Predictive Analysis of Carbon Footprint for Forest Cover in India

Utsav Gavli
Dept. of Computer Engineering
Vivekanand Education Society Institute of Technology
Mumbai, India
2020.utsav.gavli@ves.ac.in

Nikkita Gurnani
Dept. Computer Engineering
Vivekanand Education Society Institute of Technology
Mumbai, India
2020.nikkita.gurnani@ves.ac.in

Sonal Belani
Dept. of Computer Engineering
Vivekanand Education Society Institute of Technology
Mumbai, India
2020.sonal.belani@ves.ac.in

Namrata Avhad
Dept. of Computer Engineering)
Vivekanand Education Society Institute of Technology
Mumbai, India
2020.namrata.avhad@ves.ac.in

Mrs Lifna C.S
Asst. Professor Computer Engineering
Vivekanand Education Society Institute of Technology
Mumbai, India
lifna.cs@ves.ac.in

***Abstract*—Forests cover about 30% of the Earth's land surface. As forests grow, their trees take in carbon from air and store it in wood, plants and under the soil. If not for forests, much of the carbon would remain in the atmosphere in the form of Carbon diOxide (CO2). In most of the developing countries, the increasing rate of GHG emissions is considered as a major cause of concern. India is leading in terms of GHG emissions as compared to other countries. The vegetation cover comprises only 24.39% of the geographic area of India. The primary objective of this proposal is to identify the relationship between the increase in GHG emissions and forest cover in metropolitan cities. An additional objective is to predict the amount of afforestation required for each area to cope up with the GHG emissions over the next 25-years.It can be achieved using time series forecasting models like ARIMA ,SARIMA and other machine learning models. The proposal provides suggestions on optimal techniques like use of renewable resources, such as Solar power for sustainable afforestation and to cope up with loss of GHG emission.**

Keywords: GHG Emission , Vegetation Cover , ARIMAX , SARIMA , Solar Power , Machine learning , Renewable Energy

I. INTRODUCTION

A carbon footprint is the total amount of greenhouse gases that are generated by human activities. Some of the major greenhouse gases are CO2 i.e carbon dioxide, CH4 i.e methane, N20 i.e Nitrous Oxide. Annually, India generates 2.88 billion tonnes of carbon dioxide through various activities, Nitrous Oxide generated is 272 million tonnes , Methane generated is 897 million tonnes. Out of India's total population, 141 crores (about 35% of total) live in urban regions. The average urban Indian generates 1.32 tons of carbon dioxide over the course of a year. The 493 million people who live in metropolitan areas in India are responsible for production of 650 million tons(about 22 % of the total) of CO2. According to the survey of the Global Climate Risk Index (CRI) of 2017, India is 14th on the list of most vulnerable countries. India ranked the second highest for the rate of deforestation after losing 668,400 hectares of forest cover in the last 30 years. India also topped the chart for biggest increase in deforestation between 1990 and 2020 with a difference of 284,400 hectares in forestry loss. According to Global Forest Watch, from 2001 to 2022, India lost 2.19 MHA of tree cover, equivalent to a 5.6 % decrease in tree cover since 2000, and 1.11 Gt of CO emissions. This research aims to calculate the content of carbon across various states of India and calculate its relationship with forest cover. This helps to determine the requirements of the future and shift from fossil fuels which are a major source of carbon emissions to renewable energy such as solar power.

Identify applicable funding agency here. If none, delete this.

II. RELATED WORK :

This study[1] gives detailed information about the carbon footprint of agricultural crops through cultivation in India. Though the majority of the carbon emission comes from urban activities, this research focuses on the rural areas and the carbon emission produced from the crop cultivations. Various technologies and devices can be used to reduce the CF levels in the agricultural sector.

This research[2] displays the carbon emissions across various states in India and its effect on climate change. It determines the carbon emissions from various sectors and how it is useful for quantifying its impact on human activities and climate change. This study takes into consideration various sectors of transportation, industries, domestic energies, agriculture and livestock.

The Elsevier paper[3] focuses on the heterogeneity in carbon emission across different states in India. With increase in rapid urbanization and infrastructural growth, this research aims to determine the sectoral heterogeneity of carbon emissions with leading states. It concludes that the western part of India dominated the carbon footprint. The data went back to 2015.

