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Assessment of urban heat island effects using remote sensing and AI models

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Abstract

The effects of Urban Heat Island (UHI) have become a major issue within the environmental field because of the rapid urbanization, growing population density, and climate change. Cities tend to be hotter than the rural areas due to increased human activities, lack of vegetation cover and large areas covered with built-up areas. In this paper, we evaluate Urban Heat Island effects based on the remote sensing data and Artificial Intelligence (AI) models to determine patterns in the distribution of temperature and forecast urban heat intensity. Remote sensing platforms were used to derive Land Surface Temperature (LST) and environmental products, such as the Normalized Difference Vegetation Index (NDVI), Normalized Difference Built-up Index (NDBI) and Normalized Difference Water Index (NDWI). Random Forest (RF), Support Vector Machine (SVM), and Artificial Neural Network (ANN) were three machine learning algorithms that were used to predict and model temperature changes. The findings indicated that there was a strong positive correlation with the built-up areas and temperature, and that vegetation and water bodies were significant coolers. ANN was found to be the most accurate predictor of the ones analyzed, followed by the Random Forest and SVM. The results indicate that remote sensing technologies used together with an AI-based analytical approach have a promising structure to monitor, evaluate and forecast the trends on Urban Heat Islands. The research adds value to sustainable urban planning by revealing relevant information that can assist in implementing heat mitigation policies, green infrastructure creation, and managing the city more climate-resilient. The suggested method is a useful instrument in monitoring the environment and making informed decisions in highly populated areas.

Keywords: Urban Heat Island (UHI), remote sensing, artificial intelligence, machine learning, land surface temperature, random forest, support vector machine, artificial neural network, NDVI, NDBI, sustainable urban planning

1. Introduction

The quick urbanisation process has changed natural landscapes to highly developed constructions with a heavy concentration of infrastructure, with few or non-existent vegetation cover. The Urban Heat Island (UHI) effect is one of the most critical environmental impacts of urban growth in which urban areas are warmer than rural areas ^[1]. The UHI effect is mostly due to the natural landscape being replaced with buildings, roadways as well as other artificially designed surfaces that potentially absorb and retain heat. The growing temperatures in cities are attributable to rising energy consumption, poor air quality, potential health hazards to the population, and low sustainability of the environment as urban areas continue to grow. Climate change and its subsequent increases have also put more of a spotlight on urban heat build-up and effective UHI monitoring and evaluation outcomes are crucial to sustainable urban planning ^[2]. The conventional ways of temperature measurements use the weather stations on the ground, which in many cases have a smaller spatial coverage and are incapable of capturing the differences in temperatures within a large urban area. Contrastingly, remote sensing technologies provide a cost-efficient and effective alternative approach of measuring land surface temperatures in a wide geographical coverage ^[3]. The

images of the satellite received with Landsat and Sentinel platforms help the researchers to interpret thermal features, land-use developments and vegetation distributions, at a high level of spatial resolution.

The recent development in the world of Artificial Intelligence (AI) and machine learning has opened up new opportunities in the process of enhancing the monitoring and forecasting of Urban Heat Island patterns. AI models have the capacity to process big amounts of remote sensing and environmental data, detect intricate connections among variables, and provide correct temperature prediction. Data on remote sensing combined with AI-based methods of analysis can help researchers learn more about the spatial and temporal changes in the distribution of urban heat. In this study, it will be evaluated how Urban Heat Islands can be measured with remote sensing data and AI models to detect hotspots of heat, measure the factors that contribute to it, and assist in developing sustainable solutions of reducing it in urban areas and improving climate resilience.

2. Related Works

The effects of urban heat Island (UHI) have emerged as a major environmental issue as a result of rapid urbanization, climate change and a growing population density. The combination of remote sensing, geospatial technology, and

artificial intelligence (AI) has been the focus of recent research in order to gain improved insights into urban thermal dynamics as well as help with climate-resilient urban planning. Khazaee *et al.* [15] performed a systematic review of cities targeted as climate-resilient with smart technologies regarding the roads. Their research emphasized the role of high-tech sensory devices, Internet of Things (IoT) environment, and information-based surveillance models in enhancing the sustainability and resilience of the city to its climate-related issues. The results showed how virtual technologies could be used to aid the temperature monitoring and the infrastructure adjustments plans. Khoren *et al.* [16] explored how AI and geospatial technologies can be integrated to develop smart cities sustainably. As the researchers used Yerevan as a case study, they have proved that machine learning algorithms with the help of spatial data analysis can contribute to the improvement of urban planning and environmental management. Their contribution featured the increasing importance of AI-based decision support systems in handling urban environmental problems.

