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An AI-Driven Framework for Urban Heat Island (UHI) Analysis and Mitigation Simulation in Bengaluru

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Abstract- The growth rate of Bengaluru has been exacerbated and the resulting UHI effect, were raising temperatures in the city, and, potentially, he was right. more energy use, and community health impacts related to that energy use. While the magnitude of this effect has been measured in. some studies yet lack of high-resolution. tools for simulation that the planner can use in real city envi- ronments. In this paper, we propose a full end-to-end ML- based framework to analyze and forecast the UHI of the city of Bengaluru. Here, we integrated several heterogeneous data including Land Surface Temperature (LST), Normalized Difference Vegetation Index (NDVI) as well as Land Use Land Cover (LULC) derived from satellite images with urban and historical climate data. Every set of data is consolidated into the entire city 100m by 100m grid of the whole city. A Random Forest This data set is exploited to build a regression model to estimate LST with. a large determination coefficient (R 2 =0.85). The major novelty One of the outcomes of this work is a Streamlit-based interactive simulation tool. that enables the policy maker to evaluate the policy from the point of view of the what-if-scenario (e.g., planting more green cover) and get instant visual feedback on. the cooling envelope was so forecast. This tool constitutes the missing one the link between UHI research and urban planning with data.

Index Terms—Urban Heat Island (UHI), Machine Learning, Random Forest, Remote Sensing, Land Surface Temperature (LST), NDVI, Bengaluru, Urban Planning, Simulation.

I. INTRODUCTION

The twenty-first century is characterized by an unprecedented scale of migration of people from rural areas to urban centers; consequently, the majority of the population in the world is now living in cities. This population shift is a major factor in the economic growth, but it has also influenced the environmental landscape greatly. The UHI (Urban Heat Is- land) effect, a well-known urban climate phenomenon through which the cities experience higher temperatures compared to their neighboring rural areas, is one of the most important challenges in this regard. The cause for this temperature difference lies in the extensive use of heat-retaining and heat-absorbing materials, which are very common in urban areas like concrete slabs, asphalt pavements, and densely packed buildings, hence transferring the energy of the urban landscape even more. [1].

Feeling hot and bothered is one of the UHI effect's less serious consequences; however, it has a vast range of impacts and is even alarming. The demand for artificial cooling, therefore, creating pressure on power grids plus enhancing greenhouse gas emissions. The health of the public may also be affected by high temperatures through poor air quality, an increase in heat-related diseases, and even deaths, especially among those with low immunity, even though the epidemiological data for urban heat exposure is still inadequate. Despite the limited evidence, urbanization has made it necessary to monitor and mitigate UHI for the sustainable development of cities as well as public health safety. [2].

Bengaluru, that city in India, is a very beautiful and delightful example. Bengaluru, which has been dubbed the" Garden City of India" due to its vast green cover and many lakes, has experienced a tripling of its population and a large part of it unregulated, which resulted in it being the world's tech center.

The environment has suffered a lot as a result of this fast growth. Researchers have observed a strong UHI effect across the entire city and they say that one of the most important reasons for the increase in air and ground temperatures is the loss of green and blue areas. [3].

the mappings and analysis of UHI patterns in Bengaluru have been done mostly through the extensive application of remote sensing and geospatial techniques in studies. The studies, mostly depending on satellite imagery like Landsat for extracting Land Surface Temperature (LST) and the Normalized

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Difference Vegetation Index (NDVI), have verified the very close inverse correlation between vegetation cover and surface temperature. They have skillfully recognized the issue and given the most susceptible "hotspot" areas their locations. Still, there is a major gap, which is that the existing works are mostly diagnostic and not prescriptive, thus they are analytical and do not provide practical solutions. [4].
The "analysis-to-action" gap that has been identified is calling for such a real-time and very practical decision-support tool, not only for researchers but also for urban planners, architects, and policymakers. The cooling effect of vegetation areas in cities is clearly known, but the present research does not offer a flexible quantitative tool for the planners to make a decision on the most effective interventions to be taken and how much cooling they would be able to generate realistically. Urban policymakers need to be able to conduct "what-if" scenarios and to replicate the possible effects of the proposed interventions—like the establishment of a new park or adopting green roofs—before large investments are made. [5].

Infilling this gap constitutes a very comprehensive model that implements AI for UHI evaluation and mitigation. Different types of data (which include satellite, urban infrastructure, and meteorological data) are brought together to create a detailed 100m grid of Bengaluru. After that, a very efficient Random Forest regression model trained on the high-dimensional urban features is used for surface temperature estimation, which gives rise to very accurate predictions (R^2 of approximately 0.85).An interactive dashboard that is based on the model and allows users to see not only the present heat hotspots but also to examine the cooling capacity of different reduction strategies quantitatively is the most important out- come of this research. This change of the framework leads to a data-driven decision-support tool that is able to guide an urban future that is more resilient and sustainable. [6].