This paper [4] focuses on forest cover dynamics and creating a forecasting model of the Bhanupratappur Forest Division of Kanker, Chhattisgarh, India. It uses a Logistic Regression Model (LRM) to analyze the changes in forests caused by road constructions and expansion of settlements. This research uses data obtained through Landsat TM satellite imagery for the duration of 1990 to 2000. The model was assessed by comparing the model-predicted forest cover with the actual forest cover for 2010.

This paper[5] is intended to anticipate the influence of variables such as electricity, coal, etc. in the growth of carbon emissions. The data was obtained from the Alcohol Industry to train and test.

III. Proposed Idea:

A. Dataset Collection:

- 1. Greenhouse Gas (GHG) Emission in India: Data on greenhouse gas emissions in India from 1850 to 2021 was obtained from Our World in Data, an online publication that provides research and data on various global issues. The dataset includes comprehensive information on the emission trends of greenhouse gases such as carbon dioxide (CO2), methane (CH4), and nitrous oxide (N2O) over the specified period.
- 2. Forest Cover Data of India: The forest cover data for India spanning from 1975 to 2021 was sourced from the Forest Survey of India (FSI). The FSI periodically conducts assessments to monitor the extent and changes in forest cover across the country. The dataset comprises information on forest cover, including categories such as dense forest, open forest, and collected on alternate years.
- 3. Carbon Sequestration Data: Carbon sequestration data from 2011 to 2021 was acquired from the Forest Survey of India (FSI). This dataset provides insights into the amount of carbon dioxide absorbed by forests and other vegetation in India during the specified time frame, contributing to the mitigation of greenhouse gas emissions.
- 4. State-wise GHG Emission in India: The greenhouse gas emission data for each state in India from 2005 to 2015 was obtained from the Center for Study of Science, Technology and Policy (CSTEP), an independent think tank based in India. This dataset offers state-specific information on the emission of greenhouse gasses, aiding in the analysis of regional variations and contributing factors.
- 5. State-wise Solar Power Capacity: This dataset about the solar power capacity of each state was sourced from the Press Information Bureau, it depicts the solar power capacity of each state in MegaWatts(MW) over the past 5 years.
- 6. State-wise Solar Budget Allocation: This dataset represents the funds allocated(in crores) to each state for solar power generation for the past 5 years. This data was fetched from the Press Information Bureau.

For the purpose of this project, a comprehensive dataset was gathered from various reputable sources

B. Data Cleaning

In the process of extracting data from various resources, it was observed that while comprehensive information was available for most countries across different parameters, certain datasets, specifically those related to greenhouse gas (GHG) emissions and renewable energy, were not universally accessible. Consequently, a preprocessing step was necessary to ensure the inclusion of India's data spanning from 1850 to 2021, as per the scope of the study. This entailed meticulous filtering and extraction techniques to isolate and retain India-specific information, allowing for a focused analysis within the designated timeframe. Similarly, the renewable energy dataset underwent a similar treatment, ensuring that only data pertinent to India over the specified period was retained for further analysis and interpretation. This preprocessing phase was crucial in maintaining the integrity and relevance of the data, enabling a targeted examination of India's trajectory in GHG emissions and renewable energy adoption within the broader context of global trends. By consolidating and refining the datasets in this manner, the subsequent analysis can provide valuable insights into India's historical and contemporary contributions to climate change mitigation efforts and its transition towards sustainable energy practices.

C. Data Preprocessing

To ensure continuity in the forest cover dataset spanning from 1975 to 2021, interpolation techniques were employed to estimate values for the intervening years where alternate-year data was available, thereby providing a comprehensive and continuous representation of forest cover trends over the specified period. Interpolation is a mathematical method used to estimate unknown values within a range of known data points. In this study, linear interpolation was utilized, which calculates the values between two known data points based on a straight line connecting them. The formula for linear interpolation is:

$$Y = Y1 \ + (X - X_1)(Y2 - Y1)/(X2 - X1) \tag{1}$$

Where:

- - Y represents the estimated forest cover value for the year of interest.
- - Y1 and Y2 are the forest cover values for the years X1 and X2 , respectively, where X1 and X2 are the years closest to the year of interest for which data is available.
- - X represents the year of interest.

