# Strategizing Low Carbon Urban Planning Through Environmental Impact Assessment by Artificial Intelligence Driven Carbon Footprint Forecasting

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**Abstract –** Addressing the associated rise in Carbon Emissions (CE) as smart cities expand becomes paramount. Effective low-carbon urban planning demands robust, precise assessments. This research introduces a cutting-edge solution via an Artificial Intelligence (AI) -driven Carbon Footprint (CF) impact assessment. A detailed dataset, collected over 3 years, was harnessed to gather insights into vital urban factors, including CE, Energy Consumption (EC) patterns, variations in land use, transportation dynamics, and changes in air quality. The cornerstone of this research is developing the Multi-modal Stacked VAR-LSTM model. This model proposes to provide accurate CF predictions for urban environments by merging the capabilities of Vector Autoregression (VAR) with Long Short-Term Memory (LSTM) neural networks. The process encompasses dedicated assessments for each data segment, harnessing VAR to delineate interdependencies and refining these predictions with the LSTM network using the residuals from the VAR analysis. By interweaving AI-driven carbon footprint impact assessments into the urban planning discourse, this study underscores the vast potential in sculpting future urban development strategies that are sustainable and sensitive to carbon impact.

**Keywords –** Carbon Emissions, Low-Carbon Urban Planning, LSTM, Vector Autoregression, Machine Learning.

## I. INTRODUCTION

The global phenomenon of urbanization, representing the rural population migration to urban areas and the expansion of these urban centers, is inextricably linked to the aspirations of economic progress and enhanced living standards. As more and more areas transition into urban hubs, there is a corresponding surge in infrastructure development, economic activities, and a concentration of resources to support the burgeoning populace [1]. However, while urbanization brings about economic growth, cultural amalgamation, and technological advancements, it is not without its adverse impacts. One of the most pressing consequences of rapid urbanization is its environmental toll. Urban centers, with their dense constructions, transportation networks, and industrial activities, tend to produce a significantly higher Carbon Footprint (CF) than their rural counterparts. Green spaces, which act as the lungs of an area, frequently diminish, approaching concrete structures.

Consequently, the balance between natural ecosystems and built environments gets disrupted. This leads to increased greenhouse gas emissions and paves the way for phenomena like the urban heat island effect, compromised air quality, and strain on natural resources. Thus, the progression of urbanization, if not managed sustainably, poses profound challenges to both the environment and the essence of urban living [2].

Building on the environmental challenges posed by unchecked urbanization, an unequivocal need emerges for meticulous planning and assessment mechanisms, namely, Environmental Impact Assessment (EIA) for urban development initiatives. EIA serves as a model that assesses the possible environmental significance of planned projects or policies, allowing decision-makers to consider environmental aspects at the very outset of planning processes [3]. In the context of urban planning, this implies assessing how different developmental projects, infrastructure enhancements, and urban activities influence the CF and the overall ecological balance of the city. Implementing EIA in urban planning ensures that potential environmental harm, especially concerning Carbon Emissions (CE), is identified, quantified, and mitigated before irreversible damage occurs [4]. Furthermore, it proposes a structured pathway for integrating sustainable practices into the urban development framework. By predicting the environmental repercussions of urban actions and offering alternatives, EIA becomes an indispensable tool, guiding cities towards a sustainable path where economic development and environmental stewardship coexist harmoniously.

The infusion of Artificial Intelligence (AI) into EIA provides a transformative approach to addressing the complexities of urban development and its ecological implications. AI's advanced algorithms can efficiently process big data, identifying intricate patterns and relationships that might elude traditional analytical methods [5]. Specifically, when examining multifaceted urban systems, AI has the potential to predict CE by assimilating and analyzing data across numerous sectors like Energy Consumption (EC), land use, transportation, and air quality.

This holistic approach ensures a comprehensive understanding of the cumulative impact of different urban factors on the environment. However, leveraging AI for such endeavors is not without challenges. One significant hurdle is integrating and harmonizing diverse datasets to form a coherent input for the AI models. Frequently sourced from different agencies and in varying formats, these datasets need meticulous preprocessing. Another challenge lies in capturing the inherent interdependencies between the urban factors and potential non-linearities in their relationships, requiring models with depth and breadth. Addressing these challenges necessitates the deployment of sophisticated models, which handle multiple datasets simultaneously and account for the intertwined nature of urban systems, ensuring accurate and actionable visions for urban planning.

The present study focused on EIA in terms of CF forecast centered around Da Nang, Vietnam, a coastal city with dynamic urban development patterns. Situated on the South China Sea, Da Nang serves as a hub in Vietnam's urban narrative, witnessing rapid transitions in its land-use dynamics and grappling with consequent environmental shifts. In addressing the intricacies of urban CF prediction, a series of methodological approaches are proposed for different urban dimensions. A comprehensive dataset forms the background of this study. Collected for three years (From January 2020 to December 2022), the data paints a vivid picture of Da Nang's urban landscape. The dataset encompasses multiple facets such as monthly CE across various sectors, intricate details of EC patterns, and shifts in land application to transportation dynamics and air quality indices.

Further, a novel multi-modal stacked VAR-LSTM model is proposed for this work. This model integrates the predictive controls of Vector Autoregression (VAR) and Long Short-Term Memory (LSTM) neural networks, promising an enriched capability to forecast the CF. The idea of this model is to first subject each dataset to its specific methodological assessment, after which interdependencies within the dataset are assessed using VAR. Following this, the residuals from VAR, representing variations unexplained by the model, are channeled into the LSTM for training. The subsequent predictions from VAR and LSTM are then aggregated, synthesized, and refined, ensuring a holistic and accurate prediction of Da Nang's future CF.

The structure of the paper is as follows: Section 2 provides a review of related literature, Section 3 describes the methods used, Section 4 introduces the proposed model, Section 5 suggests the results and their analysis, and Section 6 concludes the study.

## II. LITERATURE SURVEY

Several research studies have focused on the critical issue of CE and its predictive analysis using Machine Learning (ML) and AI methodologies. Natarajan et al. [6] emphasize the importance of ensemble learning models in predicting CO2 emissions, specifically for light-duty vehicle designs. They introduce a unique technique, categorical boosting (Catboost), which efficiently processes data, catering to transportation-related CE. Meanwhile, [7] relies on historical data spanning 50 years from the World Bank datasets to predict future CO2 emissions. They aim to project the upcoming decade's CE patterns using different ML models. On a different tangent, Anthony et al. [8] underline the trends and impact of data learning models concerning energy and CF, introducing Carbon tracker as a tool to track and predict the same, advocating for responsible computing in the ML domain.

