An Integrated Study on the Global Blockchain-Enabled Carbon Credit Market: AI-Driven Predictive Modeling, Liquidity Analysis, and Strategic Benchmarking of India's Framework

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List of Abbreviations

AI - Artificial Intelligence

ANN - Artificial Neural Network

ACVA - Accredited Carbon Verification Agency

BEE - Bureau of Energy Efficiency

CCTS - Carbon Credit Trading Scheme

CDM - Clean Development Mechanism

CER - Certified Emission Reduction

EU ETS - EU Emissions Trading System

NAPCC- National Action Plan on Climate Change

PAT - Perform, Achieve, and Trade

MAPE - Mean Absolute Percentage Error

RMSE - Root Mean Squared Error

MRV - Monitoring, Reporting, and Verification

ABSTRACT

This research provides an integrated method for examining the global blockchain-based carbon credit market using AI-based predictive modeling, liquidity analysis, and strategic benchmarking of India's carbon credit system. The market trends were predicted using predictive models, such as Linear Regression, XGBoost, and Facebook Prophet, and liquidity was determined through daily returns, Amihud Illiquidity Ratio, and turnover ratios. The outcomes state that the Linear Regression, used as a baseline model, resulted in an RMSE of 0.45 and R^2 of 0.39, meaning it had a moderate predictive power. In contrast, the XGBoost model achieved better performance with the best RMSE (0.34) and highest R^2 score (0.56), whereas Prophet gave more interpretable trend-based predictions, with a MAPE of 17.65% and an R^2 score of 0.79. In the Indian context, the presented research is based on the conceptual benchmarking approach, where the 2022 Energy Conservation Act and the future CCTS (20252026) are compared with the global standards, and the analytical review is conducted on the emerging technologies, including blockchain and AI. Strategic benchmarking came up with recommendations that were operational in nature to foster transparency, reliability, and market engagement. These results indicate that implementing AI-based forecasting is feasible in blockchain-based carbon markets and provide India with an opportunity to become a competitive hub in the digital carbon market.

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PREFACE

The presented research project is an embodiment of my academic experience in data science and my personal interest in sustainable finance and environmental markets. The study aims to provide an integrated method for examining the global blockchain-enabled carbon credit market, combining AI-driven predictive modeling, liquidity assessment, and strategic benchmarking of India's carbon credit framework. The work is motivated by the increasing demand to establish transparent, efficient, and trustworthy systems of carbon credit trading, as well as the gap in the application of predictive modeling and liquidity analysis to the carbon markets based on blockchain. My Research work used Linear Regression, Time Series Prophet, and XGBoost to predict the market trends, and the liquidity analysis was done using daily returns, Amihud Illiquidity Ratio, as well as turnover ratios. Furthermore, the CCTS (2025) scheme in India was benchmarked strategically to determine possible ways to enhance the structure.

CHAPTER 1
INTRODUCTION

INTRODUCTION

Carbon credits have become an important tool in the global fight against climate change by assigning a market value to carbon emissions. One carbon credit is the entitlement to emit one metric ton of carbon dioxide or an equivalent amount of other greenhouse gases. Credits are generated by activities that cut or eliminate emissions like renewable energy, afforestation, or carbon capture, and can be bought and sold among parties wanting to reduce their emissions.

Carbon credit trading enables firms or nations with excess emissions beyond their allowance to buy credits from others who have a surplus, achieving environmental responsibility and economic efficiency. This is done in two major markets: government-regulated compliance markets and corporate-based voluntary markets. Though efficient in theory, conventional carbon markets have limitations like double counting, delayed verification, and an absence of transparency.

Blockchain technology has been able to tackle these issues effectively. With the possibility of transparent, tracked, and counterfeit-proof recording of credit issuances and transactions. Tokenization was introduced with initiatives like KlimaDAO, Toucan Protocol, and Celo that tokenize carbon credits, making them publicly tradable on decentralized platforms, and opening up access to the wider global market.

Blockchain-enabled carbon credit trading works by creating a secure, transparent, and immutable digital ledger for carbon credits. Every credit is encoded to the blockchain, encompassing a validated unit of Co_2 decrease. These tokens can be bought and sold without intermediaries by the participants, who are companies, investors, or regulators of a decentralized platform. Smart contracts are self-enforcing, ownership-tracking, and regulatory-compliant rules and regulations. This mechanism enhances transparency, minimizes fraud, and enables real-time monitoring of credit issuance, transfer, and retirement.

In this research, predictive modeling was used to forecast future trends for the tokenized carbon credit market. A Linear Regression model was created as the baseline to predict major market indicators and monitor possible growth trends. To more accurately capture temporal structure within the data, Prophet was utilized for time series forecasting. Also, XGBoost was utilized to improve predictive performance by adding lag-based features and regression accuracy optimization. The dataset, obtained from KlimaDAO, spanned October 2021 to July 2025 and consisted of on-chain transaction data. Based on this data, liquidity analysis was also performed to evaluate trading activity, market volatility, and the depth of decentralized carbon markets. The figure 1.1 represents the framework of this project:

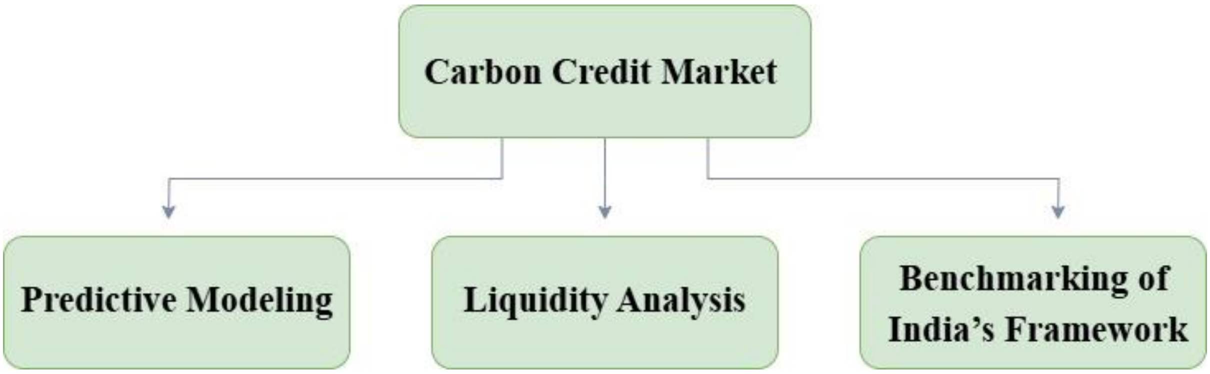

Fig 1.1 Project Framework

This study is also concerned with development of India's carbon credit system. With the 2022 Energy Conservation (Amendment) Act, and the impending Carbon Credit Trading Scheme (CCTS) in 2025–26, India has signaled high levels of intent towards developing a domestic carbon market. But in contrast to global decentralized systems, the Indian system is still in its infancy, more so in the adoption of technologies like blockchain and AI. This study compares India's strategy to international norms and highlights the need for further innovation, infrastructure development, and digitalization. The goal is to acknowledge the advancements made thus far and the way forward for India to become a leader in the digital carbon credit economy.

1.1 OBJECTIVES

- To build AI-based models based on KlimaDAO's on-chain data (Oct 2021–July 2025) to predict carbon credit market trends.
- To study the market liquidity by evaluating trading activity, volatility, and depth in decentralized carbon platforms.
- To compare India's changing carbon credit system, shaped by the 2022 Energy Act and future CCTS (2025-26), with international standards.
- To examine India's preparedness for integrating blockchain and AI and propose measures for enhancing its digital carbon market infrastructure.

1.2 RESEARCH QUESTIONS

1. How effective are AI-driven predictive modeling techniques in forecasting market trends within the blockchain-enabled carbon credit ecosystem using decentralized on-chain transaction data from October 2021 to July 2025?
2. How can liquidity analysis of blockchain-based carbon credit transactions help identify trading patterns, market volatility, and the overall maturity of decentralized carbon markets?
3. How does India's carbon credit framework, led by the 2022 Energy Conservation Act and the upcoming CCTS (2025–26), integrate new technologies such as blockchain and AI in comparison to global standards? What technological innovations and infrastructure are needed for India to establish itself as a globally competitive hub in the digital carbon credit economy?

CHAPTER 2

LITERATURE REVIEW

LITERATURE REVIEW

The authors used different methodologies to explore the application of Blockchain technology in the Carbon Credit markets, particularly its potential to make trading mechanisms more transparent, efficient, and capable of detecting fraud. Several studies focus on blockchain-based solutions that enhance monitoring and verification operations, and some emphasize the overarching consequences of decentralized systems in the delivery of trust and responsibility. Researchers also explore the policy and regulatory environments in India, analyzing the institutional processes and market forms influencing the emerging carbon credit environment in the country. Thus, this review is categorized into two parts: one focusing on blockchain-enabled carbon credit market studies and the other on India's Carbon Credit Framework.

