A Deep Learning Approach for Monitoring Urban Growth and Analysing Surface Urban Heat Islands over Hyderabad, Telangana, and Visualisation through Interactive Leaflet Web Map

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Abstract

Due to the rapid urbanisation over metropolitan cities, land surface temperature and urban expansion are negatively affected which results in downgrading of urban thermal environment. Current study uses Landsat 5, Landsat 8, and Sentinel-2 imagery from 2003, 2013, and 2023 to monitor urban expansion in the Greater Hyderabad Municipal Development (GHMD), a city in the Indian state of Telangana. Urban and non-urban training dataset are created using high resolution Google Earth images and ground surveys. Random Forest (RF) classification is used to categorise data and produce the preliminary classification result. The pure classified urban and non-urban pixels from RF were later used to label data for deep learning (DL) models. Multi-sensor satellite images were analysed for three periods, with different sensors for each year. Due to the variance in image quality, it is challenging to determine whether the urban growth was genuinely observed or merely detected due to faulty image segmentation. The 3D-CNN convolutional neural networks were trained and the transfer learning technique was used to address this problem. The 3D-CNN gives precision of 0.95 and weighted f1-score as 0.92 which proven to be the better algorithm for classifying urban and non-urban areas as compared to RF which gives 0.80% overall accuracy. The results demonstrate that all land uses are changing, with built-up areas showing the highest rise (+102.55%), whereas other land use classes have drastically decreased during the past 30 years. The relationship between Surface urban heat island (SUHI) and Normalised Difference Vegetation Index (NDVI) was showing a negative correlation because of the vegetated area affected due to urban expansion. The relationship between SUHI and Rapid Urban Growth resulted in a positive correlation because of various anthropogenic activities. The results generated are visualised in an interactive leaflet web map created using folium module in python.

Keywords CNN, Urban Growth, SUHI, Random Forest, Image Segmentation and Google Earth Engine.

Introduction

Urbanisation is an undeniable global phenomenon, marked by more than half of the world's population currently residing in urban areas, and this number is expected to increase significantly in the coming decades (United Nations, 2018). Rapid and widespread urban expansion (UE) will continue to be a global problem, posing numerous ecological and environmental problems (Seto et.al., (2012), van Valet, (2019), Chen et al., (2020a)). Accurately understanding and modelling urban growth is an essential endeavor for city planners, policymakers, and researchers, who seek to grapple with the multifaceted challenges tied to urban development. Traditional urban growth models, primarily reliant on 2D geospatial data, often face limitations when it comes to capturing the complexities of three-dimensional urban environments (Batty, 2018). Nevertheless, the emergence of 3D Convolutional Neural Networks (3DCNN) presents a groundbreaking approach to urban growth modelling. These neural networks capitalize on the intrinsic three-dimensionality of urban spaces, enabling a more comprehensive analysis of their spatiotemporal dynamics. Through the utilization of the computational power and adaptability of deep learning, 3DCNNs hold the potential to revolutionize our comprehension of urban growth, delivering invaluable insights for informed and sustainable urban planning.

Due to the rapid increase in urban growth the land surface temperature is also getting affected and can be seen via surface urban heat island effect which is the major concern over the past few decades. Surface Urban Heat Islands (SUHIs) constitute a pressing environmental challenge that results from the rapid urbanization process. This phenomenon, often referred to as the Urban Heat Island (UHI) effect, is an unintended consequence of the widespread conversion of natural landscapes into impermeable surfaces such as concrete, asphalt, and buildings. These urban surfaces absorb and retain heat throughout the day and release it gradually during the night, causing urban areas to experience notably higher temperatures compared to their surrounding rural counterparts (Oke, 1982). The implications of SUHIs extend beyond mere discomfort, encompassing far-reaching ramifications for both the environment and public health.

One of the primary consequences of SUHIs is the heightened demand for energy, particularly during hot summer periods. Urban residents increasingly rely on air conditioning to combat the oppressive heat, leading to increased energy consumption and, consequently, elevated electricity bills (Akbari et al., 2001). This surge in energy usage not only strains power grids but also contributes to greenhouse gas emissions, rendering urban areas more susceptible to climate change-related consequences (Santamouris, 2015). Moreover, SUHIs are associated with deteriorating air quality, as elevated temperatures can foster the formation of ground-level ozone and other pollutants, posing substantial health risks, particularly for vulnerable populations (Stone, 2013).