Furthermore, the challenge of corporate greenhouse gas emissions and their predictive modeling has been discussed by [9]. They innovate by introducing a Meta-Elastic Net learner framework that significantly improves the prediction accuracy of corporate CE. In region-specific studies, Han et al. [10] present a Deep Learning (DL) model tailored to the unique spatial correlations of Chinese provinces. Their LSTM-CNN combination model, enhanced with spatial weighting, predicts

CE from 2022 to 2035, underpinning the regional carbon reduction targets. Lastly, the environmental implications of AI itself are touched upon by [11]. They introduce a framework in distributed and Federated Learning (FL) that analyzes the energy and CF, shedding light on the sustainability of AI methodologies.

In contrast to the approaches cited, none have opted for a multimodal approach, highlighting the uniqueness of the proposed method in addressing CF impact assessment for urban planning.

## III. METHODOLOGIES

### *Carbon Emission Forecast Model (CEFM)*

The CEFM uses exponential development modeling to predict future CE. This model is based on the principle that urban areas, without significant interventions, might refer to an exponential increase in CE due to factors such as population growth, increased vehicular use, industrial activities, and EC.

Mathematically, it is expressed as EQU (1).

$$C(t) = C_0 e^{kt} \tag{1}$$

Where:

- $C(t)$ = CE at time $t$.
- $C_0$ = Initial CE at $t = 0$.
- $k$ = Rate of increase of CE. This constant captures the proportional change in CE for a given period.
- $e$ = Base of the natural logarithm (approximately equal to 2.71828).

### *Land Use Regression Model (LURM)*

The LURM is commonly used to approximate the spatial variability of air pollutants in urban areas. The LURM predicts concentrations of pollutants based on various land-use and geographic parameters. These can include metrics such as distance to major roads, industrial areas, green spaces, population density, and other relevant variables. Essentially, the model determines how different types of land use contribute to pollutant levels.

Mathematically, it is expressed as EQU (2)

$$P(x, y) = \alpha + \beta_1 L_1 + \beta_2 L_2 + \cdots + \beta_n L_n \tag{2}$$

Where:

- $P(x, y)$ = Predicted concentration of the pollutant at location (x, y).
- $\alpha$ = $Y$-intercept, representing the base pollutant concentration.
- $L$ = Specific land use variables (*e.g.,* distance to the nearest industrial zone, percentage of area covered by green spaces).
- $\beta$ = Regression coefficients for each land use variable.

### *Energy Consumption Impact Model (ECIM)*

The ECIM employs linear regression to analyze the impact of EC on CE. By understanding the contribution of energy sources, approaches can be formulated to transition to greener alternatives.

Mathematically, it can be expressed as EQU (3)

$$E(t) = a + b \times EC(t) \tag{3}$$

Where:

- $E(t)$ = CE due to EC at time $t$.
- $EC(t)$ = EC at time $t$.
- $a$ and $b$ are constants.

### *Transportation Emission Estimation Model (TEEM)*

The TEEM utilizes linear regression to predict CE resulting from transportation activities in urban areas. This model emphasizes that vehicular types, fuel types, traffic density, and transportation infrastructure impact CE from transport.

Mathematically, it is represented as EQU (4)

$$T(t) = c + d \times TD(t) \tag{4}$$

Where:

- $T(t)$ = CE from transportation at time $t$.
- $TD(t)$ = Transportation data metric at time $t$.

- $c$ and $d$ are constants.

*Air Quality & Carbon Correlation Model (AQCCM)*

The AQCCM leverages multivariate regression to begin links between CE and air quality. Recognizing that specific CE has more pronounced impacts on air quality can facilitate targeted interventions.

Mathematically, it's given by EQU (5)

$$Q(t) = f + g_1 \times AQD_1 + g_2 \times AQD_2 + \cdots + g_n \times AQD_n \tag{5}$$

Where:

- $Q(t) =$ CE manipulating air quality at time $t$.
- $AQD =$ Specific air quality metrics (*e.g.,* levels of particulate matter, NO2 concentrations).
- $f$ is the intercept, and $g$ are the regression coefficients for each air quality metric.

## IV. PROPOSED MODEL

*Problem Statement*

Urban areas are intricate systems with interdependent subsystems, each manipulating the environmental CF. As cities grow, sustainable and low-carbon urban planning becomes critical. Yet, the challenge lies in untangling the intricate relationships between urban factors and their collective impact on CE.

*Definition*

Let's define our urban environment with a multivariate time series $U$, where each series $U_i$ represents a distinct urban factor outlined previously: Carbon Emissions Forecast (CEF), Energy Consumption Impact (ECI), Land Use Regression (LUR), Transportation Emission Estimation (TEE), and Air Quality & Carbon Correlation (AQCC). Each of these series is observed over time $t$, leading to a matrix representation, EQU (6)

$$U = \begin{bmatrix} U_{CEF,1} & U_{CEF,2} & \cdots & U_{CEF,t} \\ U_{ECI,1} & U_{ECI,2} & \cdots & U_{ECI,t} \\ \vdots & \vdots & \ddots & \vdots \\ U_{AQCC,1} & U_{AQCC,2} & \cdots & U_{AQCC,t} \end{bmatrix} \tag{6}$$

Given this matrix, this work's primary aim is to predict $U_{i,t+1}$ for all $i$ the subsequent step in the series for each urban factor. The overall carbon footprint $C$ at any time $t$ can be represented as a function $f$ of these urban factors, EQU (7)

$$C(t) = f\left(U_{CEF,t}, U_{ECI,t}, U_{LUR,t}, U_{TEE,t}, U_{AQCC,t}\right) \tag{7}$$

where

- $U$ : Multivariate time series matrix representing different urban factors.
- $U_i$ : Individual time series for specific urban factors like CEF, ECI, LUR, TEE, and AQCC.
- $C(t)$: CF at time $t$.
- $f$ : Function mapping the interplay of urban factors to the CF.