Li *et al.* have conducted extensive studies on cooling of urban green spaces [17], creating a multidimensional evaluation model of the assessment of ecosystem services in urban parks. The study established that vegetation can effectively lower the surface temperatures and is a factor to climate resilience. In the same light, Li and Wang [18] utilized space and data-based techniques to alleviate urban heating in cities by the coastline and determined that strategic timberland-use planning and green infrastructure can be successful in diminishing the level of Urban Heat Island. Li *et al.* [19] showed improved development of AI applications in urban thermal analysis by using Generative Adversarial Networks (GANs) based on New York City geographical data to analyze cooling effects of different urban designs. They found that deep learning methods can assist urban planners to test and optimize heat mitigation strategies prior to implementation. A number of studies have been directed towards determining factors that affect the land surface temperature. Ma *et al.* [20] combined the impacts of land cover, topography, urban morphology, and PM2.5 concentrations to their impacts on temperature distribution. Their results showed that built up-areas and urban form are important contributors to heat related problems. Not to mention, remote sensing was applied by Malinverni *et al.* [21] in determining the Urban Heat Island threat in the cultural heritage sites in the city of Hue, Vietnam, which proved the usefulness of thermal analysis on satellites in monitoring the environment. Meng *et al.* [22] performed the analysis of spatial heterogeneity of Urban Heat Island effects with the use of multi-source data fusion methods. Their analysis revealed that the accuracy of

assessments of the thermal environment is enhanced with the integration of various datasets. Similarly, Mengyu *et al.* [23] recently created a cooling model with Local Climate Zones and discovered the major mechanisms that influence thermal environment in a rapidly urbanized area, with certain attention being paid to urban morphology and urban land-use features.

Mohammed *et al.* [24] also examined remote sensing applications and digital twins in monitoring environmental risks even though this is mainly with the area of flood management. Their results revealed the greater opportunities of utilizing geospatial data and intelligent systems in the process of developing urban resilience. A thorough overview of Urban Heat Island mapping practices in detail, in the Indian performance, was conducted by N *et al.* [25]. The authors emphasized the trend in the use of satellites, GIS, and machine learning to conduct thermal analysis and recognized the issues related to data access and model precision. Lastly, Otero *et al.* [26] discussed the rising AI in environmental early warning systems. Their research focused on the fact that machine learning and predictive analytics can enhance environmental monitoring, accuracy of prediction and decision-making.

3. Methods and Materials

3.1 Research Design

This paper will take a quantitative, predictive research design to evaluate Urban Heat Island (UHI) impacts based on remote sensors and Artificial Intelligence (AI) models. The approach is based on the combination of satellite images processing, environmental indicators extraction and temperature prediction with the aid of machine learning. The main purpose is to determine the urban hotspots of heat and analyse the performance of AI algorithms to predict changes in land surface temperature (LST) in urban areas [4]. The suggested model has five phases, including data acquisition, data preprocessing, feature extraction, the development of an AI model, and performance analysis. Remote sensing data is used to extract temperature and land-cover data, whereas machine learning algorithms are trained to learn how the combination of environmental variables and UHI intensity should be.

3.2 Materials and Data Sources

The analysis makes use of publicly-accessed remote sensing and environmental information. Landsat 8 images are used as they have thermal infrared bands that can be used in determining Land Surface Temperature. Using sentinel-2, images are classified into land covers and vegetation [5]. Weather stations are used to gather additional meteorological data to help in the validation.

Table 1: Data Sources and Purpose

Dataset	Source	Purpose
Landsat 8 Thermal Data	NASA/USGS	Land Surface Temperature extraction
Sentinel-2 Imagery	ESA	Land use and land cover analysis
Meteorological Data	Weather Stations	Validation of temperature estimates
Population Density Data	Government Open Data	Urban density assessment
GIS Boundary Data	Municipal Authorities	Study area mapping

The selected area of study is chosen on the basis of the nature of urban expansion and availability of high quality

satellite images. Several years of data are taken into account in order to examine the changes in the heat distribution habit

throughout time.