D. Model selection

The impact of carbon footprint on forest cover in India, the selection of ARIMA, SARIMA, and LSTM models was based on their specific strengths in analyzing time series data.

ARIMA :

The ARIMA model was chosen for its ability to capture the temporal dependencies and trends in the data. It is well-suited for understanding the dynamics of carbon footprint and forest cover changes over time. The simplicity of the ARIMA model makes it easy to interpret and implement, while still being able to capture both short-term and long-term patterns in the data. However, ARIMA does assume that the underlying data is stationary, which may not always hold true for complex time series data.

SARIMA :

To address the seasonality present in environmental datasets like carbon footprint and forest cover, the SARIMA model was also utilized. SARIMA extends ARIMA to handle seasonal patterns in the data, making it more suitable for modeling the complex seasonal variations in carbon footprint and forest cover data. By capturing both the seasonal and non-seasonal components of the data, SARIMA provides a more comprehensive analysis of the patterns and trends in the data.

LSTM :

Lastly, the LSTM model was employed for its ability to capture long-term dependencies in the data. As a type of recurrent neural network (RNN), LSTM is well-suited for learning patterns in sequential data, such as time series data. This makes LSTM particularly useful for understanding the relationship between carbon footprint and forest cover over time, as it can automatically learn relevant features from the data. However, LSTM models can be computationally expensive to train and require careful tuning of hyperparameters.

E. Model Building

We have used 3 methods for model evaluation to predict and forecast the values which are: Direct method,Addition method and Linear method for yearly data.

Direct method :

The Direct method involved a straightforward approach of directly inputting the target value,Total GHG emission, into the model for prediction and forecasting. This method streamlined the process by using the target variable without any intermediary steps, providing a clear and direct path to forecasting.

Addition Method:

In contrast, the Addition method took a more intricate approach by applying the model individually to the independent variables CO_2, CH_4, and NO. The predicted and forecasted values of these variables were then summed to determine the total greenhouse gas emissions. This method provided a detailed breakdown of the contributions of each independent variable to the overall greenhouse gas emissions, offering a more nuanced understanding of the data.

Linear Method :

Similarly, the Linear method employed linear regression to predict and forecast the values of CO_2, CH_4, and NO. These predicted values were then aggregated to obtain the total greenhouse gas emissions forecast. Interestingly, both the Linear and Addition methods yielded the same output, suggesting that both approaches were equally effective in forecasting total greenhouse gas emissions.

SARIMA - Direct / Addition

Seasonal Autoregressive Integrated Moving Average (SARIMA) model stands out as a robust methodology, particularly adept at handling datasets with distinct seasonal patterns. Key Components of SARIMA include Seasonal Component (S): The seasonal aspect of SARIMA encompasses three fundamental elements: Seasonal Autoregressive (SAR) Terms: These terms account for the relationship between the current observation and past observations from the same season. Seasonal Differencing (I): This component addresses seasonality by differencing the series at the seasonal lag. Seasonal Moving Average (SMA) Terms: SMA terms capture the relationship between the error term and past error terms at the seasonal lag. Autoregressive Component (AR): SARIMA's autoregressive component explores the dependency between the current observation and previous observations at non-seasonal lags. Moving Average Component (MA): The moving average component models the error term as a linear combination of past error terms at non-seasonal lags. The SARIMA model is denoted as SARIMA(p,d,q)(P,D,Q)[S], where: p, d, q are the non-seasonal ARIMA parameters. P, D, Q are the seasonal ARIMA parameters. S is the seasonal period.

ARIMA - Direct / ARIMAX- Addition

The Autoregressive Integrated Moving Average with Exogenous Variables (ARIMAX) model emerges as a powerful extension of the traditional ARIMA model, offering the ability to incorporate external variables, or "exogenous" variables, into the forecasting process. This unique feature makes ARIMAX particularly well-suited for predicting carbon emissions.