The objective is to model and predict this function accurately $'f'$, given the inherent interdependencies between the urban factors and potential non-linearities in their relationships.

*Study Area: Da Nang, Vietnam*

Da Nang, a prominent coastal city on the South China Sea at the mouth of the Han River, holds a pivotal position in Vietnam's urban and economic tapestry. Centrally situated between Hanoi to the north and Ho Chi Minh City to the south, this city covers an area of approximately 1,285 square kilometers and houses a population of over 1.2 million. Historically rich and known for its sandy beaches, Da Nang has transformed over the decades due to urban migration and economic opportunities, making it one of Vietnam's major port cities. The rapid pace of Da Nang's urbanization has induced notable shifts in its land-use patterns, with expansive green spaces gradually giving way to burgeoning built-up areas. This change has impacted the city's microclimate and intensified the urban heat island effect. Concurrently, the city witnesses increasing vehicular numbers, contributing to traffic congestion and augmented carbon emissions from the transportation realm. Coupled with the challenges posed by industrial activities, Da Nang occasionally contends with air quality problems, underlining the imperative for an in-depth, AI-driven environmental impact assessment.

*Data Collection*
To understand and model the relationship between urban factors and Da Nang's CF, a comprehensive dataset representing multiple urban dimensions was collected from Jan 2020 to December 2022. This data will provide the basis for our AI-driven environmental impact assessment.

*Carbon Emissions Data (CED)*
The CED epitomizes the environmental toll of urban actions. A breakdown into transportation, residential, and industry sectors is pivotal in pinpointing significant contributors. The CED was obtained from the Vietnam Ministry of Natural Resources and Environment (MONRE), featuring monthly metric tons emissions further fragmented by sectors (**Table 1**).

**Table 1.** CED Description

| Month-Year | Total Emissions (MT) | Transportation | Industry | Residential |
|---|---|---|---|---|
| **Jan-2022** | 50,000 | 25,000 | 15,000 | 10,000 |
| **Feb-2022** | 48,500 | 24,000 | 14,500 | 10,000 |

*Energy Consumption (EC) Dataset*
Urban EC patterns, primarily when bifurcated by residential, commercial, and their sources, indicate the energy landscape and its ensuing carbon imprint. EC data was collected from the Vietnam Electricity (EVN), which offered insights into monthly consumption in kWh and its origin (**Table 2**).

**Table 2**. EC Dataset Description

| Month-Year | Total EC (kWh) | Residential | Commercial | Renewable Source (%) |
|---|---|---|---|---|
| **Jan-2022** | 1,500,000 | 900,000 | 600,000 | 20 |
| **Feb-2022** | 1,450,000 | 880,000 | 570,000 | 21 |

*Land Use Data (LUD)*
The ebb and flow of urban land utilization impacts the environmental footprint. Incorporating variables such as distance to significant environment, the percentage area of different land-use types, and transitions can provide a more holistic view. LUD was fetched from the Da Nang Department of Planning and Architecture (**Table 3**).

**Table 3.** LUD Description

| Month-Year | Built-up Area (sq. km) | Green Spaces (sq. km) | Industrial Zones (sq. km) | Water Bodies (sq. km) | Distance to Nearest Major Road (avg. km) | Distance to Nearest Industrial Zone (avg. km) | Population Density (people/sq.km) |
|---|---|---|---|---|---|---|---|
| **Jan-2022** | 600 | 400 | 50 | 30 | 0.5 | 2.0 | 1500 |
| **Feb-2022** | 605 | 395 | 51 | 30 | 0.5 | 1.9 | 1510 |

*Transportation Data (TD)*
The dynamics of urban transportation, incorporating aspects like vehicle types, road conditions, and fuel consumption, provide more profound insights into its environmental impact. TD was attained from Da Nang's Department of Transport (**Table 4**).

**Table 4.** TD Description

| Month-Year | Vehicle Kms Travelled (million km) | Public Transport Ridership | Private Car Count | Two-wheeler Count | Electric Vehicle Count | Average Fuel Consumption (liters/100km) | Total Road Network (km) | Average Traffic Speed (km/h) |
|---|---|---|---|---|---|---|---|---|
| **Jan-2022** | 100 | 500,000 | 100,000 | 500,000 | 10,000 | 8.5 | 2,000 | 40 |
| **Feb-2022** | 105 | 490,000 | 102,000 | 505,000 | 10,500 | 8.4 | 2,010 | 39 |

*Air Quality Data (AQD)*

Air quality indices, including pollutant levels and the AQI, are potent indicators of the environmental ramifications of urban endeavors. AQD was collected from Da Nang's Environmental Protection Agency, tracking key pollutants monthly (**Table 5**).

**Table 5.** AQD Description

| Month-Year | PM2.5 (μg/m³) | NOx (μg/m³) | AQI |
|---|---|---|---|
| **Jan-2022** | 25 | 40 | 80 |
| **Feb-2022** | 28 | 42 | 85 |

*Data Preprocessing*

Upon obtaining datasets encompassing various urban dimensions, it was imperative to ensure the data's quality, consistency, and usability for modeling and analysis. The initial phase involved an intricate assessment of the datasets to identify any anomalies, mainly focusing on missing values. Across datasets like CED from MONRE, EC from EVN, and TD from Da Nang's Department of Transport, there were sporadic instances of missing data points. Addressing these gaps was paramount to maintaining the integrity of the data and subsequent analyses. Depending on the nature of missingness and the data's inherent structure, a blend of imputation techniques [12], ranging from forward-fill to backward-fill to mean imputation, were judiciously applied. The essence was ensuring these imputed values seamlessly integrated with the existing time series without introducing biases or distortions.

The diverse datasets posed challenges in terms of varied scales and units. For instance, the stark contrast between EC values measured in kWh and AQD indices required harmonization. Applying the Min-Max normalization method, datasets underwent standardization to lie within a range of 0 to 1. This process made the data congruent across datasets and prepared it for efficient model training (**Table 6**). Temporal alignment was another crucial aspect addressed during preprocessing. Owing to discrepancies in recording frequencies and possible misalignments, it became vital to bring all datasets to a unified temporal resolution. This was achieved through resampling strategies, leveraging aggregation and interpolation techniques. Concluding the preprocessing, the data was methodically split. To ensure an optimal distribution for training and evaluation, a 70-30 partitioning was implemented, earmarking 70% of the data chronologically for training while reserving 30% for testing and validation.