The acceleration of urbanization exacerbates the SUHI effect by expanding the built environment, diminishing green spaces, and augmenting the number of heat-absorbing surfaces within cities. The implications of this trend extend beyond environmental and health concerns, manifesting in an increase in heat-related illnesses and energy costs. Consequently, comprehending, monitoring, and mitigating SUHIs have become indispensable facets of urban planning and sustainable development. Strategies encompassing urban forestry, green roofs, cool roofs, and reflective pavements are instrumental in combatting the SUHI effect, fostering the creation of more live-able, resilient, and environmentally sustainable urban areas in response to the challenges posed by rapid urbanization (Liu and Pandey, 2019). This paper aims to offer an insightful overview of the concepts, methodologies, and applications of 3DCNN in the domain of urban growth modelling and monitoring SUHI, underscoring its relevance in tackling contemporary urban challenges and calculating land surface temperature effect.

Materials and Methods

Three-Dimensional Convolutional Neural Networks (3D CNNs) represent a sophisticated extension of the conventional 2D CNNs into the realm of volumetric data, such as video sequences or medical imaging. This innovation allows the model to capture spatiotemporal information, making 3D CNNs highly valuable for tasks that require a holistic understanding of data across both spatial and temporal dimensions. This model's architecture integrates 3D convolutional layers, which convolve over both the width, height, and depth of the input volume, allowing it to recognize complex spatial patterns and temporal dependencies simultaneously. Furthermore, the utilization of recurrent connections within 3D CNNs has been influential in modeling temporal dynamics effectively (Tran et al., 2015). 3D CNNs represent a pivotal advancement in deep learning, catering to applications where spatial and temporal dependencies are crucial. Their ability to process volumetric data efficiently has revolutionized fields such as medical imaging, computer vision, and autonomous systems, underscoring their importance in contemporary AI research and applications.

3D CNN architecture:

The workflow of 3D Convolutional Neural Network (3D CNN) involves several key steps for processing and analyzing volumetric data. Here's an explanation of the typical workflow:
Data Preprocessing: The initial step involves preparing and preprocessing the 3D data. This includes tasks like loading the volumetric data, resizing it if necessary, normalizing the data, and potentially augmenting it to ensure it's suitable for input into the 3D CNN.

Architecture Design: The next crucial phase entails designing the architecture of the 3D CNN. This includes determining the number of layers, their type (convolutional, pooling, fully connected), and their configurations. Choices regarding kernel sizes, filter numbers, and the overall depth of the architecture are made.
Convolution and Feature Extraction: In this step, the 3D CNN starts processing the data. It employs 3D convolutional layers, which are equipped with learnable filters that traverse the input volume to extract features across both spatial and temporal dimensions. These layers progressively capture increasingly complex patterns and details from the data.
Pooling or Subsampling: After each convolutional layer, it's common to introduce pooling layers. These layers serve to reduce the spatial dimensions of the data while retaining crucial information, which aids in managing computational complexity and combating overfitting.
Fully Connected Layers: Once the features have been effectively extracted, fully connected layers may be added to the architecture. These layers typically flatten the extracted features and feed them into a conventional neural network structure to make high-level decisions, which could include tasks like classification or regression.
Loss Calculation: The network computes a loss function, which quantifies the disparity between the network's predictions and the actual target values. The choice of the loss function is task-dependent, and it varies for classification, regression, or segmentation tasks.
Back propagation and Training: The 3D CNN proceeds to fine-tune its internal parameters, including weights and biases, through back propagation. This is achieved by minimizing the loss function using optimization algorithms like stochastic gradient descent (SGD) or its variations. The training process typically involves multiple iterations (epochs) on the training dataset.

Evaluation and Validation: After training, the model is assessed on a separate validation dataset to gauge its performance and fine-tune hyper-parameters. Common evaluation metrics, such as accuracy, F1 score, or mean squared error, are employed, contingent on the specific task.