LSTM

An LSTM (Long Short-Term Memory) model was utilized for analyzing the impact of carbon footprint on forest cover in India. The LSTM model is a type of recurrent neural network (RNN) that is well-suited for learning patterns in sequential data, making it suitable for analyzing time series data such as carbon footprint and forest cover data. The LSTM model was configured with 50 epochs and 50 units. Epochs: An epoch refers to one complete pass through the entire training dataset. In this case, the LSTM model was trained over 50 epochs, meaning that the model went through the entire dataset 50 times during the training process. Units: The units parameter in an LSTM model refers to the number of memory cells or neurons in the layer. Each unit is responsible for learning and remembering patterns in the input data. Having more units can allow the model to capture more complex patterns in the data, but it also increases the computational complexity of the model.

F. Model Evaluation

Multiple metrics were used to evaluate the performance of the models, including RMSE (Root Mean Square Error), MAE (Mean Absolute Error), R-squared (R2), and MSE (Mean Squared Error). These metrics provide different insights into how well the models are performing in terms of accuracy and precision.

- RMSE: RMSE measures the average magnitude of the errors between predicted and actual values. It provides a sense of how spread out the errors are. A lower RMSE indicates better model performance.
- MAE: MAE is similar to RMSE but calculates the average of the absolute errors. It gives a more direct interpretation of the average error magnitude. Like RMSE, a lower MAE indicates better model performance.
- R-squared (R2): R-squared is a measure of how well the model fits the actual data. It represents the proportion of variance in the dependent variable (forest cover) that is predictable from the independent variable (carbon footprint). A higher R2 value indicates a better fit.
- MSE: MSE calculates the average of the squared errors between predicted and actual values. It penalizes larger errors more than smaller ones. Like RMSE, a lower MSE indicates better model performance.

The model with the highest R-squared value was selected for further forecasting. This decision was likely made because R-squared provides a measure of how well the model explains the variance in the data, making it a good indicator of overall model performance. By selecting the model with the highest R-squared value, we chose the model that best captures the relationship between carbon footprint and forest cover in India, providing more accurate forecasts for future scenarios.

GHG Emission data -

Metrics Dictionary:

'Total GHG emission direct': 'MSE': 2.467685522629966e+16, 'MAE': 138668750.51080364, 'R2': 0.9391930609594895, 'RMSE': 157088685.86343086, 'Total GHG emission addition': 'MSE': 3.552970362405361e+16, 'MAE': 159426029.13032925, 'R2': 0.9124502493294727, 'RMSE': 188493245.56613058, 'lstm': 'MSE': 2.3726318019291315e+17, 'MAE': 459414175.5659034, 'R2': 0.4153530665782684, 'RMSE': 487096684.64578277, 'Total GHG emission ARIMAX exog': 'MSE': 2.908702916621613e-07, 'MAE': 0.000537895020984468, 'R2': 1.0, 'RMSE': 0.000539323920906686, 'Total GHG emission ARIMA': 'MSE': 2.628490096836622e+16, 'MAE': 105112464.01152399, 'R2': 0.9352306298265313, 'RMSE': 162126188.41003516

Here we choose the SARIMA Direct Method, we ignored the maximum R2 which is 1 in ARIMAX because it overfits the data.

Forest cover data:-

Metrics Dictionary: 'Forest Cover prediction SARIMA DIRECT': 'MSE': 170707096.93882734, 'MAE': 11571.53548611463, 'R2': -3.1075180807023486, 'RMSE': 13065.492602226192, 'Forest Cover Prediction': 'MSE': 745045436.4426779, 'MAE': 24738.470539017453, 'R2': -16.927125796238702, 'RMSE': 27295.520446451974, 'Forest Cover Prediction ARIMAX exog': 'MSE': 11788706.400398275, 'MAE': 3189.18558041387, 'R2': 0.7163426386128545, 'RMSE': 3433.4685669739683, 'Forest Cover Prediction ARIMAX': 'MSE': 6212194.794118999, 'MAE': 2415.7131483803505, 'R2': 0.8505234820621859, 'RMSE': 2492.4274902429956

Here we choose the model with highest R2, which is ARIMA for predicting.