**Table 6.** Dataset Description

| Dataset | Original Records | Records After Preprocessing | Training Dataset (70%) | Testing Dataset (30%) |
|---|---|---|---|---|
| **CED** | 17,520 | 16,644 | 11,651 | 4,993 |
| **EC** | 1,095 | 1,073 | 751 | 322 |
| **LUD** | 36 | 36 | 25 | 11 |
| **TD** | 4,382 | 4,251 | 2,976 | 1,275 |
| **AQD** | 1,095 | 1,040 | 728 | 312 |

*Vector Autoregression (VAR)*

The VAR is a multivariate time series modeling technique that captures linear interdependencies between multiple interrelated time series variables. This model's inherent strength lies in its capability to represent the dynamic interplay amongst multiple variables, making it especially relevant for systems where variables influence one another over time. Given a set of $n$ endogenous variables and selecting an order $p$ for lags, a VAR(p) system is formulated as EQU (8).

$$V_t = c + M_1 V_{t-1} + M_2 \mathrm{V} + \cdots + M_p V_{t-p} + \varepsilon_t \tag{8}$$

Where:

- $V_t$ is a $n \times 1$ vector of observations at time $t$.
- $c$ is a $n \times 1$ vector of constants (intercepts).
- $M_i$ are $n \times n$ matrices of coefficients for each lag $i$, where $i = 1, \dots, p$.
- $\varepsilon_t$ is a $n \times 1$ vector of error terms, assumed to be white noise and are not correlated over time.

The error terms, $\varepsilon_t$, have the following properties:

1 $E(\varepsilon_t) = 0$: The expected value of the error term is 0.
2 $E(\varepsilon_t \varepsilon_t') = \Sigma$: The covariance matrix of the error term is Σ, and it remains constant over time (homoskedasticity).
3 $E(\varepsilon_t \varepsilon_{t-j}') = 0$ for $\neq 0$: Error terms are uncorrelated across different time points.

In a VAR, every variable is modeled as a function of the system's lagged values of itself and all other variables. Determining the optimal lag order $p$ for a VAR model is crucial. Using too few lags can lead to model misspecification while using too many can introduce unnecessary complexity and overfitting. Several criteria can help determine the appropriate lag length for VAR models; the following AIC model is used in this work.

*Akaike Information Criterion (AIC)*
A lower AIC suggests a better model, EQU (9).

$$\mathrm{AIC} = -2\ln(L) + 2n \tag{9}$$

where $L$ is the model's probability, and $n$ is the number of parameters.

Once the order is selected, the VAR model's parameters must be projected. The most common method used for this purpose is the Ordinary Least Squares (OLS) method. Each EQU (10) of the VAR is valued separately using OLS. Given our previous VAR(p) representation:

$$V_t = c + M_1 V_{t-1} + M_2 V_{t-2} + \cdots + M_p V + \varepsilon_t \tag{10}$$

Using OLS, we minimize the sum of squared residuals across all equations. The coefficients are determined using a technique that minimizes the difference between the actual and predicted values (residuals).

*Proposed Multi-Modal Stacked VAR-LSTM for CF Prediction*
**Fig 1** presents the Multi-modal Stacked VAR-LSTM that capitalizes on the strengths of VAR and Long Short-Term Memory (LSTM) neural networks. The first step in the prediction step is to source the crucial datasets representing different urban factors. These datasets include Carbon Emissions Data ($U_{CED}$), Energy Consumption ($U_{EC}$), Land Use Data ($U_{LUD}$), Transportation Data ($U_{TD}$), and Air Quality Data ($U_{AQD}$). The datasets are preprocessed to eliminate missing values and outliers. After loading the preprocessed datasets, represented as $U_i$, each dataset undergoes a unique methodological assessment specific to its nature:

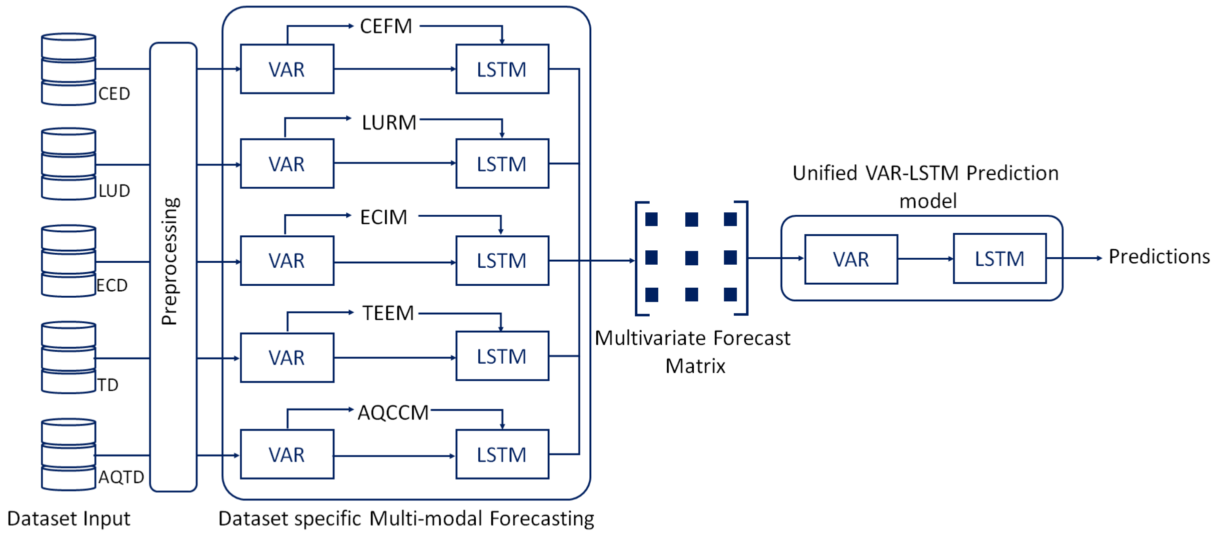


**Fig 1.** Proposed Multi-Modal Stacked VAR-LSTM Model.

For $U_{CED}$ : CEF is applied.
For $U_{LUD}$ : LUR is used.
For $U_{EC}$ : ECIM comes into play.
For $U_{TD}$ : TEEM is applied.
For $U_{AQD}$ : AQCCM is used.