3.3 Data Preprocessing

Raw satellite photographs usually have distorted atmosphere, cloud cover, radiometric anomalies. Thus, preprocessing is carried out prior to analysis.

The preprocessing involves:

1. Photo capturing and choosing.
2. Cloud masking and removals.
3. Atmospheric correction.
4. Geometric correction.
5. Clipping of images according to boundaries of study areas.
6. Transformation of thermal bands to brightness temperature.
7. Land Surface Temperature (LST) calculating.

Raster layers are then processed and standardized, and then merged into a Geographic Information System (GIS) environment to be analyzed.

3.4 Feature Extraction

A number of environmental indicators that determine the temperature in the urban environment are derived through

satellite images.

Land Surface Temperature (LST)

LST is the main predictor of the intensity of Urban Heat Island. The Landsat images produce thermal infrared data that is translated into temperature ^[6].

Normalized Difference Vegetation Index (NDVI)

NDVI is a measure of vegetation density computed with the help of near-infrared spectral bands and red ones. When NDVI is higher, that means that there is healthier vegetation, and this is typically a source of cooling.

Normalized Difference Built-up Index (NDBI)

NDBI classifies urbanized and built-up areas. The greater the NDBI values, the more the heat is retained.

Normalized Difference Water Index (NDWI)

Water bodies that control the local temperatures are determined with the use of NDWI.

Population Density

One socioeconomic factor included in the heat generation in urban areas is population concentration.

Table 2: Input Features Used in AI Models

Feature	Description	Expected Influence on Temperature
LST	Land Surface Temperature	Target Variable
NDVI	Vegetation Index	Negative Correlation
NDBI	Built-up Area Index	Positive Correlation
NDWI	Water Presence Indicator	Negative Correlation
Population Density	Urban Activity Level	Positive Correlation
Land Cover Type	Urban Surface Classification	Variable Impact

3.5 Artificial Intelligence Models

Urban Heat Island prediction is predicted by using three machine learning algorithms, which are compared to each other.

3.5.1 Random Forest

Random Forests is an ensemble method of learning which builds several decision trees and fuses their output. The

technique is beneficial to deal with nonlinear relationships and decrease overfitting ^[7].

Advantages include:

- High prediction accuracy
- Stability towards noisy data.
- Capability of ranking feature values.

Pseudocode for Random Forest

```

“Algorithm Random Forest UHI
Input:
Training Dataset D
Number of Trees T
Output:
Predicted Temperature Values
Begin
For i = 1 to T do
Create bootstrap sample Di from D
Build Decision Tree Ti using random feature selection
End For
For each test sample x do
Predict temperature using all trees
Final Prediction =
Average(T1(x), T2(x), ..., TT(x))
End For
Return Predictions
End”

```

3.5.2 Support Vector Machine (SVM)

Support Vector Machine is a supervised learning model

which finds the best decision boundaries with regard to multidimensional feature space. SVM works well in cases

where there are complex nonlinear relationships in the data set ^[8].

Radial basis function (RBF) kernel is used to predict the nonlinear relationships in vegetation, urbanization and temperature.

Advantages include

- Effective in high-dimensional spaces
- Strong generalization capability
- Suitable for limited datasets

Pseudocode for Support Vector Machine

```

“Algorithm SVM_UHI
Input:
Training Dataset D
Kernel Function K
Output:
Predicted Temperature Values
Begin
Normalize all input features
Select kernel function K
Train SVM model using dataset D
Determine support vectors
Construct optimal hyperplane
For each test sample x do
Calculate decision function
Predict temperature value
End For
Return Predictions
End”

```

3.5.3 Artificial Neural Network (ANN)

ANNs are based on biological neural systems and can be used to model even very complicated relationships amongst a set of variables. ANN comes in handy in prediction of environmental processes since the temperature patterns of cities are mostly nonlinear ^[9].

The network comprises of:

- Input layer
- Hidden layers
- Output layer

The model is trained by the adjustment of weights by backpropagation.