The carbon emitted in the year 2021 is 3.9 billion tonnes and if we don't take necessary steps to reduce it it will reach 5.18 billion tonnes. On the contrary the forest cover of India is 713789 sq km in the year 2021 and it will only reach 752254.17 sq km. The carbon sequestrated in the Indian forest is 7.204 billion tonnes in the year 2021. The annual gain over the last 10 years is 541 million tonnes. The carbon sequestrated in the year 2021 is 39.4 million tonnes. The ideal forest cover required to offset 3.9 billion tonnes of carbon emission is 7012329.97 sq km.which is larger than the geographical area of India As the rate of increase in carbon emission is significantly more than the rate at which the carbon sequestration and forest cover is growing.

G. Results

Year	original_emission	Total_ghg_emission_direct	Total_ghg_emission_linear	Total_ghg_emission_addition	Total_ghg_emission_arimax_exog	Total_ghg_emission_arimax
2001	2019021660	2.090044e+09	2.102618e+09	2.102618e+09	2.019022e+09	2.082245e+09
2002	2017562400	2.144205e+09	2.135139e+09	2.135139e+09	2.017562e+09	2.149533e+09
2003	2088233880	2.188557e+09	2.166190e+09	2.166190e+09	2.088234e+09	2.215228e+09
2004	2162795810	2.279903e+09	2.240605e+09	2.240605e+09	2.162796e+09	2.298520e+09
2005	2239350740	2.332360e+09	2.313255e+09	2.313255e+09	2.239351e+09	2.374339e+09
2006	2327488030	2.397872e+09	2.366712e+09	2.366712e+09	2.327488e+09	2.454412e+09
2007	2475741210	2.489791e+09	2.476096e+09	2.476096e+09	2.475741e+09	2.547122e+09
2008	2623861870	2.581686e+09	2.548739e+09	2.548739e+09	2.623862e+09	2.645661e+09
2009	2756778930	2.655058e+09	2.627465e+09	2.627465e+09	2.756779e+09	2.751006e+09
2010	2847361420	2.722331e+09	2.708652e+09	2.708652e+09	2.847361e+09	2.851172e+09
2011	2957348500	2.814150e+09	2.788263e+09	2.788263e+09	2.957348e+09	2.954544e+09
2012	3155205640	2.918987e+09	2.890869e+09	2.890869e+09	3.155206e+09	3.062352e+09
2013	3220519650	3.028120e+09	3.007014e+09	3.007014e+09	3.220520e+09	3.178170e+09
2014	3333282800	3.117678e+09	3.066173e+09	3.066173e+09	3.333283e+09	3.304699e+09
2015	3438725700	3.204190e+09	3.149638e+09	3.149638e+09	3.438726e+09	3.434132e+09
2016	3564861130	3.321146e+09	3.252332e+09	3.252332e+09	3.564861e+09	3.570347e+09
2017	3621199130	3.418503e+09	3.347016e+09	3.347016e+09	3.621199e+09	3.705819e+09
2018	3783796140	3.519806e+09	3.438700e+09	3.438700e+09	3.783796e+09	3.842072e+09
2019	3815779680	3.649375e+09	3.569540e+09	3.569540e+09	3.815780e+09	3.986561e+09
2020	3638071190	3.775579e+09	3.689244e+09	3.689244e+09	3.638071e+09	4.135568e+09
2021	3900927010	3.886618e+09	3.798895e+09	3.798895e+09	3.900927e+09	4.297858e+09

Fig. 1. Comparison table for GHG emission in India for (2001 to 2021)

Metrics Dictionary: 'Total GHG Emission direct': 'MSE': 2.467685522629966e+16, 'MAE': 138668750.51080364, 'R2': 0.9391930609594895, 'RMSE': 157088685.86343086, 'Total GHG Emission addition': 'MSE': 3.552970362405361e+16, 'MAE': 159426029.13032925, 'R2': 0.9124502493294727, 'RMSE': 188493245.56613058, 'lstm': 'MSE': 2.3726318019291315e+17, 'MAE': 459414175.5659034, 'R2': 0.4153530665782684, 'RMSE': 487096684.64578277, 'Total GHG Emission Arimax exog': 'MSE': 2.908702916621613e-07, 'MAE': 0.000537895020984468, 'R2': 1.0, 'RMSE': 0.000539323920906686, 'Total GHG Emission ARIMAX': 'MSE': 2.628490096836622e+16, 'MAE': 105112464.01152399, 'R2': 0.9352306298265313, 'RMSE': 162126188.41003516

