urban settings (Tanoori *et al.*, 2024). ML has become a crucial tool in environmental studies, primarily due to its ability to manage large datasets and model complex relationships, including linear and nonlinear patterns among variables (Lin *et al.*, 2024). In the context of UHI research, ML continues to be significant, drawing on various factors such as NDVI, NDBI, NDWI, and other environmental and topographical characteristics. Several types of ML algorithms are available for these analyses. For instance, linear regression (LR) is a fundamental statistical approach to model the relationship between a dependent variable and one or more independent variables. Another frequently employed algorithm is Support Vector Machines, which is proficient in addressing classification and regression challenges and is capable of managing data with nonlinear associations (Bansal and Quan, 2024). Artificial neural networks (ANNs) are also noteworthy. It is highly adaptable and functions similarly to the human brain. These facilitate the efficient identification of complex relationship patterns. However, training ANNs typically requires substantial data. RF is a key technique that

Table 2: UHI classification range (Liu *et al.*, 2021)2021

| UHI class | Formula |
|---|---|
| Class 1 low | LST<mean-(2xSD) |
| Class 2 sub-low | Mean-(2xSD)≤LST<mean-SD |
| Class 3 moderate | Mean-SD≤LST<mean |
| Class 4 sub-high | mean≤LST<mean+SD |
| Class 5 high | LST≥mean+SD |

builds several decision trees and combines their predictions to improve accuracy and consistency; the RF model is widely used (Varentsov *et al.*, 2023). This approach effectively processes large volumes of data and has shown remarkable accuracy, which is why it is frequently employed in predicting LST and the UHI phenomenon (Oukawa *et al.*, 2024).

*UHI classification*

UHI Classification is crucial for understanding how heat interacts with urban environments. Effective UHI classification helps identify areas particularly vulnerable to temperature fluctuations, which often experience declining air quality and increased energy consumption for cooling (Wang *et al.*, 2024). This data can support planners and policymakers in confronting heat-related challenges and influence future urban development approaches to mitigate the effects of UHI (Shao *et al.*, 2023). The following section will explore the significance of UHI classification and its methods. Identifying heat-vulnerable areas is essential for classifying regions at risk of elevated temperatures. This method facilitates the detection of urban sites where temperatures are considerably higher than those in adjacent areas (Shi *et al.*, 2021). Understanding which areas are at risk due to temperature changes enables urban planners to prioritize interventions, such as increasing vegetation, creating green spaces, or using reflective materials. These approaches have the potential to strengthen spatial management and increase urban resilience in the face of heat challenges (Chondrogianni and Stephanedes, 2022).

*Statistical methods*

To achieve effective UHI classification, it is necessary to find a method that aligns with the various characteristics of the data and the types of visualizations required. The Natural Breaks approach successfully reveals natural clusters in LST data, drawing attention to zones with markedly different levels of heat intensity (Lu *et al.*, 2021). Next, the equal interval method divides the data into intervals of equal size, offering a straightforward classification approach; however, it may need to adequately reflect changes in temperature distribution (Zhang *et al.*, 2024). By utilizing the quantile method, groups of equal size are established, which facilitates a balanced distribution among classes. Nonetheless, this can lead to disparities in temperature ranges when the data distribution is significantly skewed. Finally, widely used for studying heat distribution, the standard deviation (SD) method classifies areas based on their deviation from the mean LST. This method is particularly suitable for urban environments with severe hot spots and adheres to objective classification criteria (Hou *et al.*, 2021). The literature review indicates that effective methods for UHI classification exist, with the SD method standing out as a strong approach. This method classifies areas based on their deviation from LST, enabling a more detailed quantification of UHI concentrations. In this study, the SD method will be applied, segmenting the classifications into five unique classes, as illustrated in Table 2.

By categorizing the data into five classes, this classification strategy enables a comprehensive analysis of the UHI phenomenon. It reveals the distribution trends of UHI across the study region and acts as a guide for recognizing sites with heightened temperature levels. This information can help develop targeted strategies for effective heat management in those areas. The literature review provides a clear framework for the research guidelines, as illustrated in Fig. 3.

*Dataset preparation*

Satellite imagery from 2016 to 2022 was acquired from both Landsat 8 and Sentinel-2 during the data preparation phase for this study. To represent the