Testing: Following training and validation, the model is subjected to testing on a new, unseen dataset to gauge its ability to generalize to real-world data. Testing outcomes are instrumental in assessing the model's practical utility and real-world effectiveness.

Deployment: If the 3D CNN demonstrates satisfactory performance during testing, it can be deployed for practical applications.

The methodology used for implementation of 3DCNN is shown in Figure 1. The graphical architecture has been shown in Figure 3.

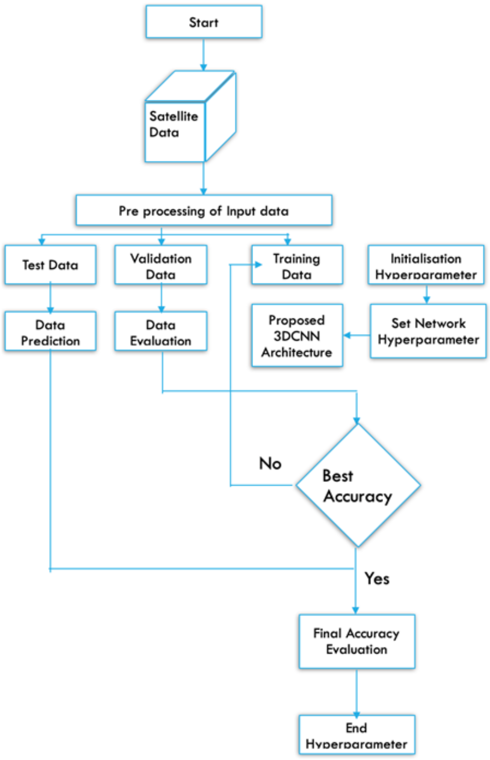

Fig. 1 Flow chart of the methodology for 3D CNN.

Estimation of Surface urban heat island:

Estimating the Surface Urban Heat Island (SUHI) involves a combination of data collection, analysis, and modelling. Figure 2 is a general methodology for estimating SUHI:

Urban-Rural Temperature Difference Calculation:

Calculate the temperature difference between urban and rural areas. This involves comparing temperature measurements from urban and rural locations. The rural location serves as a reference for understanding the urban heat island effect.

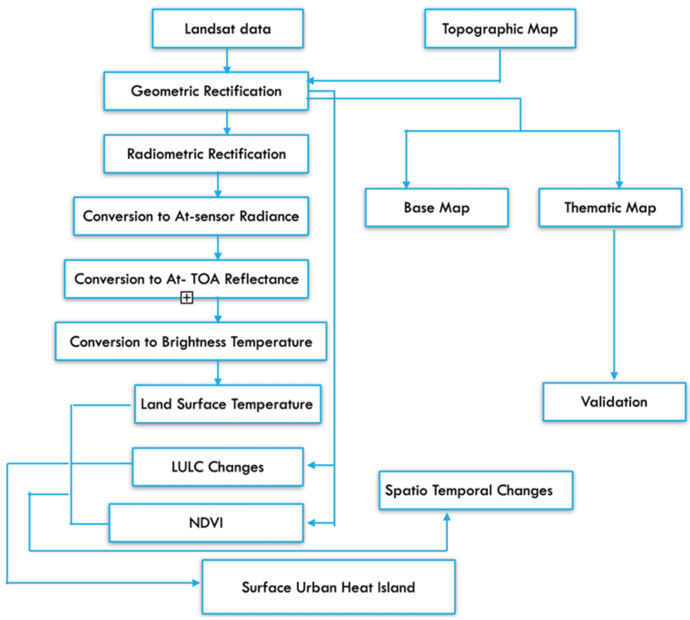

Fig. 2 Flow chart of the methodology for SUHI.