Here's a breakdown of this dictionary: Different models are evaluated: There are entries for 'LSTM', 'ARIMAX', 'ARIMAX-EXOG', and some variations related to emission types ('direct' and 'addition'). Performance metrics are provided: Each model entry includes MSE (Mean Squared Error), MAE (Mean Absolute Error), R-squared (coefficient of determination), and RMSE (Root Mean Squared Error). These metrics offer insights into how well each model performs in predicting emissions. 'ARIMAX-EXOG' stands out: This model achieves a perfect score (R-squared of 1.0 and very low MSE and MAE) which suggests it might be overfitting the data (meaning it performs well on the training data but may not generalize well to unseen data). Other models show trade-offs: 'ARIMAX' and 'direct/addition' variations seem to have a good balance between R-squared (indicating fit) and error metrics (MSE, MAE, RMSE). 'LSTM' has a lower R-squared but potentially lower errors, suggesting a different strength - it might capture more complex patterns but may not perfectly match the overall trend.

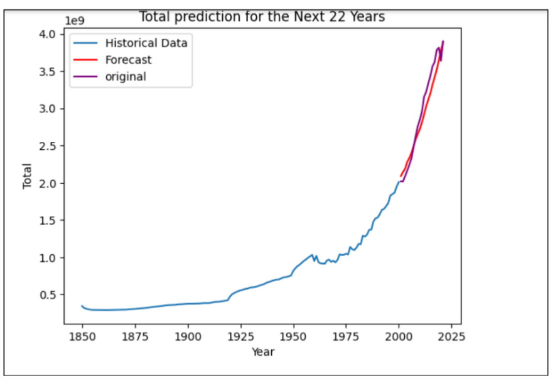

Fig. 2. GHG emission line graph for prediction from 2001 to 2021

Based on the R-square score we have selected the SARIMA model(direct approach).

Based on the R-square score we have selected the SARIMA model(direct approach).

H. Forest Cover

Metrics Dictionary: 'Forest Cover Prediction direct SARIMA': 'MSE': 170707096.93882734, 'MAE': 11571.53548611463, 'R2': -3.1075180807023486, 'RMSE': 13065.492602226192, 'Forest Cover Prediction SARIMA': 'MSE': 745045436.4426779, 'MAE': 24738.470539017453, 'R2': -16.927125796238702, 'RMSE': 27295.520446451974, 'Forest Cover Prediction ARIMAX EXOG': 'MSE': 11788706.400398275, 'MAE': 3189.18558041387, 'R2': 0.7163426386128545, 'RMSE': 3433.4685669739683, 'Forest Cover Prediction ARIMAX': 'MSE': 6212194.794118999, 'MAE': 2415.7131483803505, 'R2': 0.8505234820621859, 'RMSE': 2492.4274902429956

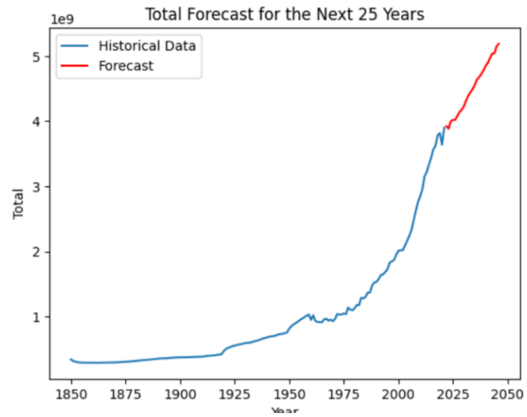

Fig. 3. GHG emission line graph for forecast of next 25 years

Year	forest_cover_prediction_sarima_direct	forest_cover_prediction_sarima_addition	forest_cover_prediction_arima	forest_cover_prediction_arima_exog	Total_original_forest
2012	708453.646238	718854.451285	692640.567451	693989.539355	694963
2013	720881.285471	745398.505691	693926.863326	695903.342608	697898
2014	716825.853442	723291.994013	695755.864303	697329.311004	699786
2015	712769.845237	739285.653923	698011.277156	698751.769196	701673
2016	713377.906936	737265.176953	700601.728484	702413.755466	704883
2017	713986.032734	735359.480904	703455.424776	706074.859155	708093
2018	709280.096190	731338.563120	706515.956748	707818.193863	710171
2019	704574.234601	727495.545727	709739.002747	709561.224664	712249
2020	700410.842642	724239.742651	713089.738554	710036.001238	713019
2021	696246.041762	721379.591124	716540.802240	710508.871965	713789