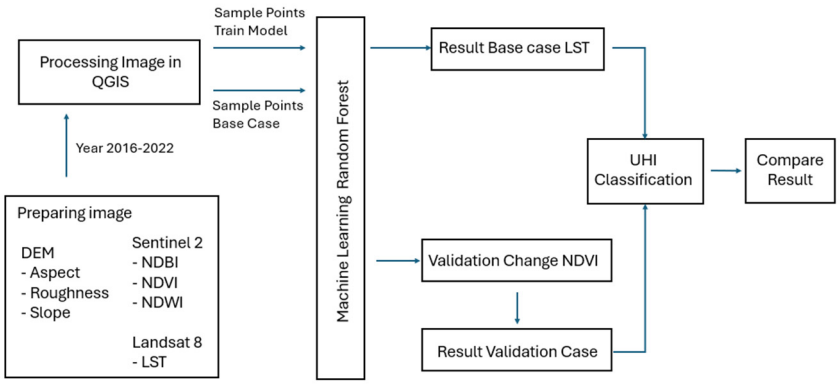


Fig. 3: Methodology of the study

temporal variability of land surface temperature (LST) and vegetation cover, three images were selected for each year, highlighting the distinct characteristics of the dry, wet, and cool seasons. It ensured that seasonal variability influencing the UHI effect would be considered, allowing the study to have more in-depth research regarding thermal and vegetation dynamics within the study area. The imagery collected was subjected to intensive preprocessing in order for the data to be correct and uniform. Preprocessing steps included radiometric calibration, atmospheric correction, and geometric alignment, aimed at reducing distortions and aligning multivariate data effectively. These methods significantly improve the dependability of variables likeNDVI, NDWI, and NDBI. Indeed, it is true that these respective indices, although different from one another, were selected as being relevant due to their ability to provide good insight into the development and interactions of vegetation-water-body-builts-up interactions during UHI dynamics. A random sampling method selected representative data across the study area. This sampling technique has played a crucial role in mitigating bias, allowing the dataset to more accurately capture the spatial variability of LST and environmental factors. Extraction was done via QGIS, a well-known open-sourced tool that manages satellite imagery. The results are in points in CSV format with their environmental variables, facilitating further analysis through ML techniques. This LST analysis, performed at a higher resolution of 20 meters (m), enriches the LST analysis, hence giving more critical and detailed spatial patterns that will allow the detection of UHI and offer the possibility of precise correlations with NDVI and NDBI for targeted strategies in urban planning (Tao *et al*., 2024). The chosen resolution will allow for the effective capture of the study area's inherently fragmented urban landscape, providing sufficient detail for localized analysis of UHI dynamics and vegetation interactions. This preparation phase created a robust dataset that not only supports the analysis of the UHI effect but also lays the foundation for assessing nonlinear relationships between NDVI adjustments and LST. The extensive temporal and spatial coverage broadens the applicability of the study's results for urban planning and efforts related to climate resilience.

*ML process*

In this stage, the RF algorithm is applied, a commonly used method for analyzing complex datasets. RF is known for its accuracy and flexibility in handling diverse and nonlinear data. The RF process in this study is divided into two key phases: Base case model creation and validation. For the base case model, the dataset obtained from the prior data preparation phase is partitioned into training and testing sets, following a 70:30 distribution. It is a widely accepted method to ensure accurate results. The 70% used for training helps the RF algorithm to efficiently learn patterns and relationships in the data. The final 30% is allocated for evaluating the model's ability to predict LST values, confirming its

Table 3: Sample of dataset

| ID No. | Aspect | LST | NDBI | NDVI | NDWI | Roughness | Slope |
|---|---|---|---|---|---|---|---|
| 1 | 218.6500 | 42.3075 | 0.1415 | 0.2110 | -0.2680 | 6.0000 | 3.0400 |
| 2 | 218.6590 | 40.7079 | 0.1595 | 0.2243 | -0.2587 | 6.0000 | 3.0400 |
| 3 | 225.0000 | 40.7079 | 0.1417 | 0.2460 | -0.2682 | 6.0000 | 3.6912 |
| 4 | 161.5650 | 40.3114 | 0.1472 | 0.2209 | -0.2456 | 7.0000 | 0.7513 |
| 5 | 45.0000 | 42.6150 | 0.1885 | 0.1951 | -0.2307 | 4.0000 | 0.3360 |
| 6 | 218.6590 | 42.3075 | 0.1294 | 0.1760 | -0.2377 | 6.0000 | 3.0400 |
| 7 | 218.6590 | 40.7079 | 0.1206 | 0.2184 | -0.2764 | 6.0000 | 3.0400 |
| 8 | 225.0000 | 40.7079 | 0.1612 | 0.2286 | -0.2494 | 6.0000 | 3.6912 |
| 9 | 161.5650 | 40.3114 | 0.1469 | 0.2230 | -0.2542 | 7.0000 | 0.7513 |
| 10 | 161.5650 | 39.9388 | 0.1495 | 0.2328 | -0.2502 | 7.0000 | 0.7513 |
| 11 | 78.6900 | 39.9388 | 0.1436 | 0.2327 | -0.2465 | 5.0000 | 2.4217 |

accuracy in forecasting LST for new data.