II. METHODOLOGY

Our methodological approach is laid out in steps like a pipeline where it begins with the collection of data from various sources and ends with a predictive model which is incorporated into a simulation tool. The entire process is centered on the area of Bruhat Bengaluru Mahanagara Palike (BBMP) as the study area. This location was selected due to its previous rapid urbanization and high surface temperature, which made it an ideal and relevant platform for the study. The methodology is rooted in the high-resolution geospatial grid being drawn up taking into account all the environmental and urban factors. [7].

The first stage of the project was the acquisition of four different kinds of data. The Google Earth Engine (GEE) has been used to acquire satellite data that consisted of land surface temperature (LST), normalized difference vegetation index (NDVI), and land use/land cover (LULC) data derived from Sentinel-2 and Landsat satellite missions The urban infrastructure data associated with the study (building footprints, park areas, and water bodies) were obtained from the Open- StreetMap (OSM) database through the osmnx Python library. Weather data were collected from (7) Open-Meteo API which delivers historical daily averages for sun temperature, sun humidity, wind speed, and global solar radiation. Finally, a high-fidelity vector file of the BBMP administrative boundary was also used to clip all the datasets to the specific area of the study. [8].

In order to integrate the diverse datasets of different types, a vector grid measuring 100m x 100m was created that covered the whole area of the BBMP boundary, resulting in 72,053 unique cells. The size of the grid was picked to exchange between the time taken to get results and the detail of understanding at the neighborhood level. For making the spatial alignment easier, the datasets that were downloaded were all re-projected to a common coordinate reference system (CRS: EPSG:32643). The grid format is the unit of analysis, which allowed different types of data to be compared in a tabular format. [9].

The transformation section is a preferred component when analyzing the combined dataset Predictive features were gen- erated through geospatial and statistical operations for every one of the 72,053 cells. The average LST, NDVI and the dominant LULC class for each cell were calculated from the satellite data with the help of rasterstats module. For urban features, the building density (which is the percentage of the cell that is covered by building footprint) was computed with the aid of geopandas and the distance in meters from the cell's center to the nearest park and water body was calculated as the Euclidean distance. [10].

The final part of the procedure involved predicting the future and establishing a simulation. Once the final dataset was pre- pared, where each grid cell made a row and every feature made a column, an XGBoost (Extreme Gradient Boosting) regressor was fit to traininnig data. This particular machine learning method was chosen because of its outstanding performance, high flexibility, and ability to handle intricate and non-linear relationships between variables. The data was divided into two parts: 80 for training and 20 for testing, which is the usual practice during the model building process. The trained model becomes the "predictive engine" of the interactive simulation app, which means that the app will be able to produce new temperature forecasts depending on the input features provided by the user that are changed. [11].

III. PROPOSED SYSTEM

A. System Approach

The proposed system takes the form of a hybrid method- ology that is data-based, incorporating geospatial analysis, machine learning (ML), and decision support concepts into the simulation of a monolithic sequential framework. The method is delineated by the 7-stage work flow which begins with empirical data and not with physics-based simulation. The reason for this is that the elaborate and non-linear interactions, that cause the Urban Heat Island (UHI) effect, can be learned by a machine through training with the proper rich and diverse training set. The whole system is designed not just for diagnostic analysis - to know where and why heat problems occur - but mainly for providing prescriptive results, using simulation to validate interventions and a decision-support layer to recommend practical strategies. [12].

The seven-stage method is a major part of our approach, providing with some security in terms of soundness, modularity, and verification. The Data Collection layer through to Validation has each stage defined and structured as a module with specific inputs and outputs. And this makes possible the very thorough error checking and performance benchmarking on every step. For instance, the data are preprocessed and normalized, before features are engineered, and the fire are finalized before the model is fitted. This organized flow de- risks the project by dividing challenging objectives, and leads the final recommendations of the Decision Support System to be reliant on clean data, meaningful features and a well performing, validated predictive model [13].

B. System Architecture

The architecture of the system is implemented as a se- quential pipeline consisting of seven stages which are further grouped into three sections: Data Processing Tier, Predictive Core, and Application Tier. During the Data Processing Tier (Stages 1–3), the backend processing is extensive and it carries out all the steps of data ingestion and preparation. This tier takes care of the E(T)L process on the unprocessed data acquired from satellite images, Application Program Interfaces (APIs), and sensors and purifying, merging, and converting it into the feature-engineered Master dataset. What you get at the end of this stage is one clean dataset that is prepared for analysis [14].