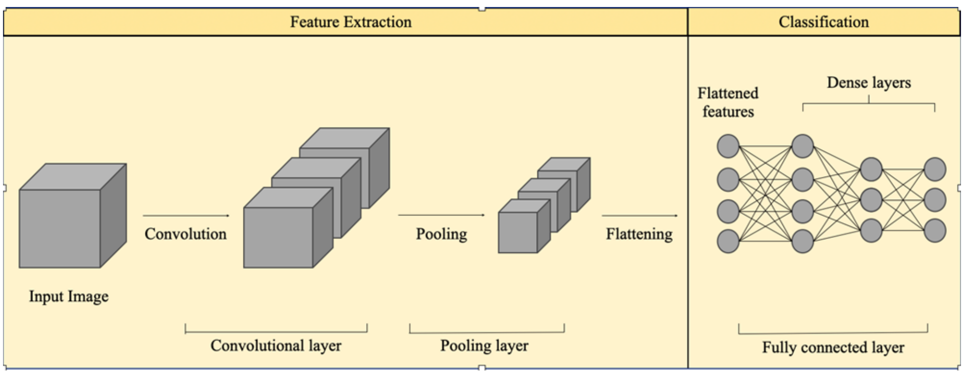

Fig. 3 Flow chart of the Architecture.

Spatial Analysis:

Use GIS tools to conduct spatial analysis, including buffer zones and spatial statistics, to assess the spatial distribution of temperature differences across the urban area. Identify hotspots or cool areas.

Temporal Analysis:

Analyse temporal patterns to determine when the SUHI effect is most prominent. This can involve daily, seasonal, and annual variations.

Remote Sensing Analysis:

Employ remote sensing techniques to assess temperature patterns derived from thermal infrared imagery. Tools like the Normalized Difference Vegetation Index (NDVI) can help assess vegetation's impact on temperature.

Results and Discussion

The result of studying urban areas often reveals significant growth trends and patterns that have become prevalent in recent years. These results are critical for understanding and addressing the dynamics of urbanization. Here are some key findings that typically emerge when analyzing the growth in urban areas: the Figure 4 Shows the change in urban growth from the year 1999 to 2016 and the recent year (2023) change is shown in Figure 5.

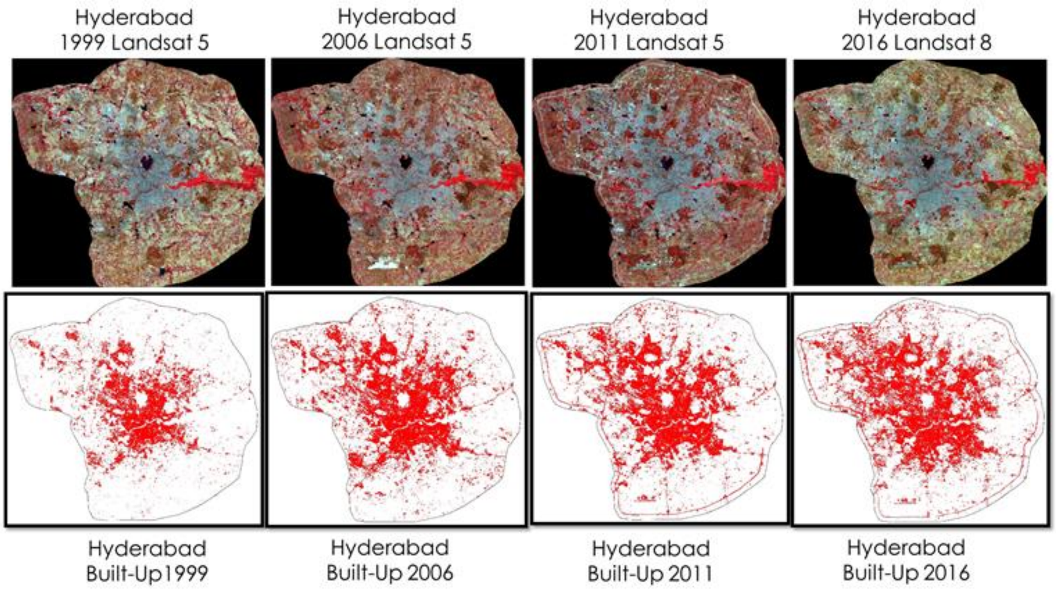

Fig. 4 Showing Change in urban growth from 1999 to 2016.