*Validation of NDVI*

In the validation process, NDVI values, -100% to +100% changes, have been done regularly in 10% intervals. During each step, the LST change was predicted by an ML model that took the changed NDVI value as input. The current approach allows for an in-depth analysis of how fluctuations in NDVI values relate to the evolving impacts of UHI. The results of this process give important information on the role of vegetation density in reducing or increasing heat in the studied urban area. The investigation also found nonlinear trends where, for some ranges of NDVI values, the LST decreased unexpectedly, which showed the sensitivity of the UHI model to vegetation changes. In contrast, a thorough analysis of these trends reveals the spectrum of NDVI values that play a role in either mitigating or exacerbating heat levels in urban settings. This information is essential for urban planning considering increasing green space as part of strategies to mitigate the UHI. The concluding step in the validation will be to categorize the Urban Heat Island (UHI) based on the confirmed LST data. The literature review indicates several methods used in the classification of UHI, among them the standard method using SD, which is widely accepted and suitable for the analysis in this research. This approach utilizes case studies to establish a standardized framework for the classification of UHI. This classification system thus allows the study to analyze how NDVI modifications would effectively impact UHI pattern changes. Comparing UHI changes between scenarios further underlines areas with high heat accumulation and, again, how vegetation density can alter urban heat. Data gathered from this process could be instrumental in facilitating specific enhancements, such as the development of green spaces or the alteration of paving materials to mitigate heat retention in the most impacted areas.

## RESULTS AND DISCUSSION

*Preparing dataset*

The study area, defined in the city plan for Chiang Mai Province, covers 429 $km^2$ and has been recognized for its notable temperature changes linked to the UHI effect. The analysis employs a random point sampling approach, using three images per year from 2016 to 2022. This approach allows for a comprehensive evaluation of the area's temperature dynamics. Landsat 8 and Sentinel-2 imagery facilitate accurate comparisons, focusing on selecting as similar dates as possible while minimizing cloud cover. The evaluation of these satellite images has resulted in the creation of over 3.2 million sample points, distributed randomly throughout the study area. This approach ensures a comprehensive representation of the diverse geographical and land use characteristics, allowing for a detailed examination of UHI differences across different regions. A sample dataset compiled for the UHI study is shown in Table 3. Each row corresponds to a randomly selected point within the area. This data was obtained from aerial imagery to ensure coverage of comprehensive seasonal and environmental variations.

The collected information provides insights into variations in terrain, slopes, and surface roughness. These data preparations will serve as the foundation

Table 4: Correlation matrix

| Variable | Aspect | LST | NDBI | NDVI | NDWI | Roughness | Slope |
|---|---|---|---|---|---|---|---|
| Aspect | 1.0000 | -0.0319 | 0.0008 | -0.0072 | 0.0136 | 0.0071 | 0.0055 |
| LST | -0.0319 | 1.0000 | 0.6004 | -0.5996 | 0.5515 | -0.2982 | -0.2993 |
| NDBI | 0.0008 | 0.6004 | 1.0000 | -0.7419 | 0.6420 | -0.2784 | -0.2789 |
| NDVI | -0.0072 | -0.5996 | -0.7419 | 1.0000 | -0.9606 | 0.3790 | 0.3812 |
| NDWI | 0.0136 | 0.5515 | 0.6420 | -0.9606 | 1.0000 | -0.3760 | -0.3788 |
| Roughness | 0.0071 | -0.2982 | -0.2784 | 0.3797 | -0.3760 | 1.0000 | 0.9915 |
| Slope | 0.0055 | -0.2993 | -0.2789 | 0.3812 | -0.3788 | 0.9915 | 1.0000 |

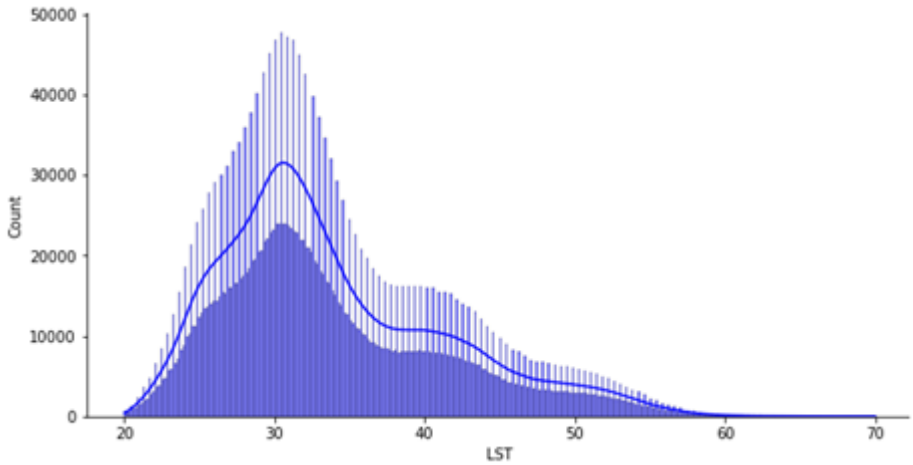


Fig. 4: Distribution of LST in train model ML

for following ML analyses.