2.1 Studies on Blockchain-Enabled Carbon Credit Markets

Ameni Boumaiza et al. (2024) examined transparency, security, and efficiency measures that could be enhanced through the use of blockchain in carbon trading. The research named ineffective traditional markets which included double counting, fraud, ineffective traceability, and lack of efficient project monitoring. Those weaknesses were addressed by a blockchain-based peer-to-peer model that includes smart contracts, distributed registries, and real-time compliance, among others. The authors compared programs like IBM Hyperledger Fabric and VeChain VeCarbon by illustrating how they help increase accountability, accuracy, and cost-efficiency. Despite the scalability, governance, and regulatory alignment issues, the paper finds that blockchain can greatly help convert carbon trading into a more visible and reliable framework to build sustainable energy futures. [1]

Adam Sipthorpe et al. (2022) discussed the increased maturity of blockchain solutions in carbon markets and their capability to enhance transparency, credibility, and efficiency. The research cited classic issues like low levels of trust, inefficiency in credit verification, and the risk of counting twice, and how tokenization, smart contracts, and distributed ledgers can improve tracking, decrease costs, and increase market scale. It has also observed the emergence of blockchain-based registries and exchanges, pilot projects and growing participation of startups and established institutions are proving their viability in practice. The study reported that blockchain is approaching maturity and has great potential to support the development of carbon markets into more transparent and trustworthy systems despite the challenges in governance, regulation, and interoperability. [2]

Amol Pandurang Yadav et al. (2025) explored the possibility of building efficient and safe markets in carbon credit with embedded environmental impact monitoring by using blockchain. It has also outlined issues in the current system such as fraud, counting twice, and the high cost of verification and has proposed solutions to solve such problems based on blockchain technology, such as tokenization, smart contracts, and real-time monitoring through the Internet of Things. Other reported examples of case studies that indicated an increase of transparency, accuracy and cost reduction include VeChain and IBM projects. Scalability, regulation, and energy use are still an issue, but the paper has also concluded that blockchain can play a significant role in ensuring more carbon credit markets are visible and legitimate. [3]

Yun Cheng Tsai (2025) analyzed the advantages of the visualization methods of blockchain in the enhancement of transparency and detection of frauds in carbon credit markets. The paper found that there are shortcomings of existing systems, such as the inability to track credits, identify anomalies, and avoid counting the same data multiple times. The paper has suggested blockchain-infused visualization structures and dashboards to fill these gaps and provide real-time visibility, more interpretable data and improved auditability. The author also claimed that these tools lower the costs of verification and increase the level of stakeholder trust because credit flows become more transparent and traceable. Despite the problem of scalability, interoperability, and regulation identified in the paper, the researchers concluded that more secure and fraud-resistant carbon credit markets are possible by using visualization-based blockchain strategies. [4]

Ameni Boumaiza (2024) explored how carbon and energy trading could be implemented in a peer-to-peer model based on blockchain technology to increase transparency, efficiency and equity. The paper has identified inefficiencies and high transaction costs of traditional systems, poor traceability and proposed a solution which is smart contract and distributed ledger-based system to provide security in transactions and trace carbon and energy flows. The study demonstrated the energy optimization and reduction of emission through modified IEEE 37-bus test system. The paper commented on scalability, regulation, and interoperability issues, but also concluded that peer-to-peer systems built with blockchain technology had a good potential to be used to build more transparent and sustainable carbon and energy markets. [5]

Alberto Ballesteros-Rodriguez et al. (2024) investigated how a tokenized form of carbon credit can be used in voluntary carbon markets through the example of KlimaDAO. It claimed that inefficiency inherent with traditional carbon trading can be improved by liquidity, transparency, and access via tokenization via blockchain. Through an analysis of the tokenomics of KlimaDAO, specifically bonding, staking, and protocol-owned liquidity, the authors both emphasised opportunities to expand the market and identified the risks of volatility, governance, and regulatory uncertainty. The paper suggested that decentralized systems like KlimaDAO show that a tokenized carbon market is feasible, but its sustainability over the long term requires more robust standards, institutional regulation, and robust governance systems in place. [6]

Ramesh Babu (2024) discussed how blockchain could be used to increase transparency, traceability, and efficiency in carbon credit trading. The paper has highlighted the use of decentralized registries and tokenization to accurately track emissions and prevent counting them twice, as well as the use of smart contracts to automate the trading, compliance, and settlement processes and reduce costs and increase liquidity. ClimateTrade and AirCarbon Exchange case studies were used in reality. Blockchain-based systems were also found to have a high potential to promote sustainability and enable global climate mitigation despite their weaknesses in terms of scalability, regulation, and adoption. [7]

Niyati Sharma et al. (2025) examined the role of artificial intelligence in the carbon credit markets and the author targets the possibility of providing transparency, efficiency, and environmental responsibility to the market. The paper brings attention to the AI methods, such as machine learning, predictive modelling, natural language processing, and blockchain, which are used to optimize the process of emissions monitoring, automate compliance, and ensure liquidity in the markets. Although the paper admits that there are such obstacles as data privacy, algorithmic bias, and regulatory barriers, the paper still finds that AI-based systems have massive potential in reinventing carbon credit markets and influencing the development of global climate finance. [8]

Bama Raja Segaran et al. (2025) explored the incorporation of machine learning with carbon credit systems based on blockchain, and the author dwells on solving the problem of greenwashing in sustainability reporting. The analysis identifies the potential of efficient ML methods to be integrated into decentralized blockchain structures and help to verify and guarantee traceability and the overall integrity of carbon credit transactions. The framework will reduce the misreporting and manipulation of carbon offsets by reinforcing transparency and accountability. Even though the paper does not ignore technical constraints and regulatory challenges, it shows that the integration of ML and blockchain could serve as the promising solution to create more reliable carbon credit markets and develop climate governance. [9]

Tengwei Cai et al. (2024) discuss the importance of blockchain technology in the formation of the digital economy, and the author dwells on the potential of this technology to promote structural efficiency and eliminate environmental issues using artificial neural networks. The paper focuses on the role of blockchain in enhancing economic transaction transparency, decentralization, and trust, and ANNs can be used to eliminate the adverse environmental effects of the digitalization process by allowing sophisticated monitoring, prediction, and optimization. Introduction of these technologies is put forth as a gateway to a balanced economic growth and sustainability agendas. In spite of the limitations pointed out in the paper in terms of scalability, regulatory loopholes, and the complexity of implementation, it concludes that blockchain-ANN frameworks can both spur innovation in the digital economy and contribute to global environmental protection projects. [10]

2.2 Studies on India's Carbon Credit Framework

Manjunatha N (2024) discussed the development and operation of carbon credit trading in the Indian setting and the author concentrates on the sustainability development and fulfilling climate change promises. The author puts emphasis on the carbon credit generation and trading of the Clean Development Mechanism (CDM), stating that India is one of the biggest producers of Certified Emission Reductions (CERs). The paper highlights the potential benefits of carbon markets to the Indian industries in their renewable energy uptake, technological development and monetary gains as well as the challenges facing the carbon markets that include uncertainty in regulations, unstable market demands and low awareness of the stakeholders. The paper concludes that despite the fact that carbon credit trading has the potential to serve the climate policy and economic development of India, its success depends on the enhanced regulatory practices, institutional support, and orientation towards the global goals of sustainability. [11]

Adeeth A. G. Cariappa et al. (2025) analyzed carbon farming projects in India to determine how they related to inclusivity, additionality and permanence in the context of survey data of 841 farmers in seven project villages in Haryana and Madhya Pradesh. The research established that the engagement was mostly dominated by large land owners and non-marginalized caste groups and marginalized farmers and women participated insignificantly. Research indicated that monetary benefits were not received by 99% of farmers and thus the disadoption rates were high approximately 28%. Moreover, the use of Carbon Core firms showed a high level of continuity and adoption of regenerative practices in contrast to corporate subsidiaries or blended models. In general, the research findings indicated structural exclusion, low financial incentives, and permanency issues that weaken the effectiveness of carbon farming in India in the long term. [12]

Vineeta Arora (2021) examined the accounting of carbon credits in India to determine how the concept has helped to reduce the emission of greenhouse gases and create economic opportunities. The paper has addressed the processes of trading carbon under Kyoto Protocol and Clean Development Mechanism (CDM), with India being one of the biggest emitters of Certified Emission Reductions (CERs). With help of the example of the Delhi Metro Rail Corporation, the paper demonstrated the kind of savings of electricity by regenerative braking (30 %) and big carbon credits. The results showed that despite the fact that carbon credits are handled as intangible assets, there is no clear and consistent accounting framework that is used by India in reporting and management of such credits. The paper has highlighted the importance of having standard processes, transparency in the trading as well as adherence to the international accounting standards. The author concluded that carbon credit accounting has a great potential of climate mitigation as well as revenue generation though there is a need to have strong institutional and regulatory backing. [13]