After this, VAR is applied for each dataset input to represent the interdependencies within each dataset $U_i$. An optimal lag order is resolute using criterion methods such as the Akaike Information Criterion (AIC). With the specified lag $p$, the VAR is then projected. From this VAR, residuals $\epsilon_t$ are extracted. These residuals, representing the unexplained variations by the VAR, are then applied to train the LSTM. Predictions are then caused for each $U_i$ using the VAR, these predictions are refined using the LSTM's ability to predict residuals. Once the individual predictions from LSTMs for each dataset are generated, they are aggregated into a multivariate time-series matrix $U$, EQU (11)

$$U = \begin{bmatrix} \text{Forecast}\left(U_{CED,1}\right) & \text{Forecast}\left(U_{CED,2}\right) & \dots & \text{Forecast}\left(U_{CED,t}\right) \\ \text{Forecast}\left(U_{EC,1}\right) & \text{Forecast}\left(U_{EC,2}\right) & \dots & \text{Forecast}\left(U_{EC,t}\right) \\ \vdots & \vdots & \ddots & \vdots \\ \text{Forecast}\left(U_{AQD,1}\right) & \text{Forecast}\left(U_{AQD,2}\right) & \dots & \text{Forecast}\left(U_{AQD,t}\right) \end{bmatrix} \tag{11}$$

In this matrix, the Forecast $(U_{CED,1})$ represents the forecasted value of CED at the next time point, Forecast $(U_{EC,1})$ represents the forecasted value of EC at the next time point, and so on for other urban factors. This structure ensures that the subsequent model is fed with the predicted values for each urban factor across future time points, aiding in the accurate forecasting of the CF.

The resulting matrix $U$ contains the refined forecasts for each urban factor. The interdependencies between these factors are then modeled using VAR on this matrix. As with individual datasets, an optimal lag order for $U$ is determined. The VAR is then valued for the matrix, and residuals specific to this multivariate setup are extracted. These residuals fuel the training of a unified LSTM. The ultimate prediction is then made using the VAR for $U$, further refined by the LSTM's prediction on residuals.

*Algorithm: Multi-Modal Stacked VAR-LSTM for CF Prediction*
**Input:** Multivariate time-series datasets for urban factors: $U_{CED}, U_{EC}, U_{LUD}, U_{TD}, U_{AQD}$.
**Output:** Prediction for the next step in the series for each urban factor: $U_{i,t+1}$.

1. **Initialization:**
    - 1.1 Load datasets: $U_{CED}, U_{EC}, U_{LUD}, U_{TD}, U_{AQD}$.
    - 1.2 Set the number of lags $p$ for VAR.
    - 1.3 Define LSTM parameters (*e.g.,* number of layers and units per layer).
2. **Dataset-Specific Forecasting:**
    - 2.1 **For Each** dataset $U_i$ :
        - 2.1.1 Apply specific methodology (*e.g.,* CEF for $U_{CED}$, LUR for $U_{LUD}$) to the dataset.
        - 2.1.2 Model interdependencies using VAR on $U_i$ :
            - 2.1.2.1 Determine optimal lag order using methods such as the Akaike Information Criterion (AIC) or the Bayesian Information Criterion (BIC).
            - 2.1.2.2 Estimate the VAR for $p$ lags.
        - 2.1.3 Extract residuals $\epsilon_t$ from the VAR.
        - 2.1.4 Train an LSTM on these residuals.
        - 2.1.5 Generate forecasts for each $U_i$ using the VAR, refine the forecast with the LSTM's prediction on residuals.
    - **2.2 End For**
3. **Matrix Formation:** Aggregate LSTM outputs from step 2 into a multivariate time-series matrix $U$
4. **Unified VAR-LSTM Prediction**
    - 4.1 Apply VAR on matrix $U$ to model interdependencies:
        - 4.1.1 Determine optimal lag order for the matrix $U$.
        - 4.1.2 Approximation of the VAR.
    - 4.2 Extract residuals from the VAR for the matrix $U$.
    - 4.3 Train a unified LSTM with these residuals.
    - 4.4 Generate a combined forecast for the subsequent time step using the VAR and refine this forecast with the LSTM's prediction on residuals.
5. **Output:** Prediction for the CF for the subsequent time step based on all urban factors, integrating the outputs of VAR and LSTM.

## V. EXPERIMENTAL ANALYSIS

The experiments were directed on a computing system with an Intel Core i9-9900 K CPU, 64 GB RAM, and an NVIDIA RTX 3090 GPU. The system ran on a Linux Ubuntu 20.04 LTS operating system. They used the Python programming language, version 3.8, to deploy the model. Libraries such as TensorFlow 2.4 and sci-kit-learn 0.24 were employed to facilitate DL and statistical computations, respectively. To evaluate the performance of the proposed model, we adopted several metrics that measure the accuracy and reliability of predictions. Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) were primarily used to quantify the difference between predicted and actual values. Additionally, the R-squared value was used to measure the proportion of variance in the dependent variable that is predictable from the independent variables, offering insight into how well the proposed model explains the variability of the dataset.

We compared the performance of the proposed model with several baseline models. These included traditional time series models such as ARIMA and Prophet, and other DL models like vanilla LSTM and GRU. Including these models allowed for a more thorough understanding of the strengths and potential areas of improvement for the proposed model in predicting urban CF. For training our Multi-modal Stacked VAR-LSTM, a set of specific hyperparameters was selected after a series of preliminary experiments.

The learning rate was set at 0.001, applying the Adam optimizer due to its adaptive learning rate properties. The number of layers in the LSTM was set to 3, with 128, 64, and 32 units in each successive layer, which struck a balance between model complexity and computational efficiency. A dropout rate of 0.2 was applied between LSTM layers to prevent overfitting. The VAR's lag order 'p' was empirically set to 5 after evaluating model performance over a range of lag values. A value of 64 was selected for batch size, ensuring consistent model updates while not overly burdening the computational resources. Lastly, the model was trained for 100 epochs, with early stopping implemented to halt training if validation loss did not improve for 10 consecutive epochs.