*ML process*

The analysis utilizing the prepared datasets with the RF ML algorithm was divided into two segments: 70% for training and 30% for testing the model. The resulting $R^2$ score was 0.54. The reliability of the analysis is determined by the combination of datasets sourced from both satellites. In addition, variations in date and time may impact heat, humidity levels, sunlight, and clouds, which can change from one day to another (Wang *et al.*, 2022). Table 4. illustrates the relationships among the various variables. A key observation is the high correlation of 0.9915 between Roughness and Slope. It indicates a close connection between these two factors and suggests they tend to change in the same direction. Regions characterized by steeper inclines tend to display increased surface roughness. Therefore, both Roughness and Slope can be considered as variables that represent comparable geographic features, despite their differing interpretations. NDVI and NDWI exhibit a strong negative correlation of -0.96067, indicating that they are related in opposite ways. NDVI reflects vegetation density, while NDWI focuses on moisture content. It means that when vegetation is abundant (high NDVI), moisture levels in the area tend to decrease (low NDWI) (Zhou *et al.*, 2022). This observation is typical of dry areas where there is a significant amount of dense vegetation. NDVI values that are less than zero reflect non-vegetative surfaces, such as bodies of water, snow, clouds, or bare ground. LST and NDVI show a strong negative correlation of -0.59966, highlighting the relationship between LST nature and vegetation density. As NDVI increases, LST decreases, indicating more dense vegetation. The occurrence is attributed to the role of plants in temperature regulation, as they offer shade and promote evapotranspiration. Consequently, areas with denser vegetation can lessen the effects of the UHI phenomenon.

Fig. 4. demonstrates a dataset that is evenly

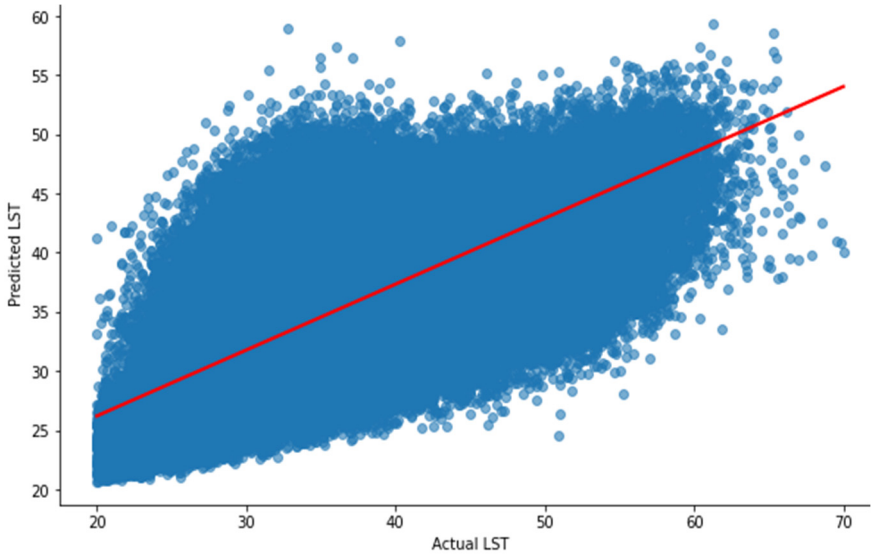


Fig. 5: Results of ML predictions compared to actual values

Tabel 5: Range of UHI classification

| Class | Range start | Range end |
|---|---|---|
| Low | - | 32.56 |
| Sub-low | 32.56 | 35.22 |
| Moderate | 35.22 | 37.88 |
| Sub-high | 37.88 | 40.54 |
| High | 40.54 | - |

distributed for model training, successfully encompassing both low and high-temperature values. This comprehensive range enhances the ML model's ability to learn from and predict temperatures across various scenarios. However, the graph also indicates the presence of outliers, with temperatures reaching as high as 60 °C to 70°C in a small area. The occurrence of these extreme temperature values is likely linked to regions that experience substantial heat buildup, especially in cities where infrastructure, including roads and buildings, raises temperature levels. By including these outlier data points, the model can recognize regions with distinctive heat patterns. Addressing these outliers will be considered to improve the model's accuracy by eliminating potentially misleading data.

Fig. 5 compares the forecasted values from the RFs model with the actual LST. The points in the graph represent the pairs of actual and forecasted LST measures; the red line represents the trend in their relationship. There is a general consistency observed between the forecasted and actual values, suggesting that as the actual LST increases, the forecasted values also tend to rise. The model captures the surface temperature trends in a very effective way, though there is a little variability around the trend line, according to which the model may not be as accurate, especially for these exceeding 50°C LST values. The data point distribution reveals that the model is highly precise in the range of 30 to 50°C, with most points being in close proximity to each other and to the trend line. While the RF model performs well in this temperature range, some variations are inaccurate for very high temperatures or regions with a complex topography. Overall, while predictions serve as a valuable tool for understanding and addressing UHI effects, there is a pressing need for their refinement in areas that face extreme temperature challenges.