Kishor P. Bholane (2025) analyzed the situation, opportunities, and challenges of carbon credit trading in India in the present situation. The paper has identified some of the important government initiatives, including the Clean Development Mechanism, the Energy Conservation (Amendment) Bill 2022, and the introduction of the Indian Carbon Market. The results indicated that India has emerged as one of the largest carbon markets with more than 35 million credits being issued between 2010 and 2022 and surpassing China in retired credits by 2023. The report has described significant business involvement of big firms such as Jindal Vijaynagar Steel and Torrent Power in the trading and other notable opportunities as renewable energy and waste-to-energy projects. Nevertheless, several obstacles including low awareness, complicated verification processes, and the high cost are present. In general, the study found that carbon credit trading can be of great use to the climate objectives of India provided that it is backed by more powerful policies and streamlined procedures. [14]

Subrata Gorain et al. (2021) analyzed carbon credits as a possible instrument of lowering greenhouse gas emissions and promoting sustainable development with the help of the secondary data. The research has pointed out that India is well placed as a source of big

Certified Emission Reductions especially in renewable energy and forestry facilities. It discovered that carbon credit trading presents economic advantages in the form of revenue, and transfer of technology and job opportunities. Meanwhile, issues such as fluctuation of prices, inadequate awareness and poor regulatory systems were observed. The study concluded that carbon credits are capable of making a significant contribution to environmental protection, as well as, economic growth provided they are supported by proper policies. [15]

Prajakta Rohit Zirkande et al. (2024) explored the situation of carbon credit in India by analyzing secondary data on the opportunities and challenges of this phenomenon. The market potential has been estimated by the study to be more than 5 billion dollars of carbon farming credits when applied nationally; however, the policies such as the Paris Agreement, NAPCC, and the PAT scheme were used to support the same. The results pointed to the prospects of renewable energy, carbon farming, and global partnerships, as well as the significance of technology and voluntary activities. Simultaneously, the barriers included the lack of clarity in the regulations, complicated verification procedures, and the lack of awareness. The author stated that a well-established institution and policy can make the carbon market in India a major contributor to the climate objectives and the economic development of the country. [16]

2.3 Summary and Research Gap

In this review, we see that globally, the carbon markets that are blockchain-enabled have been known to enhance transparency and trust but are yet to address some of the challenges such as scalability, uncertainty in regulations and ensuring genuine transparency. In India, initiatives such as CDM and PAT are promising, although poor regulation, high costs and smallholder participation are a major challenge. The majority of the previous studies have focused on either the policies or the technical side of blockchain, leaving predictive modelling and liquidity analysis under-researched because of high illiquid assets and fragmented data. This study addresses these gaps by analyzing global blockchain-enabled carbon credits based on KlimaDAO data and insights to improve sustainable carbon markets.

CHAPTER 3
METHODOLOGY

METHODOLOGY

This study has a structured methodology, as it starts with the collection of data from a blockchain-based carbon credit platform, such as KlimaDAO. The dataset is then preprocessed, whereby exploratory analysis, cleaning, and feature engineering are performed to make it accurate and consistent. Predictive modeling is then done based on Prophet, Linear Regression, and XGBoost, and Liquidity analysis based on Amihud illiquidity ratio and trading volume. The outcomes are then discussed through visualization and interpretation, creating actionable insights and implications with a major focus on the global carbon credit market. The figure 3.1 illustrates the detailed methodology of this project:

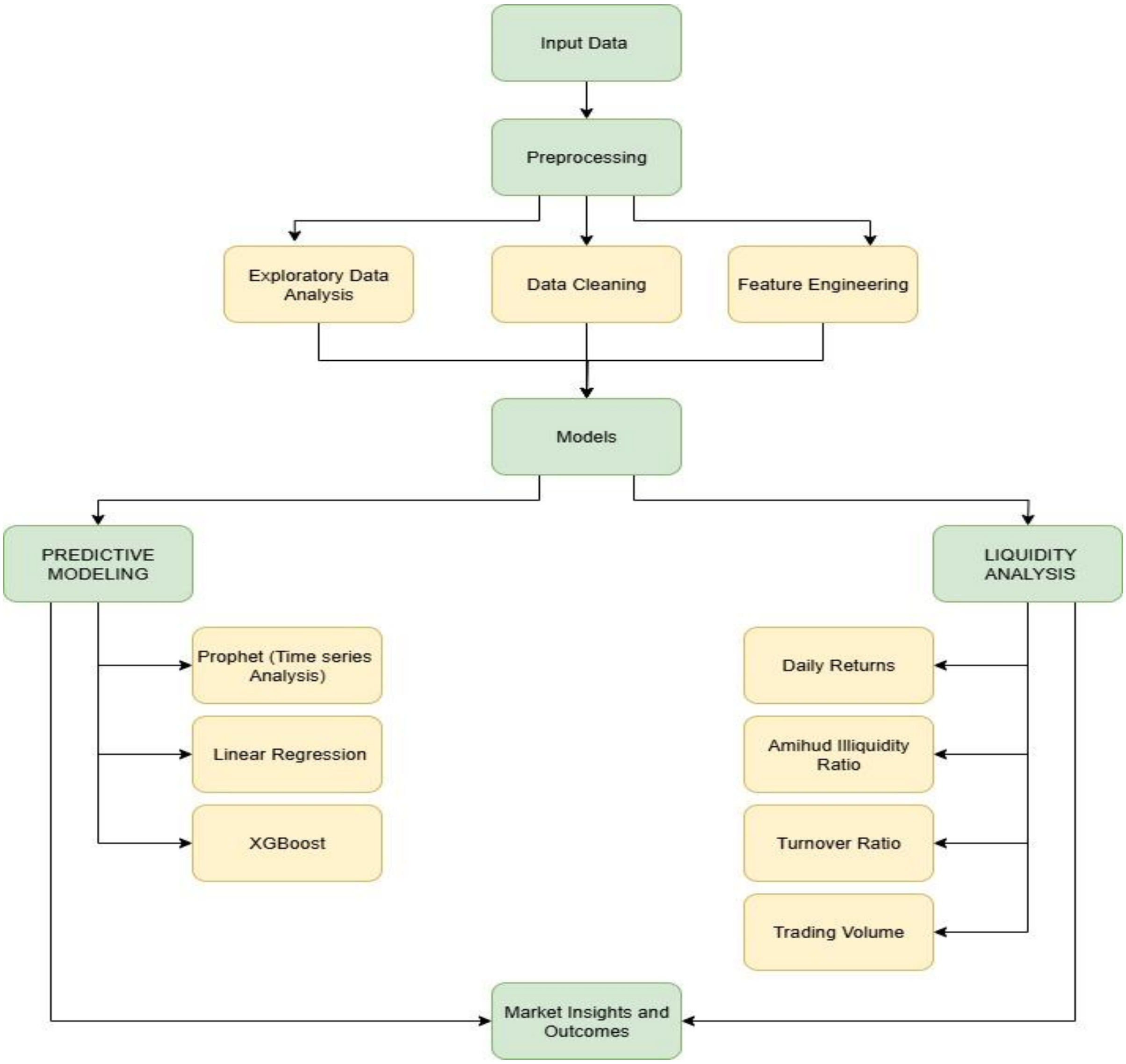

Fig 3.1 Methodology

For the Indian context, this study follows a conceptual benchmarking approach, examining the 2022 Energy Conservation Act and the upcoming CCTS (2025–26) against global standards. Along with the analytical review of emerging technologies such as blockchain, AI, and the necessary infrastructure to understand how India can emerge as a competitive hub in the digital carbon credit economy.

3.1 Software Used

This research was conducted using Python within the Jupyter Notebook environment. Jupyter Notebook provided an interactive environment for data preprocessing, exploratory data analysis, model building, and visualization that enabled the flexibility to explore the dataset and analyze findings. Python was used as the core programming language, which offered a wide range of libraries to support the entire workflow.

3.2 Libraries Used

- **Pandas:** A powerful Python library for data manipulation and analysis, providing data structures like DataFrame.
- **NumPy:** A fundamental package for scientific computing with Python, supporting large, multi-dimensional arrays and matrices.
- **matplotlib.pyplot:** A Python plotting library for creating static, animated, and interactive visualizations.
- **seaborn:** A statistical data visualization library built on Matplotlib, offering an easy-to-use interface for attractive and informative graphics.
- **sklearn.preprocessing.StandardScaler:** A utility to standardize features by removing the mean and scaling to unit variance.
- **sklearn.linear_model.LinearRegression:** A module for implementing linear regression models for predictive tasks.
- **sklearn.model_selection.train_test_split:** A utility to randomly split datasets into training and testing subsets.
- **sklearn.metrics:** Metrics for evaluating model performance in regression tasks.
- **Prophet:** A library for time-series forecasting that models trends and seasonality.
- **xgboost.XGBRegressor:** A gradient boosting library used for high-performance predictive modelling.

3.3 Data Required

The data used in this study is the transactional and market data from the blockchain-based carbon credit platform KlimaDAO, covering the period from October 20, 2021, to July 13, 2025.The dataset has 1363 rows and essential variables needed in predictive modeling and liquidity analysis: Date, Open, High, Low, Close, Volume, and Market Cap. The columns contain information on the market activity, price movements, and liquidity which allows a detailed analysis of the carbon credit market. The figure 3.3.1 provides a detailed discussion on the columns of the dataset:

Column	Description
Date	The specific date of the trading record.
Open	The opening price of KlimaDAO carbon credits on that date.
High	The highest price reached during the trading day.
Low	The lowest price reached during the trading day.
Close	The closing price of the carbon credit for the day.
Volume	The total number of carbon credits traded on that day.
Market Cap	The total market capitalization of KlimaDAO carbon credits on that date.