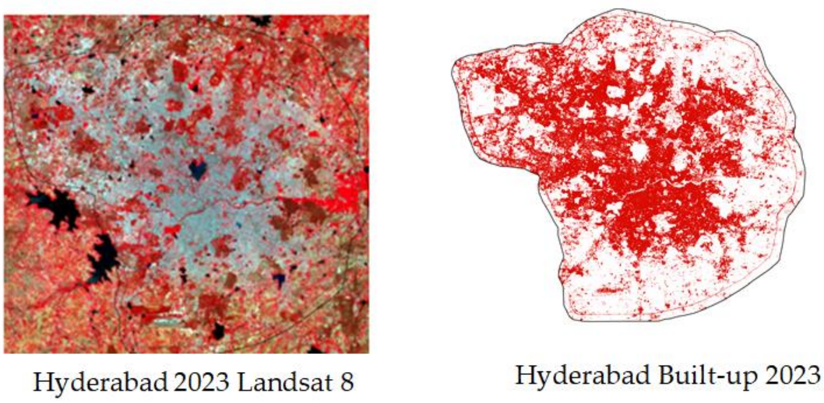

Fig. 5 Showing Change in urban growth in 2023.

Hot Spot Urban Growth in Hyderabad City: Hotspot areas in urban growth typically refer to regions within a city or urban area where development and growth are particularly intense or concentrated. The result shows the intense urban growth in one part of Hyderabad and can be considered as hot spot for the city as shown in Figure 7.

Model Accuracy: The model accuracy and loss has been shown for each epoch in Figure 8.

Estimating Surface Urban Heat Island: The results and discussion section of a study on the Surface Urban Heat Island (SUHI) typically provides an in-depth analysis of the findings and their implications. Below is the result generated for the Hyderabad city from 2006 to 2022 at every five-year interval as shown in Fig. 10.

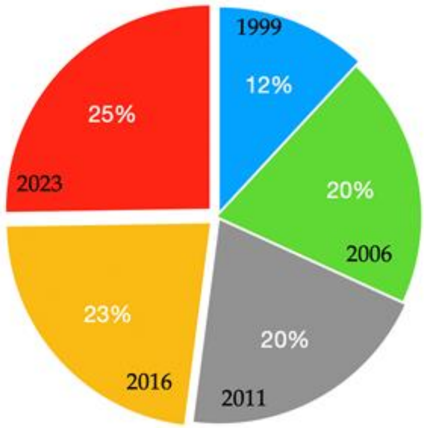

Fig. 6 Showing Change in urban growth in percentage from 1999 to 2023.