In conclusion, the RF model satisfyingly predicts LST, closely aligning with actual values. Even though

it is slightly inaccurate at some points at higher temperatures, the overall predictions remain consistent with observed data. These results can be leveraged for the analysis and management of (UH) effects, including the validation of NDVI.

*Calculation of the standard division range*

The literature review of the UHI classification process for this research indicates that the SD method is the most commonly used approach and is an effective methanol for grouping areas based on average LST distribution in the study area. It serves as a valuable tool for recognizing regions with markedly increased temperatures and those susceptible to heat-related effects. For the LST base case used in this analysis, the SD value was 2.66, with a mean LST of 37.88°C, as outlined in Table 2. It allows for the division of UHI classification ranges according to the principles of SD, resulting in five temperature levels: Low, Sub-low, Moderate, Sub-high, and High, as shown in Table 5.

Determining these ranges allows for a precise categorization of regions according to different surface temperature levels. Locations identified as Low experience temperatures that are far below the average, in contrast to those in the High classification, which show temperatures that are substantially above the average. These high-temperature areas are particularly susceptible to the effects of the UHI phenomenon. This classification analyzes high-temperature areas and pinpoints regions requiring immediate management. The SD equations can also be utilized for NDVI validation in other case studies. This strategy allows for the assessment of temperature shifts associated with NDVI changes. It lays the groundwork for exploring the impact of land use and vegetation on temperature dynamics within the study area.

*UHI classification with NDVI validation*

The NDVI values would be normalized in a range for the sake of the testing process that should validate the ML model developed for the LST calculation. Later on, the predictions calculated would be fed into UHI Classification, which classifies areas depending on the intensity of heat and the effect of the UHI phenomenon. Dispersion in NDVI values between -100% and +100% gives a very clear trend of area classification, represented in Fig. 6. This analysis underscores the trend of UHI modifications related to shifts in vegetation in the area, as depicted by the hot spot distribution on the map. UHI is classified into five distinct categories according to Table 5, and the number of heat points in each category is examined for comparison. It was noticed that with the increase of NDVI values, the number of areas