Fig 3.3.1 Data Description

3.4 Formulas Used

1. Daily Return

$$\boldsymbol{R_t = \frac{P_t - P_{t-1}}{P_{t-1}} = \frac{P_t}{P_{t-1}} - 1}$$

Where:

- R_t= Daily return on day t
- P_t = Closing price on day t
- P_{t-1} = Closing price on day t – 1

2. Absolute Return

$$\boldsymbol{|R_t| = \left|\frac{P_t}{P_{t-1}} - 1\right|}$$

Where:

- $|R_t|$ represents the magnitude of daily return, irrespective of direction.

3. Amihud Illiquidity Ratio

$$\boldsymbol{ILLIQ_t = \frac{|R_t|}{V_t}}$$

Where:

- $ILLIQ_t$= Amihud illiquidity measure at time t
- $|R_t|$ = Absolute daily return
- V_t = Trading volume on day t

4. Turnover Ratio

$$\boldsymbol{TO_t = \frac{V_t}{MC_t}}$$

Where:

- TO_t = Turnover ratio at time t
- V_t = Trading volume
- MC_t = Market capitalization at time t

5. Cumulative Return

$$\boldsymbol{CR_T = \prod_{t=1}^{T}(1 + R_t)}$$

Where:

- CR_T= cumulative return up to time T
- R_t = daily return at time t (in decimal form, e.g., 0.02 for 2%)

3.5 Data Cleaning

The data was subsequently cleaned before the analysis in order to make it accurate, consistent, and easy to work with. The column names were first cleaned in terms of removing the unnecessary symbols, whitespaces, and reduction of spaces by underscores that gave the structure a clean look and uniformity. All the important financial variables, including Open, high, low, close, volume, and market capitalization, were then cleaned and coded in numeric form. Commas and symbols or signs of any non-numeric values were removed, and the missing values were wisely taken to avoid inconsistencies. Date column was changed into the standardized datetime format. The cleaning was followed by the generation of summary statistics to give a quick overview of the trends in the data. The data was clean, properly arranged and was ready to analyze, covering the period between October 20, 2021, and July 13, 2025. This was to ensure that the later stages of Exploratory Data Analysis, Predictive Modeling, and Liquidity Analysis can be performed on data that is reliable and consistent.

3.6 Exploratory Data Analysis

Exploratory data analysis was performed to understand the underlying characteristics of the dataset and extract meaningful insights. This involved descriptive statistics, trend analysis, correlation studies and return-based evaluations. The focus was on determining the price movement, trading, volatility and long-run market performance of carbon credits.

3.6.1 Closing Price Trend

The price trend analysis of the last price shows that there is great volatility during the initial stages of trading. The average closing price was $162.4, with a median of $7.8 which is significantly smaller, depicting the skewed distribution. In early 2021, the prices reached the highest point of $3,694.5, which was subsequently corrected by almost 98% in a year before reaching a minimum of $0.12. After 2022, the market has stabilized, and the values are constantly below $10, and have a limited variability. This pattern reflects an early bubble-like phase, presumably caused by speculative trading and policy-driven momentum, and later a stabilization period as the market became mature and the speculative market faded.

Fig 3.6.1 Time Series of Closing Prices of Carbon Credits

3.6.2 Trading Volume Trend

The trading volume had significant fluctuations within the period under analysis. Average volumes were approximately \$1.23 million, with a high of \$7.2 million that was observed in early 2021. However, after 2022, the average daily volumes decreased dramatically to below \$100,000. This tendency can be seen as a very volatile trading climate within the early months, with steep price movement up and down, and then a phase of reduced activity as speculative activity in the market was reduced and the general liquidity decreased. This low liquidity may add to high price inefficiency and volatility, and thus it can be difficult to make big trades without high slippage.

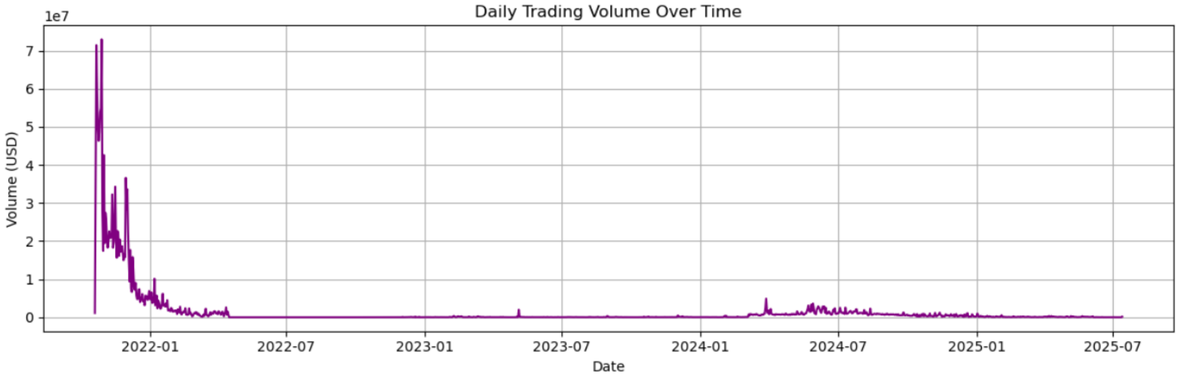

Fig 3.6.2 Daily Trading Volume of Carbon Credits

3.6.3 Distribution of Daily Returns

The average daily returns were 0.18% with a standard deviation of 6.94, which indicated that there was not much variation in the daily returns; however, the overall variation was high. There were also extreme events, and the largest daily gain was +172.5% and the lowest -67.8%. Even though the returns distribution is concentrated around zero, the existence of fat tails would suggest that rare but significant events are predominant in the market. This high kurtosis tendency is indicative of a risk-on, risk-off market structure, in which unexpected shocks (i.e. regulatory announcements, changes in policy, or global carbon market developments, etc.) can lead to disproportionately large effects. These dynamics highlight the susceptibility of the market to sudden volatility, where the risk control and careful trade policies need to be crucial.

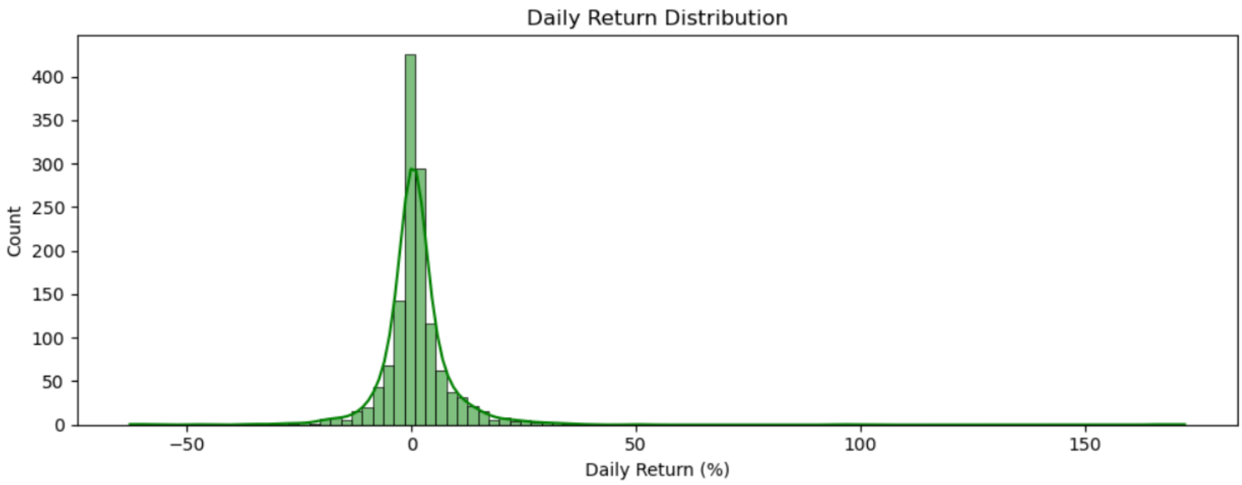

Fig 3.6.3 Distribution of Daily Percentage Returns

3.6.4 Daily Percentage Return Over Time

The percentage returns on carbon credits on a daily basis show that the majority of price fluctuations are in the range of zero; however, extreme fluctuations like +172.5% gains and -67.8% losses provide evidence that the market is also susceptible to sudden policy or regulatory shocks. To traders, this is important because carbon credit positions may be quickly priced up and down, and volatility may spread over several days. Effective involvement in this market thus involves effective risk management, hedging, and stop-loss procedures, because even small exposures can cause huge gains or losses in any turbulent periods.