Fig. 4. Comparison table for forest cover in India(2012 to 2021)

Here's a breakdown of the above dictionary: There are four models being compared: 'direct SARIMA', 'SARIMA', 'ARIMAX-EXOG', and 'ARIMA'. Each likely refers to a specific statistical method used for forecasting. The models are named based on the prediction target ("Forest Cover Prediction") and the method used. 'direct' might indicate a variation focused on a specific aspect of forest cover. Performance metrics are included: Each model entry contains MSE (Mean Squared Error), MAE (Mean Absolute Error), R-squared (coefficient of determination), and RMSE (Root Mean Squared Error). Lower error values (MSE, MAE, RMSE) and a higher R-squared value generally indicate better model performance. 'ARIMAX' and 'ARIMAX-EXOG' outperform 'SARIMA' models: Based on R-squared, 'ARIMAX' and 'ARIMAX-EXOG' seem to fit the data considerably better. Their error metrics (MSE, MAE, RMSE) are also lower. 'ARIMAX-EXOG' might be the best option: While 'ARIMAX' shows good results, 'ARIMAX-EXOG' has the lowest overall error and the highest R-squared, suggesting it might be the most accurate predictor of forest cover in this case. Negative R-squared values for 'SARIMA' models: It's interesting to note that the 'SARIMA' models have negative R-squared values. This typically indicates the model performs worse than just predicting the average forest cover.

Based on the R-square score we have selected the ARIMA model.