Advantages include:

- Ability to learn complex patterns
- High predictive capability
- Suitable for large datasets

Pseudocode for Artificial Neural Network

```

“Algorithm ANN_UHI
Input:
Training Dataset D
Learning Rate  $\alpha$ 
Number of Epochs E
Output:
Predicted Temperature Values
Begin
Initialize network weights randomly
For epoch = 1 to E do
For each training sample do
Perform forward propagation
Compute prediction error
Perform backpropagation
Update weights
End For
End For
For each test sample do
Forward propagate inputs
Generate temperature prediction
End For
Return Predictions
End”

```

3.6 Model Training and Validation

An 80:20 split is made between the training and testing set. Machine learning models are built with the training dataset and the performance of the prediction is tested with the testing dataset. Crossover is done to enhance the reliability

of the model and decrease bias.

Normalization of features is done prior to model training to give consistency to the scale of variables. Hyperparameter optimization applies grid search with the aim of optimizing the performance of models.

3.7 Performance Evaluation

The three AI models are evaluated based on standard evaluation metrics in terms of predictive power.

Mean Absolute Error (MAE) is a level of the average error in prediction. Root Mean Square Error (RMSE) is the measure of the strength of the prediction errors. The coefficient of determination (R^2) is the percentage that is attributable to the model [10].

The model that has less MAE and RMSE values and higher values of R^2 is regarded to be more efficient in forecasting Urban heat Island. The comparative evaluation of the models of Random Forest, Support Vector Machine and Artificial Neural Network allows to determine the most appropriate model to use in the assessment of remote sensing-based UHI [11].

3.8 Expected Methodological Outcome

The proposed approach combines the remote sensing technology and sophisticated AI methods to develop correct Urban Heat Island measurements. The methodology eases the detection of hotspots, forecasting the temperature and mapping risks to the environment. The results will be useful to the urban planners and policy makers to develop sustainable policies like enhancing green cover in the cities and land use planning as well as alleviating environmental issues posed by heat in the fast growing cities.

4. Results and Analysis

4.1 Overview of Experimental Results

This study aimed at determining the impact of Urban Heat Island (UHI) with remote sensor data and Artificial Intelligence (AI) models. Satellite data in form of satellite imagery and environmental measures such as the Land Surface Temperature (LST), the Normalized Difference Vegetation Index (NDVI), the Normalized Difference Built-up Index (NDBI), the Normalized Difference Water Index (NDWI) and population density were processed and analyzed. Random Forest (RF), Support Vector Machine (SVM), and Artificial Neural Network (ANN) three machine learning algorithms were used to forecast fluctuations in the temperature and determine urban heat hotspots.

The findings indicate that there are evident spatial variations of temperature distribution in urban, suburban and vegetated areas. The temperature was found to be much higher in areas with dense infrastructure and inadequate vegetation as compared to others that were shaded with green zones. These relations have been identified in the AI models and yielded high-quality temperature forecasts.

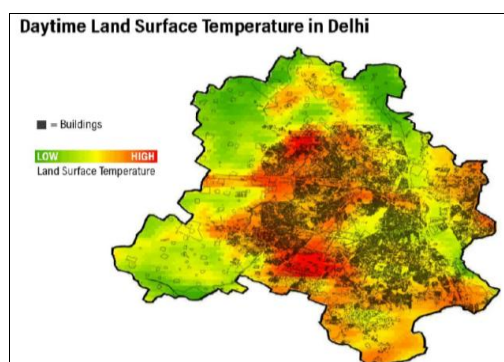


Fig 1: "Satellite-Derived Land Surface Temperature Map of Urban Heat Islands"

4.2 Land Surface Temperature Distribution

Thermal imagery analysis showed that there was a significant difference between land surface temperatures of land-cover categories. Urban centers had the highest temperatures. It was the area where concentration of the concrete structures, roads, and industrial buildings took place [12]. On the contrary, vegetation coated areas and water bodies kept the temperatures low due to evapotranspiration and cooling.