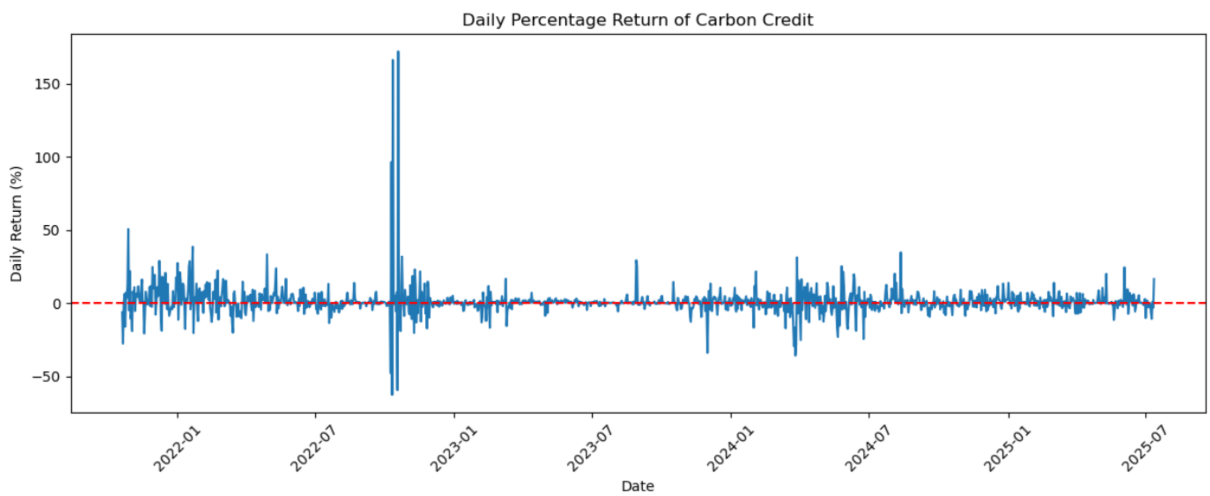

Fig 3.6.4 Time Series of Daily Percentage Returns

3.6.5 Correlation Analysis

The correlation heatmap shows that there are strong positive correlations between price-based variables (Open, High, Low, Close), and their correlation coefficients are greater than 0.99, indicating that they move almost in lockstep. Prices are as well positively correlated to volume (0.9-0.93), indicating that an increase in trading activity is also accompanied by an increase in price. Market Cap however, has a weak negative correlation (-0.11) with price and volume that could suggest that the valuation measures do not move directly with the short-term trading activity. Interestingly, only weak correlations with other variables (<0.07) appear between Daily Returns, and this is an indication that price change on a daily basis cannot be highly predicted with any of the volume or market capitalization, and that returns are more of a random process, related to external shocks than the internal market indicators.

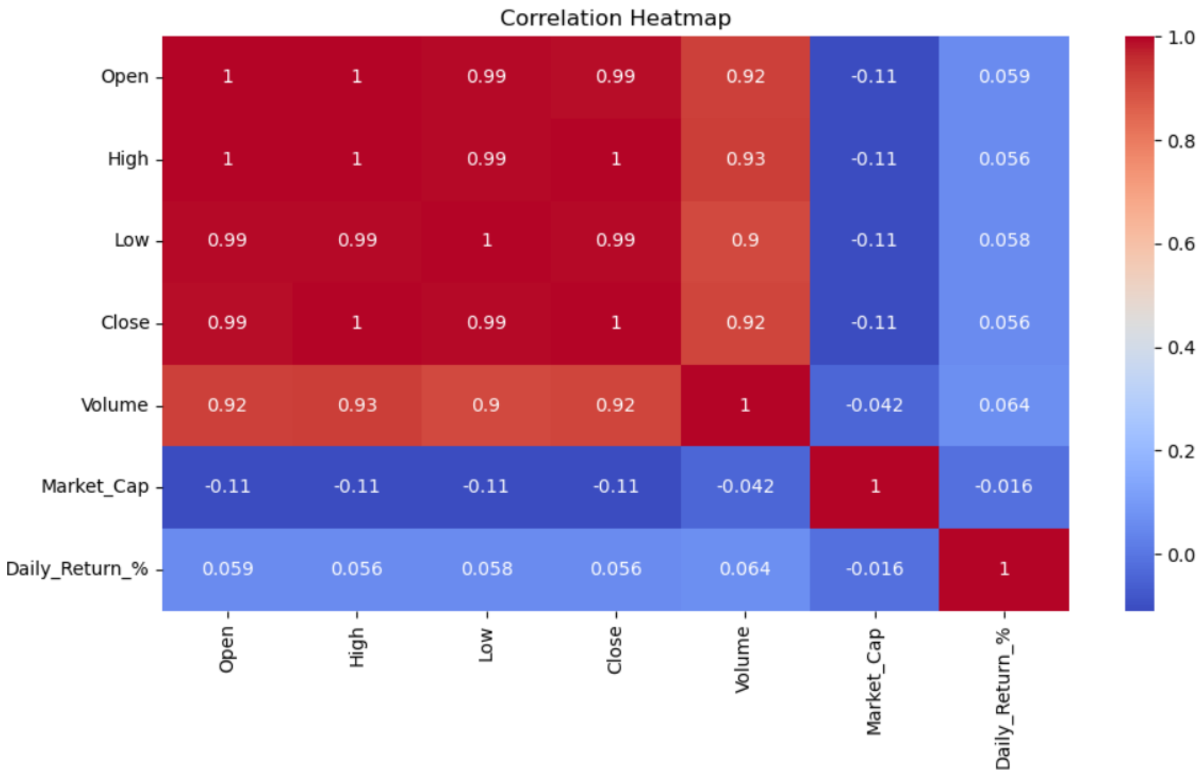

Fig 3.6.5 Correlation Matrix

3.6.6 Cumulative Return Over Time

In early 2022, the cumulative returns fell close to zero following the steep decline of the 2021 high, which showed the breakdown of the speculative profits. Since then, the increase in returns has been on an upward trend, which implies slow recovery and slow increase. By July

2025, the total returns had hit 17500%, which shows good results in the long term despite the initial volatility.

Fig 3.6.6 Cumulative Return of Carbon Credits

In summary, Exploratory data analysis reveals that the carbon credit market experienced an epic bubble in 2021, and then sharply declined and stabilized at a lower level. Trading volumes were diluted soon, and this became a liquidity issue, particularly among large traders. Price movements are highly sensitive to policy announcements and compliance cycles, and thus, the market is event sensitive. Although there are high correlations among the price variables, there are a number of modeling challenges, but the +600% cumulative growth of the sector by mid-2025 shows that there is a unique opportunity and a risk combination.

CHAPTER 4

RESULTS AND CONCLUSION

RESULTS AND CONCLUSION

4.1 Liquidity Analysis

Liquidity is a critical measure of market efficiency, indicating how easily assets can be traded without causing significant price fluctuations. In order to assess the liquidity in the blockchain-enabled carbon credit market, two metrics were used. The Amihud Illiquidity Ratio is a measure that is computed by dividing the absolute return by the trading volume, which is used to capture the price impact of trading in comparison to the market activity. The Turnover Ratio is the trading volume as a proportion of the market capitalization, which is an indicator of the activity of the entire market and the circulation of assets. The summary statistics of these indicators show high illiquidity and turnover variability, which draws attention to possible difficulties faced by market participants. These liquidity dynamics are important to understand since changes in illiquidity and turnover can affect the reliability and the strength of predictive models to a great extent.

4.1.1 Amihud Illiquidity Ratio

The Amihud Illiquidity Ratio of the carbon credit market shows a good temporal variation between 2022 and 2025. In 2022, the ratio changed between 10^{-8} to 10^{-4}, representing reasonably stable liquidity. However, there were spikes in mid-2022 and early 2023, where the values briefly surpassed 10^{-2}, which indicates the periods when small trades had relative disproportional price effects.

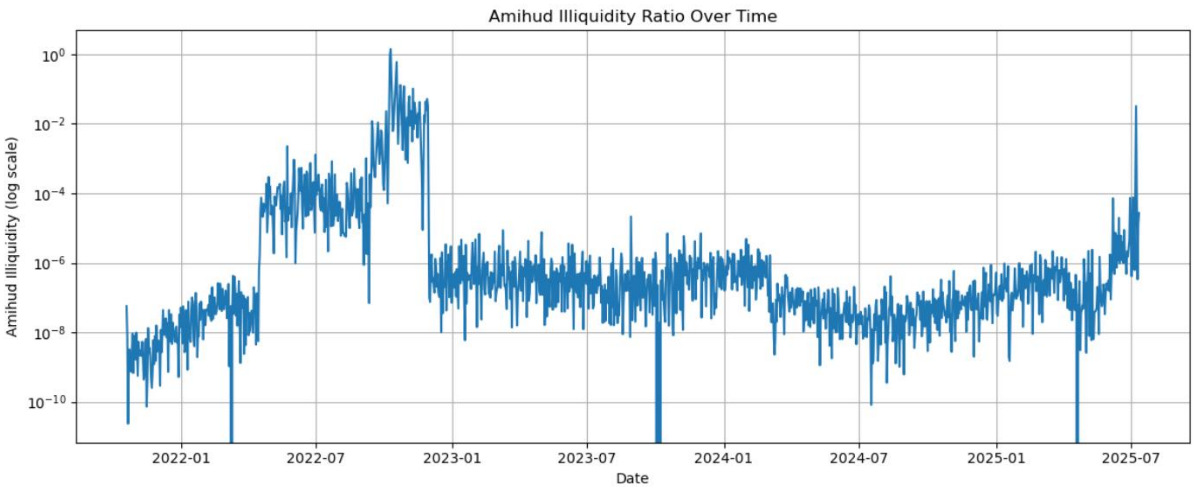

Fig 4.1.1 Amihud Illiquidity Ratio of the Carbon Credit Market (2022–2025)

This trend stayed steady until 2023-2024, with the majority of values centered around 10^{-6}, and then increased once again in mid-2025, with illiquidity levels approaching 10^{-1}. These events indicate that there is a high likelihood of event-driven illiquidity shocks in the carbon credit market, presumably to do with compliance waves, new regulation publications, or changes in carbon offset demand.