**Fig 2** and **Fig 3** presents the MAPE and RMSE performance of the proposed model for 50 epochs. The proposed model consistently improves its performance over epochs, as reflected by the decreasing MAPE and RMSE values for training and testing datasets. Beginning with a testing MAPE of 13.40% and a training and testing RMSE of 1.1 and 1.22, respectively, in the 1st epoch, it displays substantial refinement, achieving a commendable MAPE of 7.00% and an RMSE of 0.38 and 0.43 by the 50th epoch. While both metrics have chance variations, particularly in the earlier epochs, the overarching trend underscores the model's capability to adapt, optimize, and minimize prediction errors. This consistent reduction in error rates, in tandem with the model's learning trajectory, attests to its efficacy and aptitude in enhancing predictive accuracy over time.

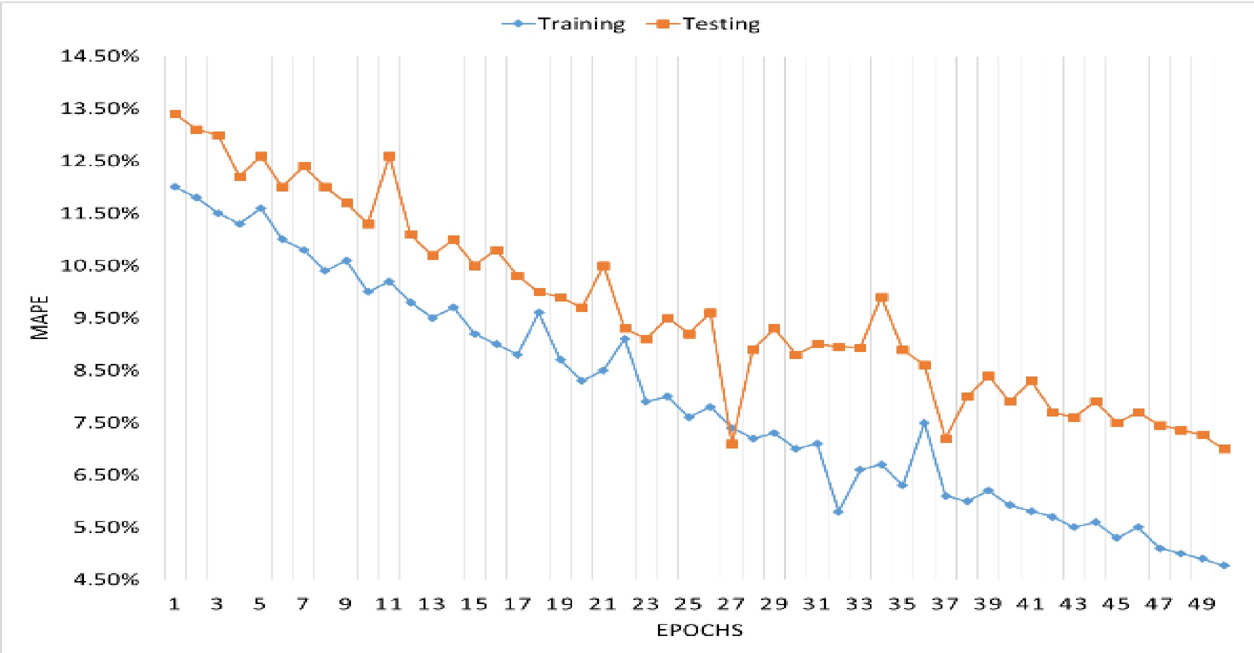


**Fig 2.** MAPE Loss Analysis.

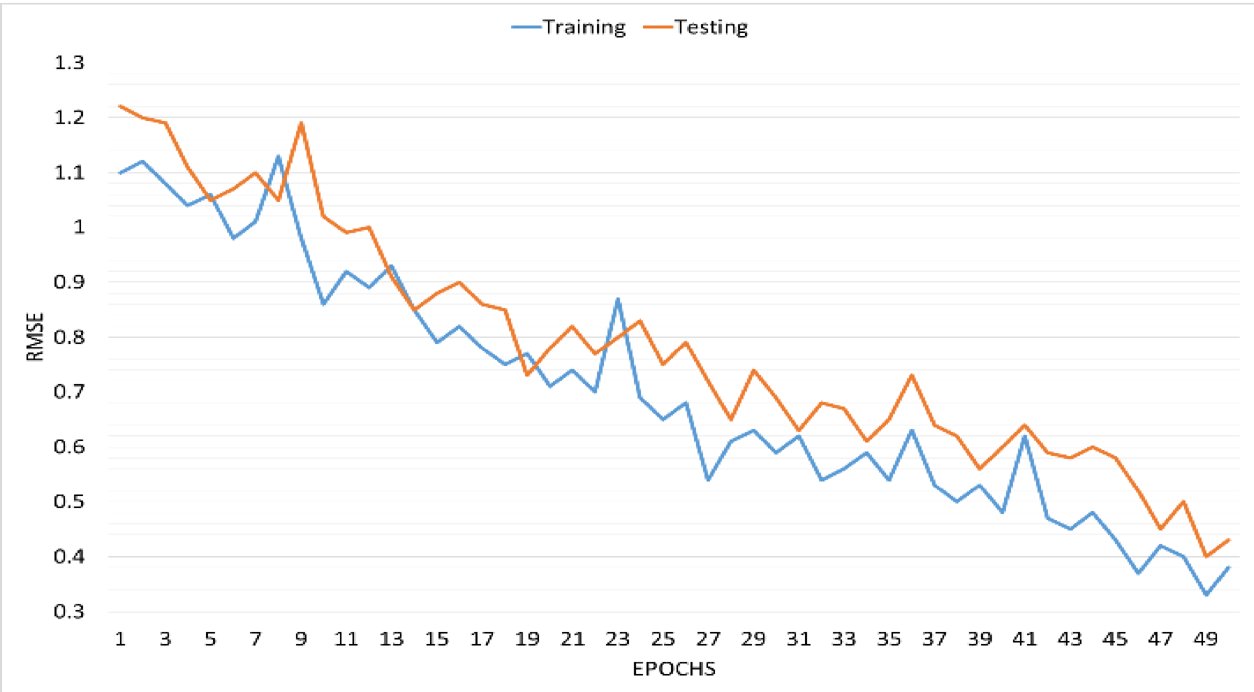


**Fig 3.** RMSE Loss Analysis.

*Comparative Analysis of Proposed VAR-LSTM with Other Models*

The proposed VAR-LSTM consistently outperforms across epochs, beginning with a MAPE (**Fig 4**) of 11.30% at the 10th epoch and reducing to 7.00% by the 50th epoch. In contrast, traditional models such as ARIMA commence at 13.80% and only decline to 9.80% by the 50th epoch. The accuracy gap is particularly evident when juxtaposed with Prophet and standalone LSTM, which initiate at 14.00% and 14.20%, respectively, and converge around 9.50% and 9.60% by the 50th epoch. This pronounced accuracy of the proposed model can be attributed to its hybrid nature, amalgamating VAR's capability of capturing linear interdependencies between multiple time series and LSTM's expertise in harnessing long-term dependencies and non-linear patterns. Meanwhile, inherently linear ARIMA may find it challenging to navigate the multivariate complexity of urban datasets. Prophet, although potent, is predominantly designed for univariate datasets with seasonal solid patterns.