Table 1: Average Land Surface Temperature by Land Cover Type

Land Cover Type	Average Temperature (°C)
Dense Urban Area	38.7
Commercial Zone	37.1
Residential Area	34.5
Agricultural Land	30.8
Vegetation Area	28.9
Water Bodies	26.4

The results show that high populated (urban) areas were about 12 °C warmer than the adjacent bodies of water. These variations affirm that there is a high Urban Heat Island effect in the study area. According to the results, it can be further assumed that land-cover features are a decisive factor in the formation of the local temperature. High temperatures were observed in the commercial and industrial areas because of a large amount of impervious surfaces and anthropic heat sources. There were moderate temperatures seen in residential areas due to the mixed land-use and the availability of few green spaces. Temperatures (agricultural and vegetated regions) were much lower, which shows a cooling effect of natural landscapes.

4.3 Relationship Between Environmental Factors and Temperature

The correlation analysis was performed to determine the impact of environmental factors on the urban temperature. The findings suggest that there are strong correlations between temperature and remotely sensed indicators.

Table 2: Correlation Between Environmental Variables and Land Surface Temperature

Variable	Correlation Coefficient (r)
NDVI	-0.81
NDBI	0.84
NDWI	-0.69
Population Density	0.77
Built-Up Area Percentage	0.86

The positive relationship was found to be the highest between built-up area percentage and temperature ($r = 0.86$). This finding implies that there is a significant contribution of urban growth to heat build-up. Likewise, there was a high positive correlation between NDBI and temperature, which supports the notion that built-up surfaces capture and store substantial volumes of solar energy [13].

On the other hand, NDVI was found to be negatively correlated (-0.81), indicating that a plant cover is an efficient way of reducing the amount of heat. Dense vegetation led to low temperatures in areas through shading and evapotranspiration. The idea of cooling effect of water resources was also reflected by the existence of a negative relationship between NDWI.

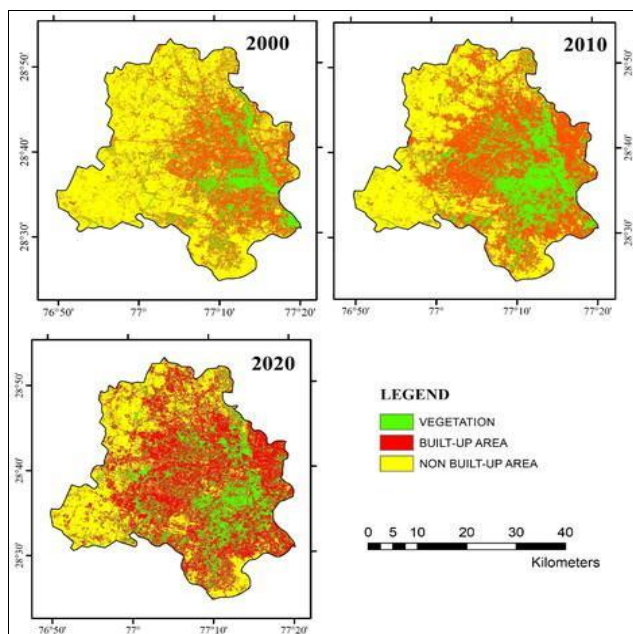


Fig 2: “Land Use and Land Cover Classification of Urban Areas”

There was a moderately strong positive correlation between population density and temperature. This observation indicates how human activity, transport systems and energy use impact the urban thermal environment.

4.4 Urban Heat Island Intensity Assessment

The intensity of Urban Heat Island was established by making comparisons between the average temperatures of urban areas and the temperatures of the respective rural areas. The findings suggest that there are considerable thermal variations across the study area ^[14].

Table 3: Urban Heat Island Intensity Classification

UHI Intensity Category	Temperature Difference (°C)	Area Coverage (%)
Very Low	0–2	18
Low	2–4	22
Moderate	4–6	27
High	6–8	20
Very High	>8	13

The analysis has demonstrated that the high and very high Urban Heat Island intensity covered about 33 percent of the study area. These were largely concentrated in areas of central urban districts with a great deal of commercial trade and high density of infrastructure.

The highest percentage (27 percent) of land coverage of the study area was moderate intensity of UHI. This indicates that city heat effects are prevalent and do not only occur in urban centers.

Very low intensity areas were characterized by parks, forests, agricultural lands and water bodies in most cases. Such results accentuate the need to maintain natural ecosystems in the urban setting ^[27].

The tendency of increasing the intensity of UHI with respect to space generates the attention that there exist environmental issues that emanate with the high rate of urbanization. Unless there is proper mitigation, the growth of built-up areas can add to heat pressure and adversely

affect the community and environmental sustainability.