4.1.2 Distribution of Amihud Illiquidity

This market asymmetry is further supported by the distribution of the Amihud Illiquidity Ratio. The pattern of most of the observations is in the lower tail (10^{-9} – 10^{-6}), which demonstrates the fact that the carbon credit market tends to be liquid, even in the average trading conditions. Nevertheless, the distribution also has a strong right tail, which goes beyond 10^{-2}. This proves that infrequent but intense events of illiquidity do exist, and this poses executed risk to traders in times of stress. When applied to carbon credits, it means that the liquidity is obtained at regular secondary trading, and structural weaknesses, including a dependence on large participants, render the market vulnerable to abrupt shocks.

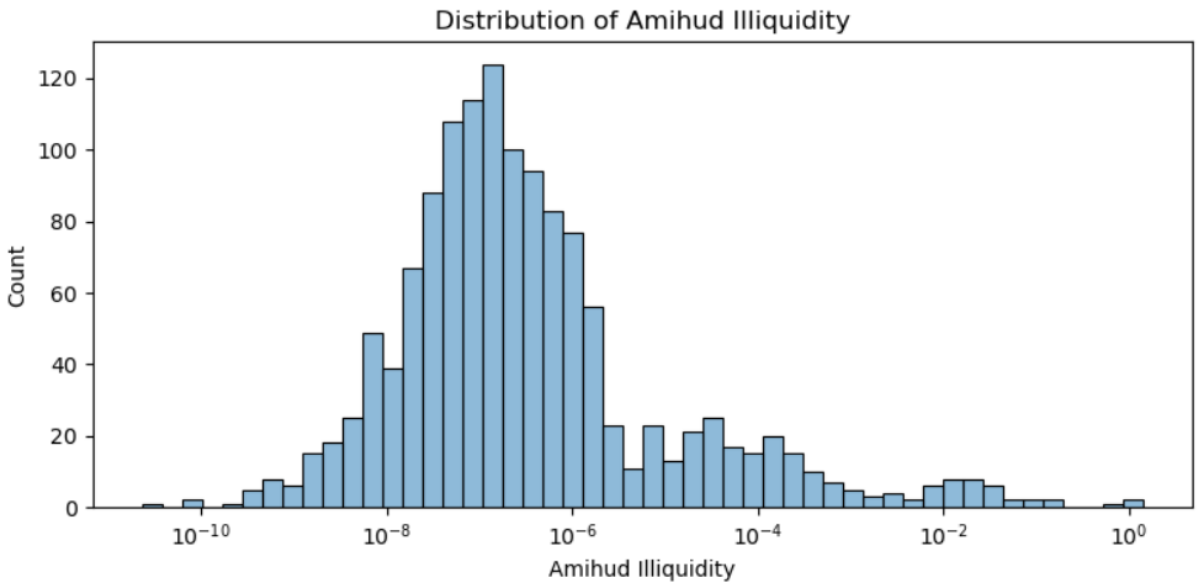

Fig 4.1.2 Distribution of Amihud Illiquidity

4.1.3 Turnover Ratio

The turnover ratio indicates the intensity of the trading market of carbon credits in terms of the remaining supply. In the period between 2024 and 2025, turnover ratios were mostly ranging between 0.02 and 0.10 with spikes as high as 0.20 in mid-2024 and in early 2025. These peaks indicate short-lived increases in trading, an event that may be due to the firms repositioning their portfolios in reaction to quarterly compliance requirements or policy adjustments. However, prolonged intervals of reduced turnover, usually less than 0.05, refer to shallow trading, and low participation. This is indicative of carbon markets: at some point in the time cycle, carbon markets are highly liquid as a result of regulations, but even at these times, base trading is still comparatively skinny relative to standard financial markets.

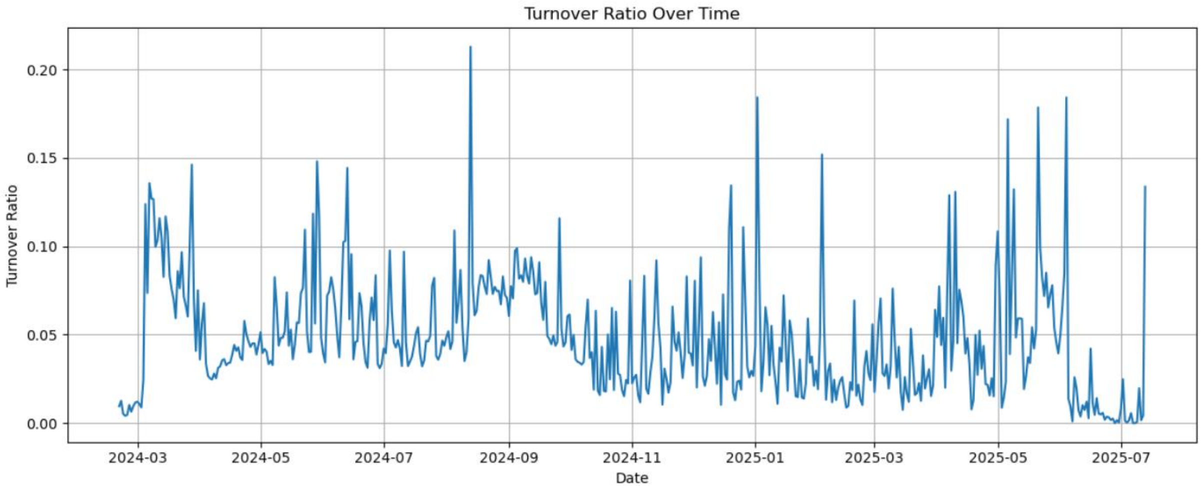

Fig 4.1.3 Turnover Ratio of the Carbon Credit Market (2024–2025)

4.1.4 Relationship Between Turnover Ratio and Trading Volume

The scatter plot shows that there is a precise positive correlation between the trading volume and the turnover ratio.

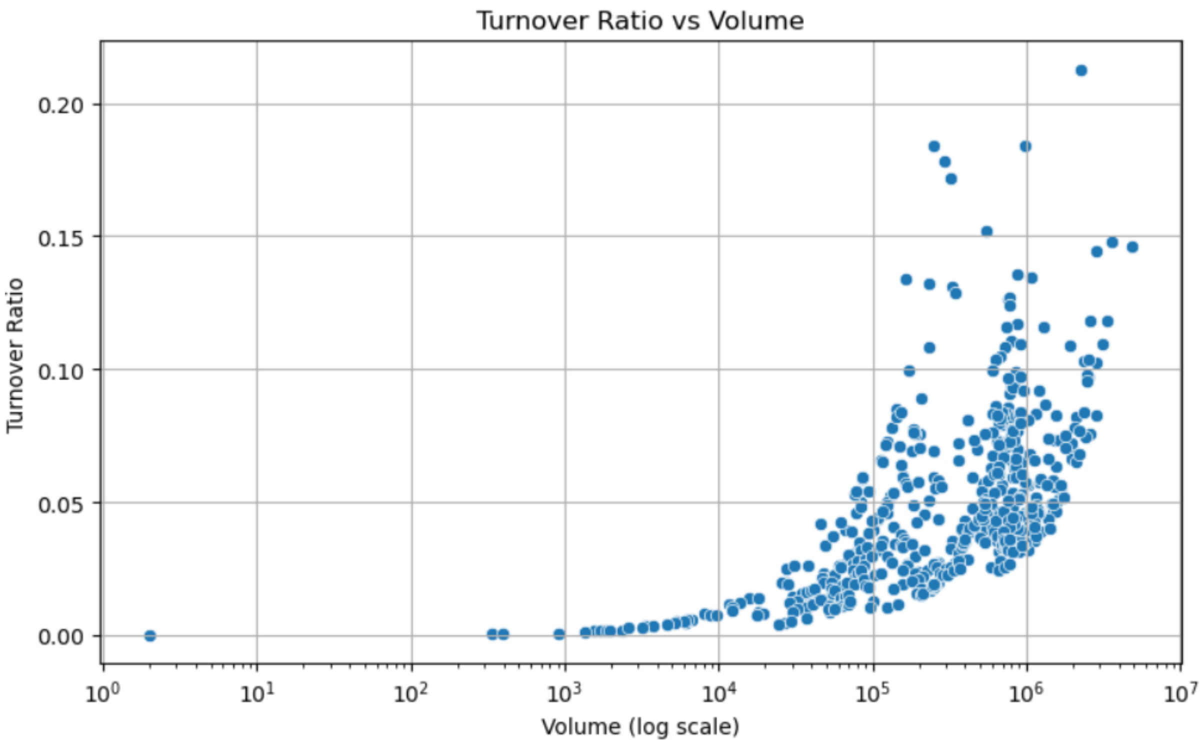

Fig 4.1.4 Turnover Ratio vs. Volume

Turnover ratios are insignificant (usually less than 0.02) at lower volumes (10^3-10^4), indicating the presence of low liquidity. With the growth of volumes to 10^5 -10^6, turnover ratios go to 0.15-0.20, which shows improved liquidity and increased participation. This non-linear relationship implies that trading volumes increase the liquidity conditions disproportionately, but after a certain threshold, the marginal effect is reduced. In the case of the carbon credit market, that means that high-density bursts of trading, commonly associated with compliance reporting dates or due to speculation, strongly improve liquidity, and low-volume trading dates do not add much to the overall efficiency of the market.