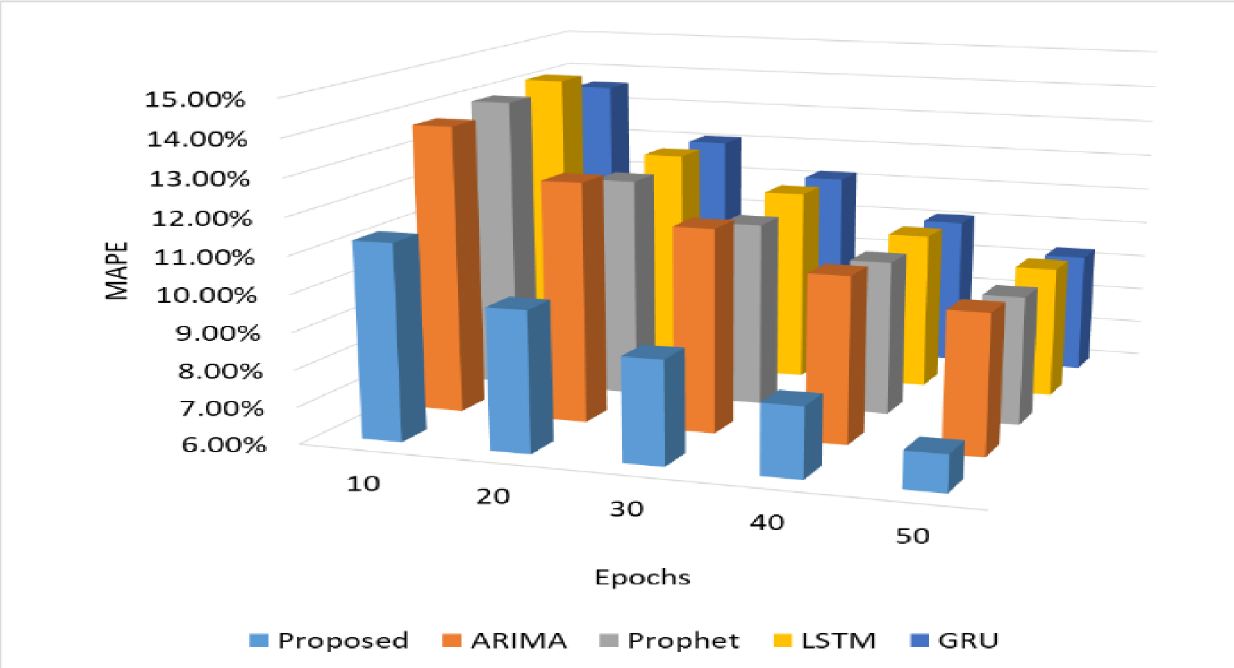


**Fig 4.** MAPE Comparative Analysis.

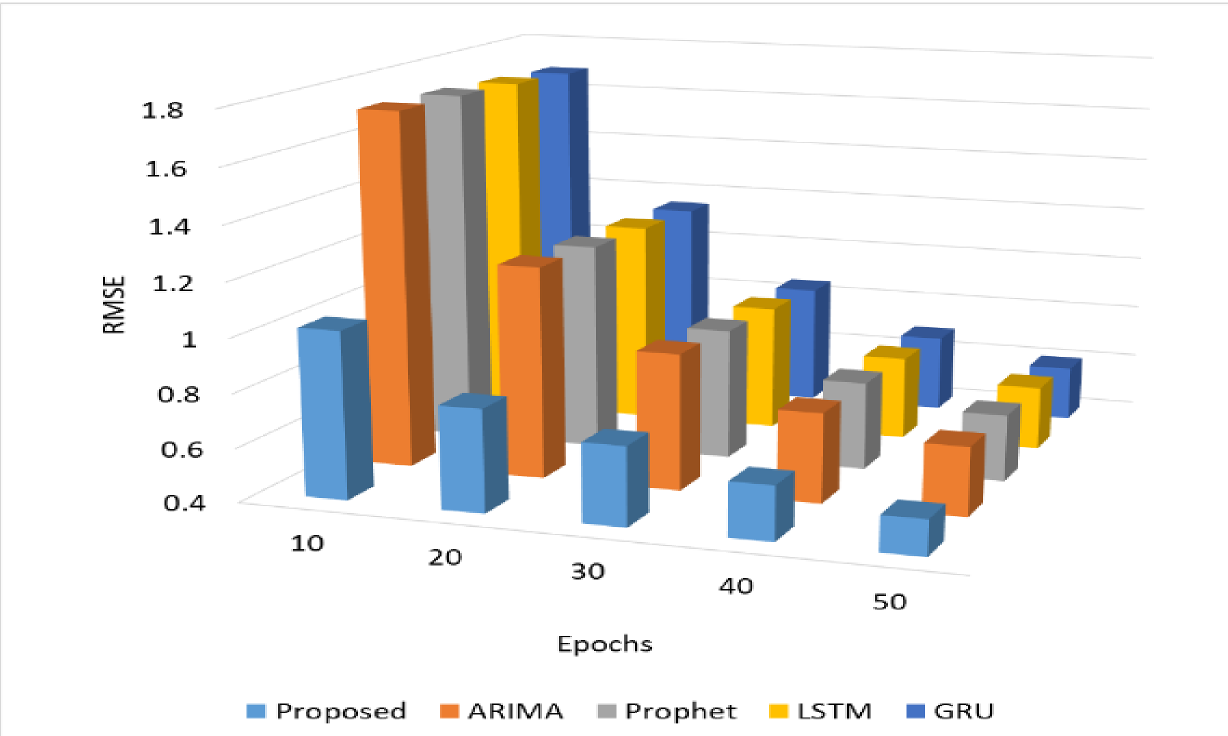


**Fig 5.** RMSE Comparative Analysis.

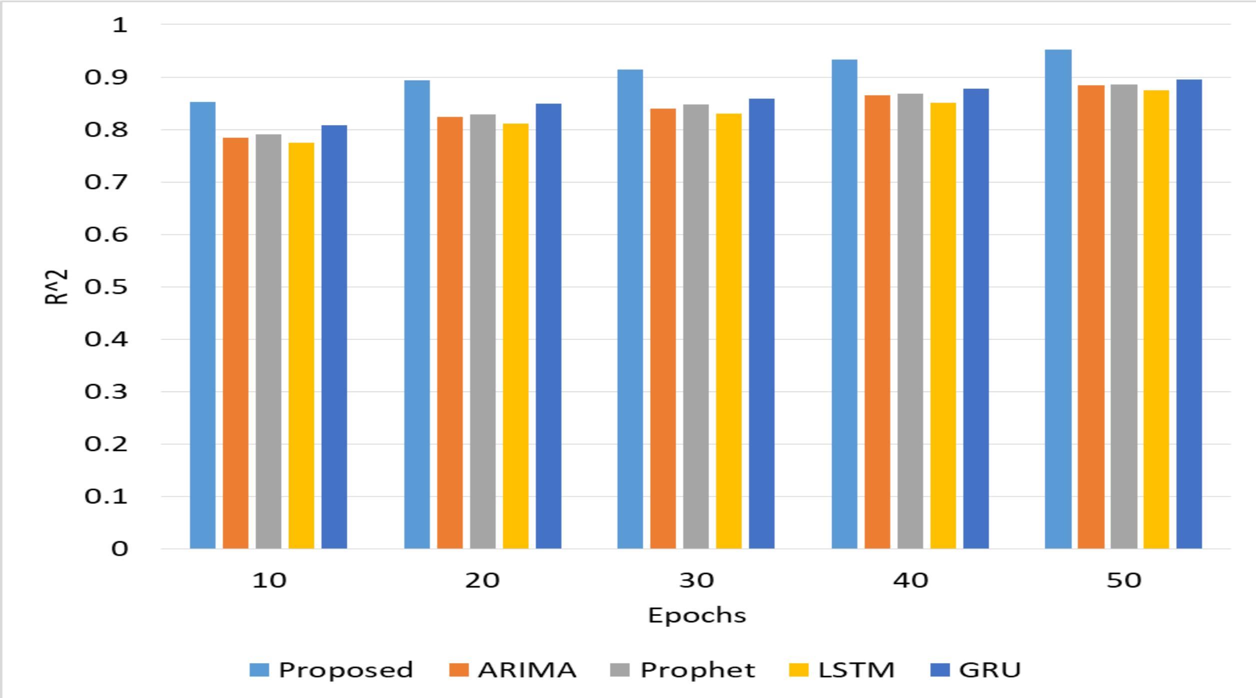


**Fig 6.** $R^2$ Comparative Analysis.

Regarding RMSE, where a lower value indicates superior predictive accuracy, the proposed model maintains its lead (**Fig 5**). With RMSE values starting at 1.021 and consistently reducing to 0.532 across epochs, it underlines the model's capability to refine its predictions iteratively. ARIMA, Prophet, LSTM, and GRU all initiate with RMSE values considerably higher than the proposed model, hovering around the range of 1.704 to 1.725. Although these models reduce their RMSE values over epochs, none rival the proposed model's precision. The robustness of the proposed model is rooted in its responsive prediction mechanism. By combining the strengths of both VAR and LSTM, the model adeptly processes multivariate inputs, accommodating their interdependencies and ensuring a more consistent prediction mechanism.

The $R^2$metric (**Fig 6**) indicates how well the variance in the dependent variable is explained using predictors. The proposed model displays a commendable fit, commencing with $R^2$ values at 0.852 and gradually rising to 0.952 across epochs. This contrasts starkly with models like the standalone LSTM, which spans from 0.77456 to 0.8742, and ARIMA, ranging between 0.78396 and 0.88454. High $R^2$values for the proposed model accentuate its proficiency in adeptly capturing and elucidating variance, mainly when modeling complex urban factors. The model's architecture inherently maps immediate relationships (through VAR) and prolonged interdependencies (via LSTM), contributing an intrinsic advantage. The data indicates complicated interdependencies in modeling intricate urban factors like CE, EC, Land