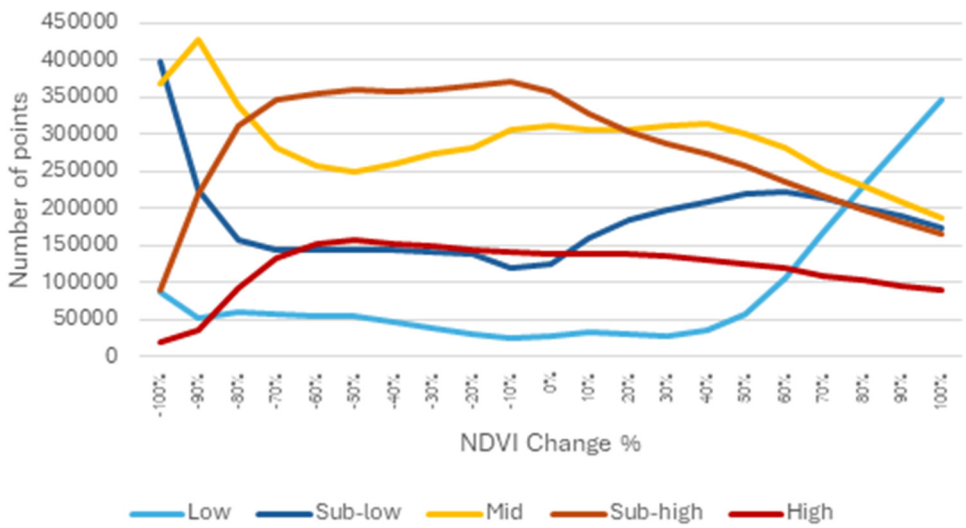


Fig. 6: Momentum of UHI change due to NDVI change

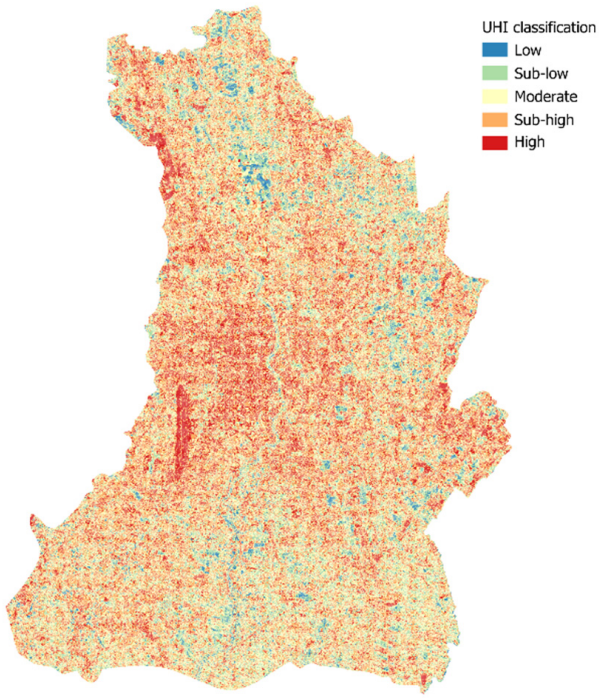


Fig. 7: Map of UHI base case of Chiang Mai

falling into the Low class (which means lesser heat) is also increasing gradually, while the areas under the High class (which means higher heat) are decreasing significantly. This attachment point demonstrates that the elevated NDVI value is associated with the cooler temperatures in that area, as anticipated. Higher vegetation can reduce temperatures through various means like water evaporation and shading; it reduces the overall temperature in that area. The trend from the NDVI loss range between -10% to -70% is expected to show an upward trend. This trend suggests that with a decrease in green space or vegetation, increased heat is experienced within the same areas, thus increasing accumulation. A notable surge in areas designated as Low occurs when NDVI values drop further between -80% and -100%, which is inconsistent with standard anticipations. The model might perceive the significantly decreased NDVI areas as water bodies; hence, it would predict lower temperatures in those places than expected. According to the graph, higher NDVI levels are associated with lower area temperatures, while lower NDVI levels lead to elevated temperatures. However, there is an anomaly where the NDVI takes a great drop: the probability increases of such areas being analyzed by the ML model as water bodies.

This mapping technique is processed using the QGIS program. Fig. 7 is a diagram that illustrates the UHI Classification for Chiang Mai Province. It is color-coded into five classes: low, sub-low, moderate, sub-high, and high. Observations indicate that the central part of Chiang Mai Province, which includes Chiang Mai International Airport, shows a lower NDVI relative to the adjacent areas. This region contains sites marked by high UHI density, represented in red.

Following knowledge of the base case for Chiang Mai Province, a comparison has been conducted with the UHI Map image of Chiang Mai Province (Fig. 8) in order to comprehend any changes in UHI, should there be any NDVI changes. When the NDVI rises from 10% to 50% and subsequently to

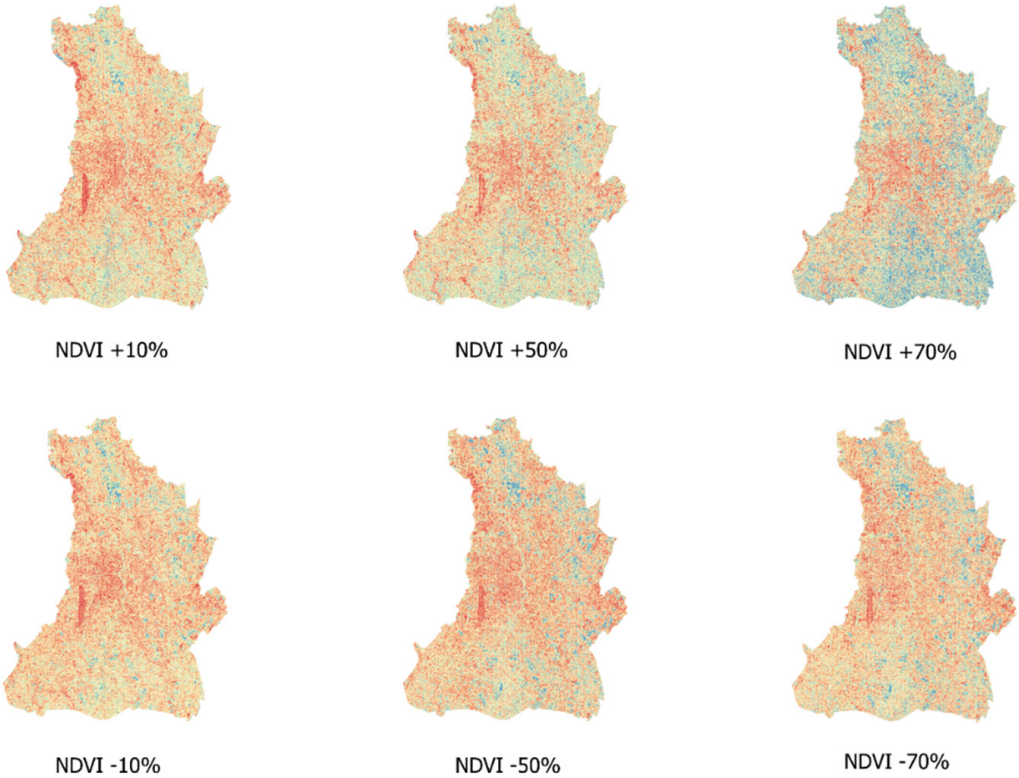


Fig. 8: Map of the UHI resulting from NDVI changes

70%, there will be a significant growth in the blue regions, which denote cold spots or Class 5 low UHI classification. In contrast, a decline in NDVI will produce only a slight effect on the data. As the NDVI rises and falls, that varies. The findings reinforce the relationship between NDVI and UHI, demonstrating that higher NDVI values are linked to a significant reduction in UHI. According to the heat map, an increase in NDVI is associated with a notable improvement in cooling within urban settings, while a decrease in NDVI corresponds to a rise in areas experiencing heat intensification.