4.2 Predictive Modeling

Predictive modelling plays a pivotal role in the dynamics of the carbon credit market as it predicts the future dynamics and comprehends the market. Due to the volatility of the situation, event-based fluctuations, and non-linearity of carbon credit pricing, sound modeling solutions are needed that would help to capture short-term fluctuations as well as the prolonged market dynamics. In this study, three predictive techniques were used: Linear Regression, Prophet (time-series forecasting), and XGBoost. Linear Regression provides a baseline for evaluating the linear relationship between features and prices, Prophet uses trend and seasonality to predict in the long run, and XGBoost makes use of gradient boosting to increase the accuracy of prediction with the complicated data. Through performance comparison, this section outlines strengths and weaknesses of both models and provides insights into their use in predicting the price of carbon credits.

4.2.1 Linear Regression

Linear regression model demonstrates that there is a strong correspondence between the real and forecasted carbon credit prices during the test period (March to June 2024). The model also adequately fits the overall rising and falling trends, especially in the times when the prices are on a spike (e.g., the March 2024 peak of approximately 4.8 units). It is however a bit overestimates when there is a sharp increase and underestimates when there is a sharp decrease and is therefore sensitive to volatility. This indicates that linear regression would be fine during the short run, but it is incapable in capturing non-linear and event-driven changes in carbon credit markets.

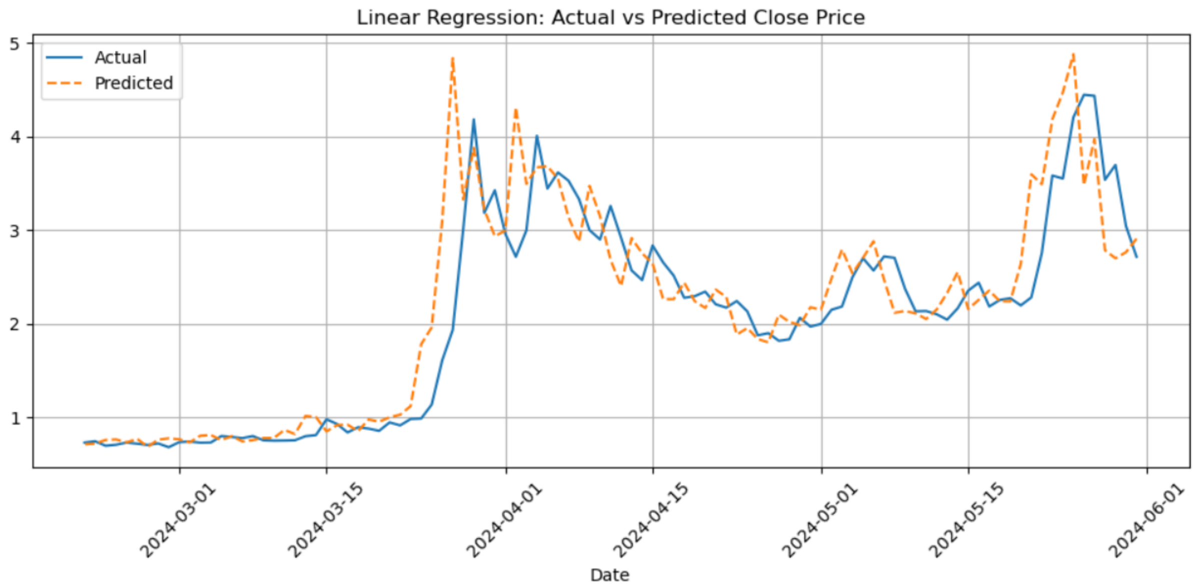

Fig 4.2.1 Linear Regression – Actual vs. Predicted Carbon Credit Prices (March–June 2024)

4.2.2 Time-Series Forecasting using Prophet

The Prophet time-series forecasting model was implemented between mid-2022 and July 2025, and it can offer both the predicted prices and the confidence intervals. The model is also useful in capturing seasonal changes and cyclical price corrections, which are in line with the observed real trends, including the early 2024 rally and correction.

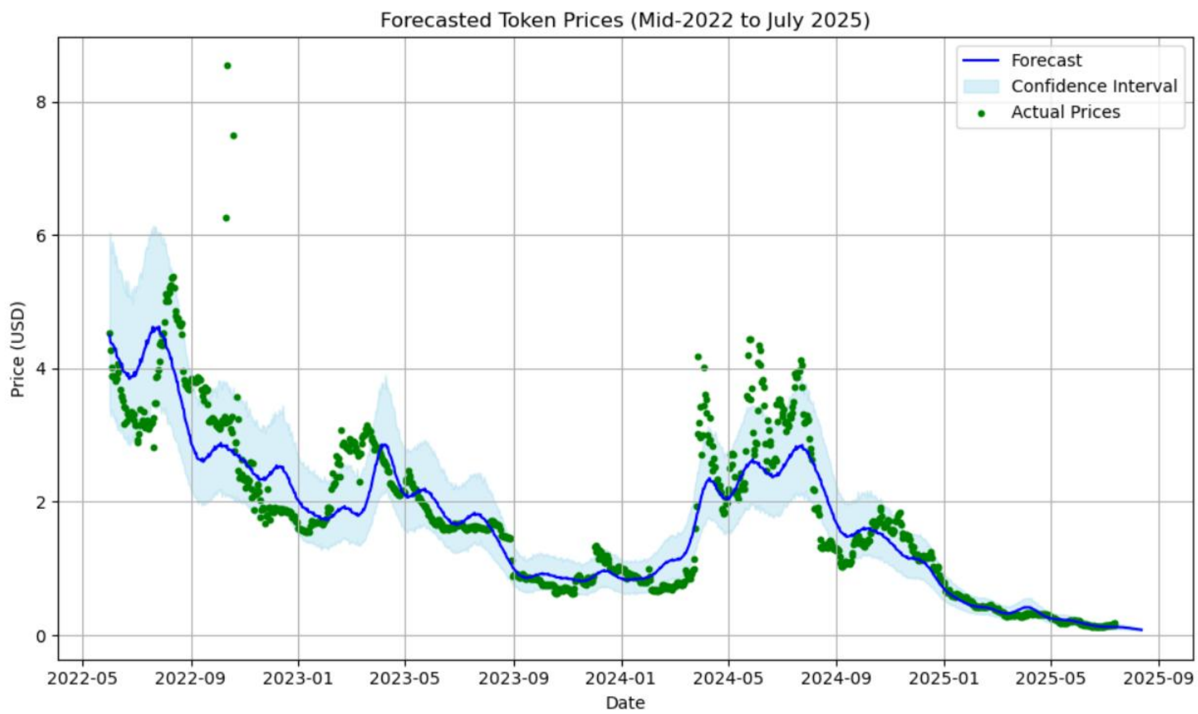

Fig 4.2.2.1 Forecasted Carbon Credit Prices using Prophet (Mid-2022 to July 2025)

The bands of confidence indicate the ambiguity of future movements, especially in the volatile times. In comparison with linear regression, Prophet is more appropriate for strategic forecasting of carbon credit prices because it is able to adapt to long-term trends and event fluctuations. The prediction, however, reveals a slow decline after 2024 that may indicate market stabilization or less speculation. The Prophet model was further used to predict prices in carbon credits from 14 July to 12 August 2025, and then the predictions were compared with the actual KlimaDAO market prices during the same period. The expected trend was relatively close to the market values, implying that Prophet is not only useful in long-term seasonality and trends but also useful in short-term forecasting. This correlation supports the strength of the model in the trading environment and makes it more applicable to market participants who require price forecasts in the near future.