Use, Transportation, and Air Quality. The proposed model is a formidable solution that leverages the strengths of time series forecasting and DL. The comparative metrics underscore the significance of model selection relative to the data's nature and structure, especially in domains as critical as sustainable urban development.

## VI. CONCLUSION AND FUTURE WORK

In addressing the growing environmental implications of urbanization, the proposed Multi-modal Stacked VAR-LSTM suggests a significant contribution to urban Carbon Footprint (CF) forecasting. Through the effective assimilation of various urban datasets, the study paves the way for a nuanced understanding of Carbon Emissions (CE) in urban areas, providing actionable insights for sustainable urban planning. Furthermore, as cities worldwide grapple with the dual challenges of urban expansion and sustainability, the role of AI-driven tools like the one proposed in this study becomes paramount. While the present model has proved its potential in CF prediction, the research horizon in this domain is vast. Future endeavors could potentially refine the model by incorporating a broader range of urban datasets, experimenting with alternative neural networks, testing its scalability across diverse urban contexts, and integrating the model into mainstream urban planning digital tools.

This study sheds light on a novel approach to gauge urban CF and sets the stage for a future where technology and urban planning converge to create sustainable urban habitats.

### Data Availability
No data was used to support this study.

### Conflicts of Interests
The author(s) declare(s) that they have no conflicts of interest.

### Funding
No funding agency is associated with this research.

### Competing Interests
There are no competing interests


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