In this way, by applying SD, the UHI classification method classifies areas of Chiang Mai Province by variation in surface temperature. During the validation process, the fluctuating NDVI values reveal a pattern where increased NDVI is associated with lower temperatures and diminished UHI, especially in urban areas. Decreasing NDVI levels lead to higher temperatures and the formation of hotspots. However, when NDVI falls below -70%, it may result in the misclassification of certain areas as water bodies within the model, which could explain the unexpected cooling forecasts. RS can be calculated NDVI from Eq. 1, and NDWI can be calculated from Eq. 2 (Patil *et al*., 2024):

$$\mathrm{NDVI} = (\mathrm{NIR} + \mathrm{Red}) / (\mathrm{NIR} - \mathrm{Red}) \quad (1)$$

$$\mathrm{NDWI} = (\mathrm{Green} + \mathrm{NIR}) / (\mathrm{Green} - \mathrm{NIR}) \quad (2)$$

Where;

NIR is the reflectance in the near-infrared band satellite.

The red band is the reflectance in the red band satellite.

The green band is the reflectance in the red band from the satellite.

The explanation for a negative NDVI is given by surfaces that reflect less light in the NIR region

compared to the red part of the spectrum. Those surfaces are considered land without vegetation and might consist of water, open land, or land with high moisture content. A negative NDVI indicates a positive NDWI value for water, given that the NDWI is computed based on the difference in reflectance between the green and near-infrared bands. A land with a primary water component, such as rivers, lakes, or reservoirs, absorbs more light in the NIR region and reflects more light in the green region, which gives a positive value of NDWI, while the NDVI is close to zero or negative. This proximity arises from the comparable light absorption traits of water in both indices, yet NDWI highlights green reflectance, which plays a significant role in the detection of water areas. The correlation of NDVI and NDWI in assessing water surfaces identifies positive NDWI and negative NDVI values over water bodies, emphasizing NDWI's role in identifying high-moisture areas (Assiri *et al*., 2024). The results indicate the significant contribution of vegetation in reducing the impacts of UHI and stress the need for deliberate urban planning strategies that focus on maintaining or expanding green areas to mitigate the increasing effects of urban heat.

## CONCLUSION

Results confirm that NDVI, the increased green space in cities, linearly reduces LST and significantly mitigates the effects related to the UHI phenomenon. These results hold considerable importance for urban planning and the development of public spaces, especially in urban areas that are dealing with the challenges of heat retention. Enhancing green spaces through parks, street trees, and green roofs remains one of the critical urban planning strategies. In this study, the relationship between NDVI and LST was nonlinear, indicating some vegetation thresholds beyond which a change in LST is observed to be abnormal. For example, though moderate decreases in NDVI were consistently associated with increased intensities of UHI, extreme NDVI decreases led to misclassifications in land types as water bodies, artificially lowering LST in such places. This finding reiterates the necessity of integrating suitable data processing strategies and superior satellite imagery when conducting urban heat assessments. Additionally, it highlights the necessity for urban planners to properly assess the type and density of vegetation being introduced, while considering the unique characteristics of different regions to ensure effective cooling outcomes. This issue is necessary to reduce temperatures and further improve the quality of life of its people. Classification of UHI according to the SD method has enabled one to better understand the variation in heat intensities across urban areas. The hotspot locations in these central urban areas, such as the area around the Chiang Mai International Airport, suggest urgent demand for mitigation strategies in such zones. It is expected that such hotspots with low vegetation density and high surface coverage of imperviousness should be recommendations for priority interventions involving vertical greening systems, cooling pavements, and urban parks to counter UHI effects. The study further expands on the significance of NDVI in maintaining equilibrium between urban density and natural cooling systems, particularly in areas facing the greatest threat from rapid urbanization. Integrating NDVI change data into general urban development enables officials to effectively target areas that need more green space to solve problems in areas with high heat levels. The field of architectural design has the potential to enhance thermal performance by employing materials that limit heat accumulation, including reflective tarps and the integration of green areas in building designs. The results have also shown the potential of ML algorithms, like RF, joined with geospatial analyses for mosaic-type dynamic predictions of changes in LST. It will enable data-driven policymaking at a high resolution targeted toward specific conditions within the urban setting. Furthermore, the current study underscores that the effectiveness of vegetation in providing cooling effects is influenced not just by its quantity, but also by its strategic arrangement and the specific types of plants involved, as indicated by the nonlinear relationships associated with variations in NDVI. These findings could be employed by urban planners and architects to apply site-specific strategies, thus increasing their effectiveness in reducing UHI effects. The results from the experiment will help place green spaces at strategic locations planners and help them in proper land use management to reduce the problems of UHI. Integrating the UHI classification findings with real-time predictions of land surface temperature, stakeholders can create more flexible