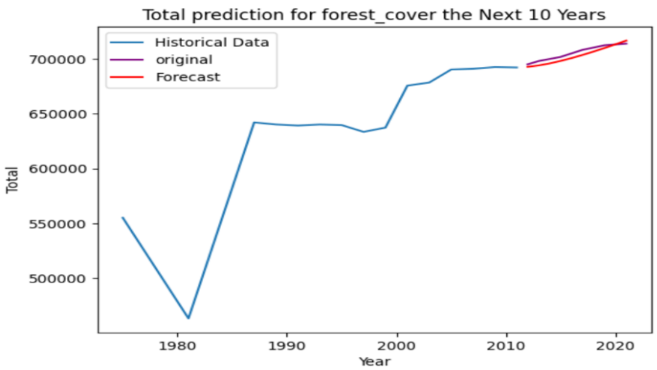

Fig. 5. Forest cover line graph for prediction from 2012 to 2021

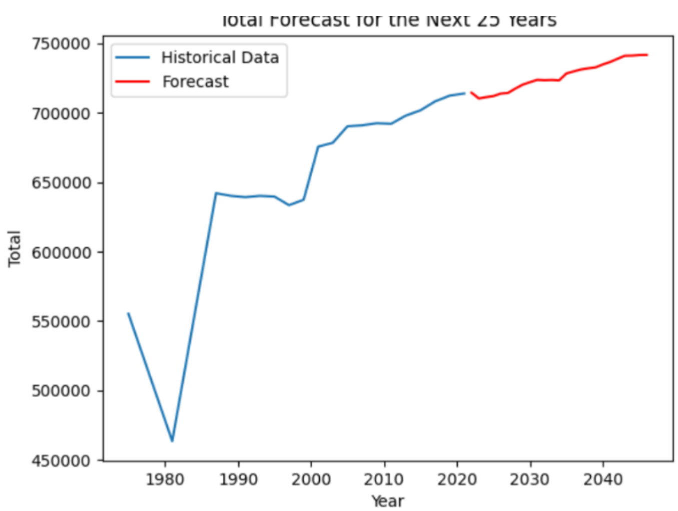

Fig. 6. Forest cover forecast for next 25 years

The issue of carbon emissions poses a significant challenge globally, with projections indicating a concerning trajectory if urgent action is not taken. In 2021 alone, carbon emissions reached a staggering 3.9 billion tonnes, with forecasts suggesting a potential increase to 5.18 billion tonnes if corrective measures are not implemented swiftly. This rapid rise in emissions far outpaces the rate at which nature's carbon sequestration mechanisms, particularly forests, can mitigate the impacts. India, for instance, possesses a substantial forest cover, amounting to 713,789 square kilometers in 2021, with projections indicating a modest increase to 752,254.17 square kilometers. Despite the significant carbon sequestration capacity of these forests, estimated at 7.204 billion tonnes in 2021, the rate of growth is not keeping pace with escalating emissions. Over the past decade, the annual gain in carbon sequestration has averaged 541 million tonnes, with 2021 seeing a sequestration of 39.4 million tonnes. However, to offset the 3.9 billion tonnes of carbon emissions, an ideal forest cover of 7,012,329.97 square kilometers would be required—a geographical area exceeding that of India itself. This stark disparity underscores the urgent need for comprehensive measures to curb carbon emissions and enhance carbon sequestration efforts to mitigate the looming threat of climate change.

IV. Future Scope and Conclusions

Our project aims to spearhead the transition to renewable energy sources, including hydro, solar, wind, biogas, and geothermal energy, with the overarching goal of significantly reducing carbon emissions. We will conduct a comprehensive analysis of current energy production levels, with a specific focus on coal and other non-renewable sources. By examining energy output trends and patterns, we will lay the groundwork for informed decision-making in our transition to renewable energy. Our project will undertake a detailed assessment of the annual costs associated with non-renewable energy sources, providing valuable insights into the financial implications of our energy practices.Through rigorous cost comparisons, we will identify renewable energy alternatives that offer cost-equivalent solutions, ensuring the financial viability of our transition. By prioritizing financial feasibility and sustainability, our solution offers a promising pathway towards a cleaner and more sustainable energy future. Through the installation of windmills and solar panels in these high-emission areas, we aim to mitigate carbon emissions effectively and make tangible strides towards environmental stewardship.

References

[1] Jemyung Lee , Oliver Taherzadeh, , Keiichiro Kanemoto , "The scale and drivers of carbon footprints in households, cities, and regions across India", Research Institute for Humanity and Nature, 2021.

[2] Qi Huanga, Heran Zheng , Jiashuo Li , Jing Mengc, Yunhui Liud, Zhenyu Wange,Ning Zhanga, Yuan Li ,, Dabo Guanc, "Heterogeneity of consumption-based carbon emissions and driving forces in Indian states, Advances in Applied Energy, ,Volume 4, November 2021

[3] Ishma Amin, Meenakshi Agarwal, Stevert Lobo, Rahul Gurnani, and Prof. (Mrs.) Priya R.L, "Concept for Mapping Carbon footprint with Change in Vegetation Cover and Population in India" ,ITM Web Conf. , Volume 32, 2020 International Conference on Automation, Computing and Communication 2020 (ICACC-2020

[4] T.V. Ramachandra , Shwetmala , "Decentralized carbon footprint analysis for opting climate change mitigation strategies in India" , Renewable and Sustainable Energy Reviews , Volume 16, Issue 8, October 2012

[5] Surbhi Kumari, ,Sunil Kumar Singh , " Machine learning-based time series models for effective CO2 emission prediction in India" , Environmental Science and Pollution Research , June 25, 2022

[6] B. Mohan Kumar , Sreejith Aravindakshan , "Carbon footprints of the Indian AFOLU (Agriculture, Forestry, and Other Land Use) sector: a review " , Arunachal University of Studies, May 24, 2022

[7] Jingwei Han , Zhixiong Tan , Maozhi Chen , Liang Zhao , Ling Yang and Siying Chen , "Carbon Footprint Research Based on Input–Output Model—A Global Scientometric Visualization Analysis " International Journal of Environmental Research and Public Health

[8] Tao Gao, Qing Liu and Jianping Wang , "A comparative study of carbon footprint and assessment standards" ,Institute of Project Management, School of Mechanics and Civil Engineering, China

[9] Andréea Lorena Radua , Marian Albert Scrieciua , Dimitriu Maria Caracotaa , "Carbon Footprint Analysis: Towards a Projects Evaluation Model for Promoting Sustainable Development " , International Economic Conference of Sibiu 2013 Post Crisis Economy: Challenges and Opportunities, IECS 2013