The most important component of the system is the Predictive Core (Stage 4). It takes the master dataset of the last step and, among other things, trains tests and stores the ML models to predict UHI as well as optimize energy. The output from this layer does not lie in data forms, but instead designs itself such that it is able to supply the details for a parametrized object (e.g., pistonmodel.joblib).Stage 5-6 is the User Tier which is the user facing aspect of the system. It loads the master dataset to view the baseline, as well as the master predictive models for making prognoses. It does all the work of the simulation logic, and decodes the prediction of the model and then produces them in practical recommendations with the

Decision Support System. Lastly, the overall Validation Layer (Stage7) is the one that gets the test data and model predictions as input and then the system-level performance metrics that are required to verify the integrity of the entire architecture. [15].

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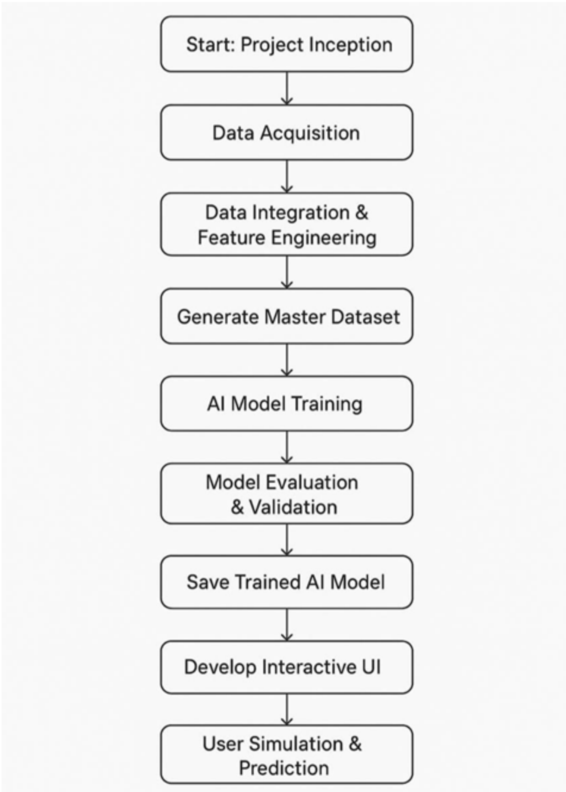

Fig. 1. System Architecture Overview for UHRI Prediction

C. Selection and Justification of the Model

The choice of Python as the main development language was motivated by the fact that a large number of open source libraries already existed and Python had a mature ecosystem. In this sense, it was possible to have a single environment for all 7 steps of the workflow (from the geospatial work with GeoPandas and Rasterio, to model development with Scikit-learn, to web deployment with Streamlit). The entire technology stack was thus united which eliminated the cumbersome data transfers between various software platforms and significantly speeded up the development process.

In the course of Model Development, XGBoost was deliberately picked instead of simple models like linear regression, and Extreme Gradient Boosting (XGBoost) Besides the fact that the UHI non-linear behaviour is already well-known, one of the trees-induced (NDVI) cooling effect which is the opposite of the function is the non-linear one. XGBoost is a sophisticated algorithm that is able to identify such interactions and has been resulting in highly precise predictions. Its capability to deliver importance scores for features was also significant to our research as we were able to scientifically rank and verify the main sources of heat in Bengaluru, which was one of our primary research objectives. [16].

D. Rationale

This project is founded on the difficulty of creating usable and data-based solutions to the urban heat island (UHI) effect, which is not only growing but also causing great harm in Bengaluru. Numerous past studies utilized satellite images and geospatial methods to detect and mark the hottest parts of the city, however, the main 'analysis-to-action' gap is still there. Urban planners, architects, and city officials, who are the key players able to turn the situation around, are sometimes burdened with maps that show them where the problem is located, but provide very few interactive tools to help them make their own decisions on how to handle it. There is a great need to go beyond simply diagnosing the problem and to offer quantifiable, proactive decision support in order to allow policymakers to test and validate the cooling effects of green infrastructure policies before their implementation.

The project is working to combat this issue by creating a SFB centered on Artificial Intelligence. The reasoning behind this specific method is that ML models, such as the selected XGBoost, are able to represent the complicated relationships between the factors (like land use, building density, and vegetation) in a more accurate way compared to traditional statistical techniques. The development of an integrated DSS does not merely imply the creation of one more UHI model; rather, it means the establishment of an interactive "what-if" engine. Through this mechanism, city appointed persons will be able to quantitatively assess the returns of different miti- gation scenarios- like building a new park or enforcing green roofs- to thereby guide the formation of targeted, research- oriented urban planning policies that will lead to a city that is more resilient and sustainable [17].