urban strategies that effectively tackle contemporary heat issues and anticipate future threats linked to climatic change. Adaptive strategies may include integrated design of green roofs, urban forests, and water elements in urban landscapes, which could mitigate urban heat impacts and improve thermal comfort. Overall, the outcomes of this experiment offer important evidence that can enhance strategic planning efforts aimed at fostering sustainable city development. Such strategies can improve the well-being of urban populations by addressing heat impacts. The research also sets a framework for extending analyses to other urban areas, adding other environmental and socioeconomic variables, and refining predictive models with better applicability. Future studies can be focused on integrating various ML algorithms or hybrid approaches to increase prediction accuracy and generalize these findings to global urban contexts. The outcomes illustrate a critical requirement to harmonize urban development with sustainable environmental strategies, thereby underscoring the demand for climate resilience and the establishment of livable cities for the benefit of future generations.

## LIMITATION AND FUTURE RESEARCH

There are various limitations associated with this study that should be considered when analyzing and applying the results. These limitations can be summarized as follows.

1) Study area size: The research was conducted in Chiang Mai Province, with distinct topographical features and land use patterns. The confined nature of this area could hinder the generalizability of the findings to other locations with varying geographic attributes.

2) Data period: The analysis relied on data from 2016 to 2022.

Consequently, it may fail to reflect the city's most up-to-date changes and could fall short in representing sustained, long-term patterns.

3) The RF model only presented an R square value of 0.54 regarding predictive power. This can either be an effect of the intricacy of environmental phenomena such as UHI or, on the other hand, an effect of some excluded variables that can be relevant to the LST, such as albedo, land use, and socioeconomic conditions. The model was sufficiently robust to extract meaningful conclusions about the relationship between NDVI and LST, thereby supporting informed urban planning efforts.

Future research aims to enhance ML accuracy by exploring alternative algorithms for predicting surface temperatures and assessing the impacts of UHI. Also, developing hybrid models that integrate multiple algorithms may improve accuracy and more comprehensive analyses. From an alternative standpoint, enhancing the analysis by integrating other factors, including relative humidity, weather conditions, and comprehensive land use, can provide a deeper insight into the impacts of UHI. Moreover, further investigations of the nonlinear relationship between NDVI and LST relate to developing strategies for mitigating heat in urban areas. Deducing NDVI thresholds beyond which vegetation can produce its most effective cooling effect enables urban planners to effectively target greening initiatives. Awareness of how seasonal changes affect the relationship between NDVI and LST may guide the scheduling of interventions, especially during peak temperature phases. It would also explore the impact of different vegetation types, such as trees, shrubs, or grass, to inform on the appropriate vegetation type in a particular urban context. This approach will facilitate a more thorough examination of how UHI impacts urban areas. In conclusion, the findings from this research can be effectively utilized in urban planning efforts. With an increased amount of information at their disposal, urban planning agencies can steer clear of variables that should be avoided, ultimately leading to improved urban planning strategies for both urban planners and policymakers in the future. Increasing green spaces in areas with significant heat accumulation and developing environmental management strategies will help lessen the impacts of UHI. These measures will improve residents' quality of life and reduce heat's environmental effects in urban settings.

## AUTHOR CONTRIBUTIONS

D. Rinchumphu, the corresponding author, conceptualization, review, and editing. N. Chanpichaigosol performed the literature review, compiled the data, manuscript edition, manuscript preparation, and revising. C. Chaichana performed the experiments and literature review, analyzed and interpreted the data, and visualization

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## CONFLICT OF INTEREST

The authors declare that there are no conflicts of interest regarding the publication of this manuscript. In addition, the authors observed ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancy.

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## ABBREVIATIONS

| | |
|---|---|
| *%* | Percentage |
| *°C* | Degree Celsius |
| *ANNs* | Artificial neural networks |
| *CSV* | Comma separated value |
| *$Km^2$* | Square kilometer |
| *LR* | Linear regression |
| *LST* | Land surface temperature |
| *m* | Meter |
| *ML* | Machine learning |
| *NDBI* | Normalized difference built-up index |
| *NDVI* | Normalized difference vegetation index |
| *NDWI* | Normalized difference water index |
| *NIR* | Near-infrared |
| *RF* | Ramdom forest |
| *RS* | Remote sensing |
| *SD* | Standard deviation |
| *UHI* | Urban heat island |

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