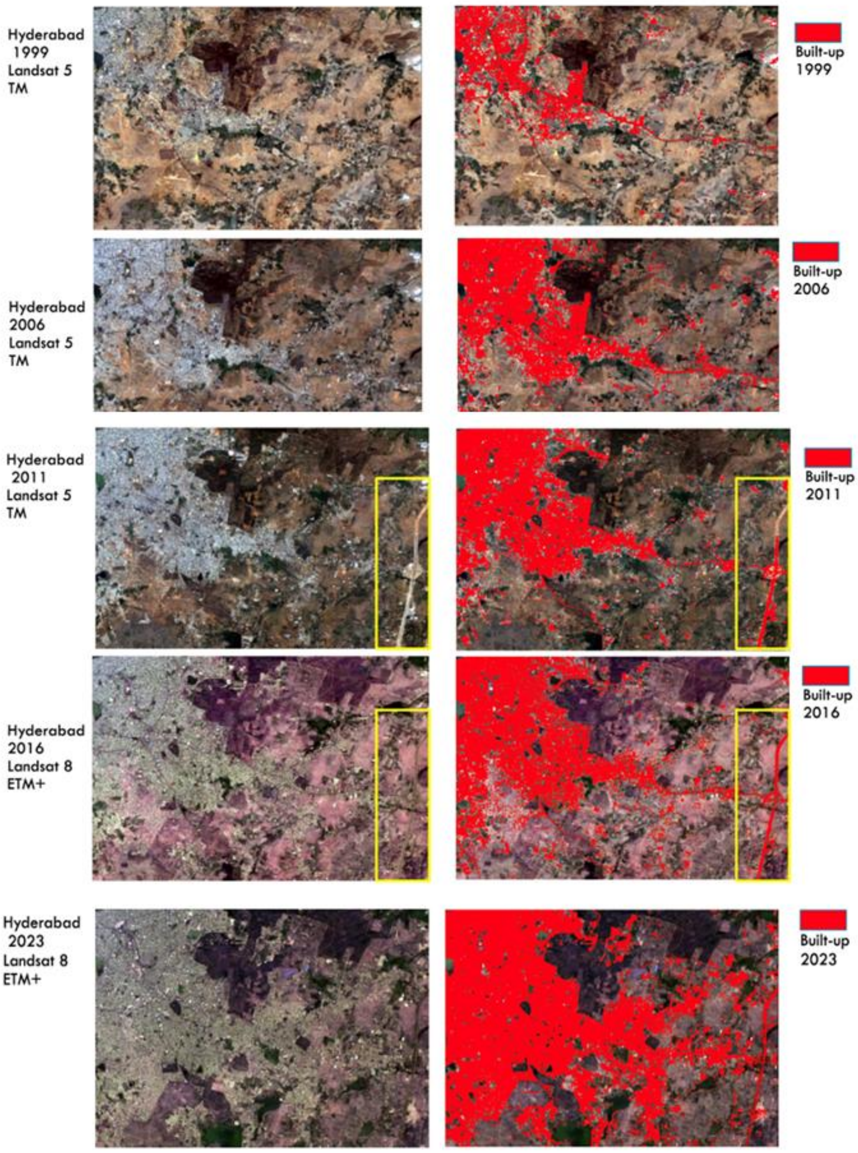

Fig. 7 Showing Change in urban growth from 1999 to 2023 and a hotspot for a city.

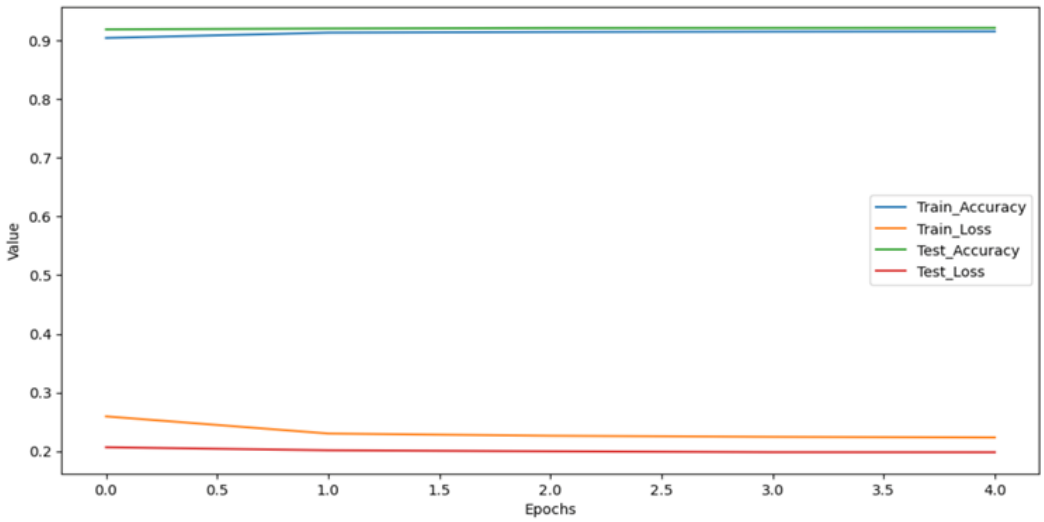

Fig. 8 Showing Change in urban growth from 1999 to 2023 and a hotspot for a city.

	precision	recall	f1-score	support
Class-1	0.95	0.94	0.94	6704332
Class-2	0.79	0.88	0.83	518693
Class-3	0.93	0.96	0.94	6019202
Class-4	0.83	0.94	0.88	189071
Class-5	0.76	0.72	0.74	798412
Class-6	0.62	0.26	0.36	196606
accuracy			0.92	14426316
macro avg	0.81	0.78	0.78	14426316
weighted avg	0.92	0.92	0.92	14426316

Fig. 9 Showing accuracy and weighed average accuracy of the model.