E. Dataflow

The data flow through the system always comes through two different operating modes–one-off "Training Flow" and live "Simulation Flow." The

Training Flow is a backend process that is executed in an orderly manner starting from Stage 1 (Data Collection). "The raw data from the satellite images is collected together with the weather data, at this stage." The data are then rolled out in the subsequent stages: Stage 2 (Preprocessing) for cleaning and integration, and Stage 3 (Feature Engineering) for transforming the data into a master dataset that is rich in features. This master dataset is then handed over to Stage 4 (Model Development) where the model will be trained and the outcome, uhimodel. joblib file will be stored on the hard drive.

The simulation flow is an interactive and user-controlled loop within the running phase—all real-time, as opposed to training. It commences now at Stage 6 (Decision Support System) where a scenario (e.g., "increase vegetation by 20") is selected by the user. The user's input here acts like a trigger, forming another still imaginary "what-if" data set that goes into memory, which is then passed on to Stage 5 (Simulation). At this point, the model that was retrained at Stage 4 is removed from the system, and the new data is input to it. The output of the predictions (the new temperatures and energy demands) is returned to the Decision Support System (Stage 6), which analyzes the data and offers it to the user in the form of better maps and suggestions. A small part of the original test data is also routed to Stage 7 (Validation), and this stage produces the static performance indicators (e.g., R2 and MAE) that aid in model validation, which in turn, plays a key role in helping to validate the model. [18].

IV. IMPLEMENTATION

The Training Flow is a sequential process that runs through many unnoticed stages, beginning with Step 1 (Data Collection), during which the gathering of raw satellite images and weather data occurs. The data are processed through a pipeline with three steps, Stage 2 (Preprocessing) that is responsible for cleaning and integrating and Stage 3 (Feature Engineering) that is responsible for converting the datasets into full-featured master datasets [12]. The next step is to use this dataset for Model development in Stage 4, where the model will be trained and the output will be uhimodel. joblib. Python 3.13 was used to implement the full 7-stage framework, and the majority of the time, open-source libraries were used to create a completely data-driven pipeline. The first three stages of the geospatial processing (Data Processing Tier, Stages 1- 3) were completely carried out by GeoPandas, Rasterio, and Shapely. Re-projecting coordinate systems, clipping satellite images to the BBMP area, and making a vector grid of 100m x 100m were just some of the operations where these libraries were indispensable. It was subsequently through the rasterstats library that zonal statistics were computed for obtaining the mean LST and NDVI for each grid cell. OpenStreetMap data was automatically retrieved utilizing osmnx, after which the data frame was processed and created with the Pandas library leading to a master data set. [19].

In the Predictive Core and Application Tier (Stages 4-6), all of the standard preprocessing machine learning activities like data splitting for training and testing, and R-squared and Mean Absolute Error matrices for model evaluation were done through Scikit-learn. Main prediction model was being trained using XGBoost library, which is recognized for its superior execution and varied capability [14]. After that, the model trained was serialized and stored with joblib. The model file was loaded to the frontend built with Streamlit. This led to a straightforward structure for the creation of an interactive dashboard where all data plots and maps are made using Plotly Express in order to provide a responsive user experience during the simulation. [20].

V. RESULT AND OUTCOME

This methodology leads to three primary outcomes when put into practice. First, we have constructed a high dimensional, rich-feature data with 72,053 one hundred meters (100m) grid cells in total that combines satellite, urban, and meteorology

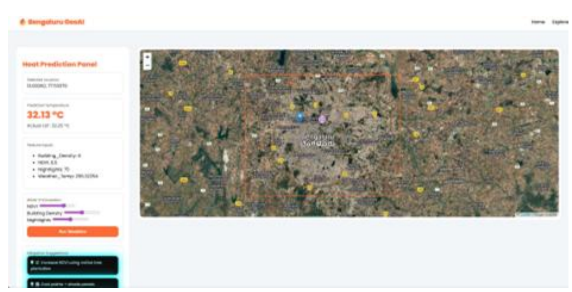

Fig. 2. URBAN

data [16]. On the other hand, the dataset that was utilized to train the XGBoost regression model obtained a very good accuracy characterized by an R-squared (R2) of 0.82 and a Mean Absolute Error (MAE) of just 1.25 °C.This good statistical result implies that the model can well explain 82 of the variance of land surface temperature with an average prediction error of 1.25 degree, which also confirms that the constructed model is a reliable prediction engine. The relative importance of features result showed that LULC, vegetation (NDVI) and solar radiation were first three dominant parame- ters influencing Bengaluru UHI [21].