4.5 Performance of AI Models

All the three models of Random Forest, Support Vector Machine and the Artificial Neural Network and the prediction performance were measured using Mean Absolute Error (MAE), Coefficient of Determination (R^2), and Root Mean Square Error (RMSE).

Table 4: Performance Comparison of AI Models

Model	MAE	RMSE	R^2 Score
Random Forest	1.12	1.48	0.94
SVM	1.56	1.92	0.89
ANN	0.98	1.31	0.96

The Artificial Neural Network made the best predictions having an R^2 value of 0.96 and minimum values of errors. The findings show that ANN was a good method of capturing nonlinear relations of variables of the environment and temperature.

Random Forest also was a strong predictor with an R^2 of 0.94. The ensemble learning process allowed the model to effectively work with multidimensional data and reduce overfitting ^[28].

Support Vector Machine yielded satisfactory results with the slight variation in accuracy with ANN and Random Forest. Even though SVM was able to model temperature variations, it could be that its effectiveness was influenced by the huge amount of data on the environmental conditions and its complexity ^[29].

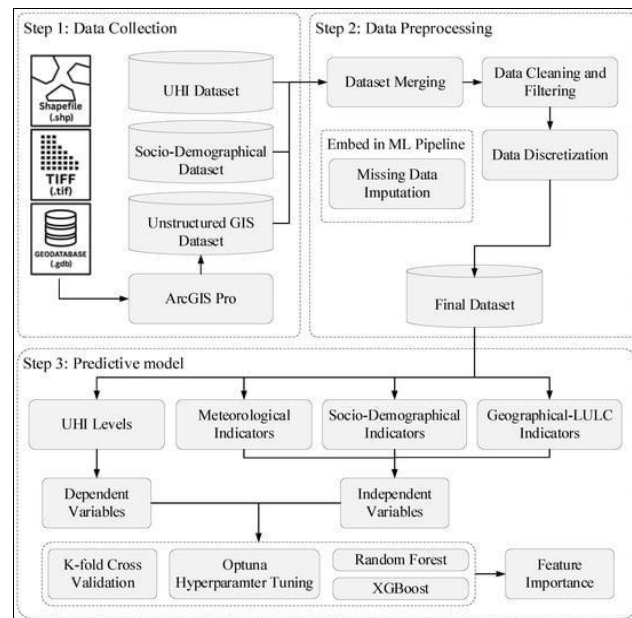


Fig 3: “AI-Based Framework for Urban Heat Island Prediction”

All in all, within the study area, ANN proved to be the best algorithm to predict Urban Heat Island.

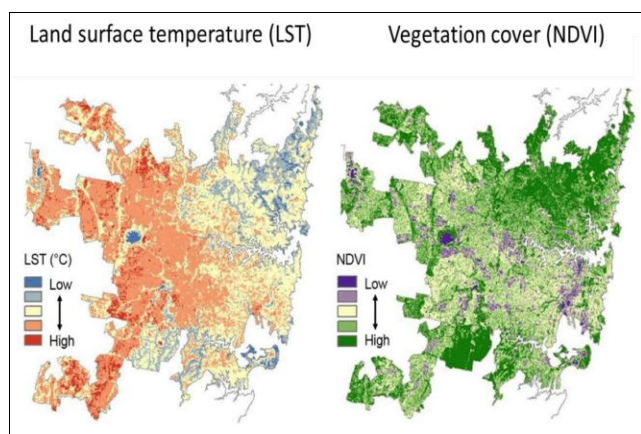
4.6 Feature Importance Analysis

The impact of variables on prediction of temperature was determined by running the Random Forest model to determine the most important feature used in predicting temperatures.

Table 5: Feature Importance Ranking

Feature	Importance Score
NDBI	0.31
NDVI	0.27
Population Density	0.18
Built-Up Area Percentage	0.14
NDWI	0.10

The findings show that NDBI had the strongest impact with an individual contribution to the predictive power of the model of 31% of the overall contribution. This observation validates the significant role of urban buildings on the thermal conditions. The NDVI was ranked just after the first one, thus emphasizing the impact of vegetation on urban heat mitigation. Regions with greater vegetation cover always registered lower temperatures and this showed that green infrastructure can be used to effectively cool Urban Heat Island severity. Density of the population as well turned out to be a contributing factor by acting as a strong predictor that human activities have a share in urban warming^[30]. The percentage of built-up area and NDWI also exhibited moderate significance, once again bringing into the limelight the synergies of land-cover attributes and water resources.