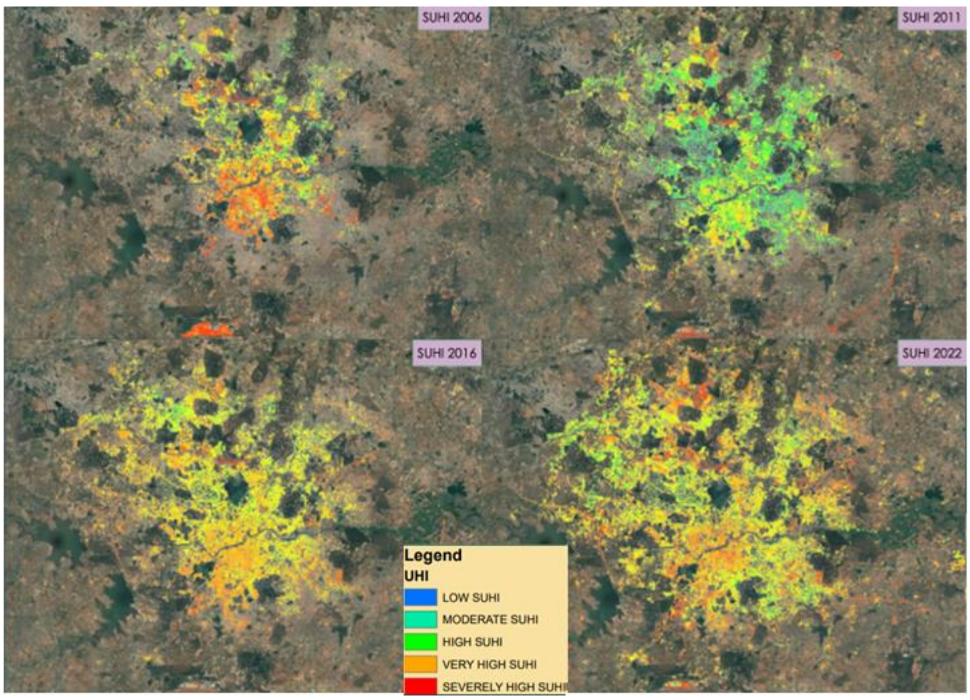

Fig. 10 Showing SUHI over Hyderabad city from 2006 to 2022 at every five-year interval.

Identifying hotspot areas is essential for urban planners, policymakers, and researchers to make informed decisions about infrastructure development, land use policies, and urban services. Balancing the economic benefits of hotspot areas with social and environmental considerations is an ongoing challenge in urban growth and development. The investigation into the Surface Urban Heat Island (SUHI) phenomenon has unveiled critical insights into the thermal characteristics of urban environments. This research has demonstrated that SUHI is a complex and multifaceted phenomenon influenced by a myriad of factors, including land use, meteorological conditions, and urban morphology. Our findings, rooted in both spatial and temporal analysis, shed light on the urban growth and SUHI together.

In conclusion, the Surface Urban Heat Island is a dynamic and intricate phenomenon that warrants continued research and practical interventions. The findings presented in this study provide a foundation for informed decision-making in urban planning, sustainability, and climate adaptation. Addressing SUHI is not merely an environmental imperative but also a means of promoting healthier, more live-able, and more resilient cities for current and future generations. As we move forward, the integration of SUHI analysis into urban policies and practices will be indispensable in shaping urban landscapes that are not only vibrant but also thermally sustainable.

Conclusion

The use of Three-Dimensional Convolutional Neural Networks for urban growth modelling represents a substantial leap forward in the field of urban planning and geospatial analysis. The capabilities of these models to capture spatial and temporal dynamics in three-dimensional urban environments open new avenues for informed and sustainable urban development. As we move forward, the integration of 3D CNN models into urban planning and policy-making processes is likely to provide substantial benefits, ultimately leading to more resilient, live-able, and environmentally responsible cities.

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Citation

Singh, R., Sachin., Rajdeep, N., Mandal, S., Pondari, S., Kumar, R., Kandrika, S. (2024). A Deep Learning Approach for Monitoring Urban Growth and Analysing Surface Urban Heat Islands over Hyderabad, Telangana, and Visualisation through Interactive Leaflet Web Map. In: Dandabathula, G., Bera, A.K., Rao, S.S., Srivastav, S.K. (Eds.), Proceedings of the 43rd INCA International Conference, Jodhpur, 06–08 November 2023, pp. 57–66, ISBN 978-93-341-2277-0.