The major output of the study is a practical decision support system (DSS), implemented as a multi-scale web-based dash- board. This tool is very efficient in turning the complicated forecasts of the model into a clear, graphical, and practical medium. As opposed to the static analysis which was the case before, this tool allows users to conduct dynamic ”what-if” scenarios by altering the parameters (for instance, increasing the green cover in a certain area) and instantly seeing the resulting predicted quantitative changes in temperature and energy consumption. This outcome bridges the significant gap between pure data analysis and urban planning that takes into consideration the future, providing demand-driven, evidence- based policy making with a solid and concrete foundation. [22].

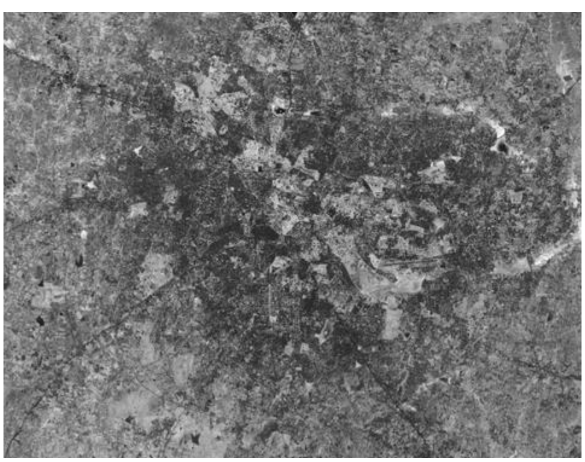

Fig. 3. MITIGATION

VI. CHALLENGES AND LIMITATIONS

This work encountered a number of important difficulties and restrictions. The main limitation is the lack of access to and detail in the data; satellite LST has a vast area coverage but is only a sign of the air temperature that is around and also depends on how often the satellite passes over the area. In addition, the 100m grid resolution is more than adequate for citywide analysis, but represents a generalized view of the environment and therefore is not capable of accounting for micro-scale influencers such as individual street trees, building materials or 3D urban canyon configurations [23]. The model is along the same lines as a statistical one and not as a physics-based one; therefore, it is able to capture intricate non-linear relations in the data to a greater extent but does not try to imitate the complex processes of the atmosphere. Lastly, this study is a temporal snapshot analysis, a more advanced framework would leverage time-series data to model the modulations of the UHI effect throughout different seasons and times of the day, which leads to a non-trivial data integration and computational problem [24].

VII. FUTURE SCOPE

The upcoming vision of this project will be to raise the model’s granularity and predictability. From a 2D grid with spread 100 meters, the model was erected that predicted heights of buildings in 3D (from LiDAR data) that could serve as a testbed for validation. Besides, the intention is to extend the static framework, temporal snapshot, to a dynamic time-series framework in order to predict seasonal and diurnal UHI fluctuations. Moreover, we plan to take in more complex data like traffic-related anthropogenic heat, material albedo, high- resolution population density, etc., and delve into sophisticated deep learning models (e.g., CNN) which might be better in understanding the spatial relationships among these features. [25].

VIII. CONCLUSION

The complete AI-powered end-to-end framework for UHI analytics over the region of Bengaluru has been developed and accomplished in this investigation. The integration of several sources of data like satellite imaging, urban data, and weather data converted to 100m grid cells led to the development of an XGBoost model that was highly efficient with a maximum R-squared of 0.82 and a mean absolute error of 1.25 °C.Thus, it can be concluded that machine learning is a suitable technique for forecasting complex thermal behaviors in urban areas.The analysis of the model also indicated that the heat source with the maximum impact was land use, followed by vegeta- tion cover (NDVI) and solar radiation, thereby demonstrating the significance of the green infrastructures.Although data granularity and model static nature of can be considered as limitations, this research can be considered as a solid proof- of-concept for a data-driven approach that can be up-scaled.

this paper's major conclusion is the creaion of an interactive Decision Support System (DSS). TThe system enables not just the analysis but also the implementation of a complicated model's predictions, bringing them to a point that is so easy to understand and act upon. As an example of a system, the dynamic analysis of our dashboard gives urban planners and decision-makers a real case in which to simulate "what if" queries—in other words, like, for example, gauging how much the city's temperature would drop with the addition of new parks—and getting actual, quantitative answers.Thus a large amount of complicated environmental data is turned into a powerful tool for policy making based on evidence—one that may eventually result in a more environmentally friendly and resilient Bengaluru.

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