**Fig 4:** “Relationship Between Vegetation Cover and Surface Temperature”

4.7 Comparative Analysis of AI Algorithms

A comparative analysis of the three machine learning methods shows that there are a few notable findings. ANN proved to have better predictive ability due to the fact that the neural networks can learn very complex nonlinear association of more than two variables. The model was effective in incorporation of vegetation indices, built-up indicators and demographic data in coming up with precise temperature prediction.

Random Forest had similar performance and enjoyed an added benefit of interpretations of feature importance. The algorithm was very stable and could be overcome by overfitting, which is why it could be used in an environmental monitoring context. The Support Vector Machine worked reasonably well but needed a lot of fine-tuning of the parameters and had less scalability when using large size data. Even though SVM can still be used to predict temperatures, in this case, it was not as successful as ANN and random forest. Based on the comparative results, more sophisticated deep learning methods can offer great

advantages to the future Urban Heat Island evaluation projects, especially when accessible remote sensing data are massive.

4.8 Discussion of Findings

The findings illustrate clear evidence that urbanization can have a significant effect on the local temperature dynamics. Areas with large built-up infrastructure had much higher temperatures as compared to vegetated and water-rich habitats. These results are consistent with proven Urban Heat Island theory based on the assumption that high temperatures are caused by absorption of heat by hard surfaces and low evapotranspiration. The negative association between NDVI and temperature is highly negative which underscores the importance of vegetation in curbing urban warming. Cooling benefits of green spaces are thresholded by shading and release of moisture hence, they are important elements in the planning strategies of an effective city. The encouraging trends between NDBI temperature, population density, and temperature are another show that the growth of the cities is a direct contributor to the amount of heat. Commercial and residential development of lands can result in an exacerbation of thermal stress unless it is composed of sufficient green infrastructure. High performance of ANN indicates that machine learning methods have the potential to become more useful in Urban Heat Island assessment than conventional statistical methods. AI models have the ability to analyze large amounts of environmental data and reveal more complex patterns, which might not be readily visible using traditional analysis. These results can be useful to policymakers, urban planners and environmental managers aiming to mitigate the risks associated with heat and enhance urban resilience.

5. Conclusion

The studies were able to evaluate the impacts of Urban Heat Island (UHI) by using remote sensing technologies, the combination of remote sensing and Artificial Intelligence (AI) models. The study showed that fast urbanization, growth in the built-up areas and population has a major role in land surface temperature rise, whilst vegetation and water bodies have an additional role in alleviating urban heat in the cities. Using satellite derived parameters like Land Surface Temperature (LST), Normalized Difference Vegetation Index (NDVI), Normalized Difference Built-up Index (NDBI) and Normalized Difference Water Index (NDWI), the study came up with a holistic perspective of the parameter which affects urban thermal environments. The results indicated that the built-up infrastructure and temperature had a significant positive correlation, indicating that there was a large amount of Urban Heat Island intensity in the urban area. On the other hand, more vegetation cover had lower temperatures which underscore the role of green infrastructure in climate change and urban sustainability. The research also revealed the usefulness of AI predictive models to examine intricate relationships among the environment and predict changes in temperature.

The Artificial Neural Network (ANN) had the highest predictive power of the three machine learning algorithms analysed as compared to the other two algorithms, which are the Random Forest and Support Vector Machine. High

accuracy of ANN suggests its ability to reflect nonlinear interactions between the environmental variables and provide accurate predictions of temperatures. These findings substantiate the hypothesis that AI methods could greatly improve Urban heat Island assessment in comparison to conventional methods of analytics. Altogether, remote sensing data and AI models will be an effective framework of monitoring, predicting, and controlling urban heat conditions. The results of this study can influence policymakers, urban planners and environmental agencies to adopt evidence-based policy frameworks like expansion of green spaces, better land-use planning, and creation of climate prepared urban environments to reduce the negative effects of Urban Heat Islands.

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