ds	yhat	yhat_lower	yhat_upper
2025-07-14	0.122290	0.092145	0.162505
2025-07-15	0.121256	0.090742	0.160531
2025-07-16	0.122463	0.092142	0.160988
2025-07-17	0.119530	0.090225	0.157122
2025-07-18	0.119139	0.088334	0.157731
2025-07-19	0.119061	0.089859	0.158171
2025-07-20	0.118488	0.089844	0.162226
2025-07-21	0.117600	0.088382	0.157862
2025-07-22	0.115912	0.089057	0.155007
2025-07-23	0.116332	0.087689	0.155418
2025-07-24	0.112810	0.083827	0.149702
2025-07-25	0.111696	0.086464	0.151693
2025-07-26	0.110879	0.081669	0.146959
2025-07-27	0.109613	0.083686	0.146405
2025-07-28	0.108081	0.080840	0.144184
2025-07-29	0.105852	0.079370	0.140261
2025-07-30	0.105584	0.079576	0.142109
2025-07-31	0.101785	0.077336	0.136985
2025-08-01	0.100219	0.076145	0.135052
2025-08-02	0.098962	0.073424	0.131303
2025-08-03	0.097349	0.072631	0.128511
2025-08-04	0.095545	0.071201	0.128156
2025-08-05	0.093170	0.068798	0.124483
2025-08-06	0.092559	0.070725	0.124413
2025-08-07	0.088892	0.069056	0.118281
2025-08-08	0.087211	0.066700	0.117605
2025-08-09	0.085824	0.064463	0.114576
2025-08-10	0.084149	0.063641	0.111067
2025-08-11	0.082326	0.061670	0.107878
2025-08-12	0.080027	0.061042	0.107704

Fig 4.2.2.2 Prophet Forecast – One-Month Out-of-Sample Validation (14 July–12 August 2025) Against Actual KlimaDAO Prices

Where:

- **ds** = date stamp
- **yhat** = The central predicted value of carbon credit prices

- **yhat_lower** and **yhat_upper** = represent the lower and upper bounds of the confidence interval, respectively.

4.3 Comparison of Linear Regression, Prophet, and XGBoost Models

4.3.1 Linear Regression

In the case of the Linear Regression model, the predictive performance was measured based on the standard regression measures. The model was able to produce a Mean Squared Error (MSE) of 0.2583, which is the general error between predicted and actual values. The Mean Absolute Error (MAE) was 0.3023, indicating that the average difference between predictions and the actual values is this. Lastly, the model achieved a value of R^2 was 0.7665, which implies that the model explains nearly 76.65 percent of the variation in the dependent variable in a relatively strong fit. The details are presented in Table 1.

Table 1: Error Metrics for Linear Regression

Mean Squared Error	0.2583
Mean Absolute Error	0.3023
R^2 Score	0.7665

4.3.2 Prophet (Time Series Model)

The Prophet model achieved a Mean Absolute Error (MAE) of 0.3445 and a Mean Absolute Percentage Error (MAPE) of 17.65% indicating that there was a moderate deviation between the predictions and actuals in both the absolute and relative terms. Its RMSE error was 0.5455, and the R^2 value of 0.7969 showed that the model was close to explaining 80 percent of the variance, which is a good balance between the size of the error and the amount of variance explained in the time series forecasting. The details are presented in Table 2.

Table 2: Error Metrics for Prophet Model

Mean Absolute Error	0.3445
Mean Absolute Percentage Error	17.65%
Root Mean Squared Error	0.5455
R^2 Score	0.7969

4.3.3 XGBoost

In this research, the XGBoost model was applied using lag features of one, two, and three days to obtain short-term dependencies on the prices of carbon credits. The data was divided into training and testing sets without randomization to maintain the time sequence, and the model was trained using 100 estimators and a squared error cost. The analysis results revealed Mean Absolute Error of 0.2825, Root Mean Squared Error of 0.3394, and R^2 of 0.5693. These findings show that XGBoost had relatively low prediction errors but was not able to capture the overall variation in price changes, and it is therefore ineffective in long-term forecasting compared to Prophet. The details are presented in Table 3.

Table 3: Error Metrics for XGBoost

Mean Absolute Error	0.2825
Root Mean Squared Error	0.3394
R^2 Score	0.5693

4.4 Benchmarking of India's Framework

The carbon credit scheme of India is a market mechanism to restrict greenhouse gas emissions in which organizations can gain and sell credits to cut their carbon intensity. it was established under the Energy Conservation (Amendment) Act, 2022, it has taken shape through the Carbon Credit Trading Scheme (CCTS) adopted in July 2024. The CCTS is an intensity-based baseline-and-credit scheme, where compliance targets are set to be achieved by FY 2025-26 and FY 2026-27, and the trading will start in late 2026. [17]

Based on the previous scheme, Perform, Achieve, and Trade (PAT) scheme, the scheme is expanded to approximately 800 entities in nine sectors that are energy-intensive, with support of digital monitoring, reporting, and verification (MRV) tools. In 2025, a parallel offset scheme was introduced that enables the registration of projects by non-obligated parties in energy, forestry, agriculture, waste, and transport.

By benchmarking against global carbon markets, this study assesses how India's system integrates emerging technologies, contributes toward its 2030 target of reducing emissions intensity by 45% below 2005 levels and net-zero goal by 2070, and identifies gaps to enhance international competitiveness.[18]

4.4.1 Current State of Technology Usage

The carbon credit system in India is based on digital Monitoring, Reporting and Verification (MRV) to monitor the carbon reduction, and the Bureau of Energy Efficiency (BEE) supervises the processes, and the Accredited Carbon Verification Agency (ACVA) conducts the third-party audit. The issuance and trading of the Carbon credit certificate will be recorded in a national carbon registry under the management of a grid controller of India through electronic platforms. Although it is required to use secure databases and digital submission systems, the incorporation of the newest technologies, such as AI, blockchain, and remote sensing, is still developing.[19]

4.4.2 Gaps and Technological Innovations

The carbon credit system in India has been struggling with poor demand, excess supply of credits under the previous PAT scheme, high verification costs of small-scale participants, a lack of transparency, and an absence of connection to the international markets. To address these loopholes and develop the competitive edge, the system should incorporate improved technologies - Blockchain as a secure and transparent registry and smart contracts as a predictive and real-time emissions tracking, anomaly detection, and real-time industrial monitoring; IoT sensors to provide the real-time monitoring of the industry; and digital trading platforms to secure the exchanges and maintain the stability of prices. [20]

4.4.3 Global Benchmarking

Carbon markets such as the EU Emissions Trading System (EU ETS) and cap-and-trade in California have been integrated with more modern Monitoring, Reporting, and Verification (MRV) schemes, which rely on the use of remote sensing and AI, and other digital technologies in ensuring the proper tracking and verification of emissions. Conversely, the market of carbon trading in India is still young and is associated with such drawbacks as the lack of digital infrastructure and interoperability. Enhancing these sectors and implementing new technological solutions will be important for India to align with global best practices.

4.4.4 Future Requirements for India's Carbon Market

In order to enhance the carbon market in India, technological infrastructure such as state-of-the-art monitoring equipment and open data portals which will enhance the level of transparency and efficiency, should be invested in. Verifiers and small enterprises should be made able to do so through capacity building to be able to report on their emissions and participate. By aligning the framework to Article 6 of the Paris Agreement, the credibility of the country internationally will improve, and making linkages to the global carbon markets will be easier. Also, encouraging the participation of the private sector and startups in carbon-related technologies can promote innovation and speed up the development of the market.

4.5 CONCLUSION

In this study, the global blockchain-based carbon credit market was explored using liquidity and predictive models. The liquidity analysis indicated that even though average daily returns were low, the market had sharp spikes, fat-tailed distributions, and large Amihud Illiquidity Ratios, indicating episodic illiquidity and systematic fragility. This volatility was also confirmed using predictive modeling: Linear Regression was most practical in terms of short-term predictions, where Prophet and XGBoost identified more complex patterns with high sensitivity to extreme market trends. However, these results present opportunities and threats of blockchain-enabled markets, where transparency potentially enhances trust, yet a liquidity shock can still be a significant problem.

At the same time, the Indian framework was aligned to international standards to assess its maturity. The 2022 Energy Conservation Act and the forthcoming CCTS (2025-26) establish a regulatory framework, but they have not yet incorporated future technologies like AI-based analytics and blockchain-oriented platforms that are becoming more and more drivers of what is considered best practice in the international arena. To become a globally competitive hub, India needs to enhance its digital infrastructure, provide transparent market mechanisms, and provide predictive analytics in the design of policies. A balance between such reforms and those in the world will lead to India getting rid of liquidity risks, as well as making itself a competitive hub in the global carbon credit system.

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Appendix

Code to Implement Linear Regression

```
[37]: #Predictive Modeling (Linear regression)
      #Feature engineering
      df['Price_Range'] = df['High'] - df['Low']
      df['Volatility'] = df['Daily_Return'].rolling(window=3).std()
      df['Target_Close'] = df['Close'].shift(-1)  # Predicting next day's close
```

```
[61]: # Drop NaNs
      df_model = df.dropna(subset=['Open', 'High', 'Low', 'Close', 'Volume', 'Market_Cap',
                                   'Daily_Return', 'Price_Range', 'Volatility', 'Target_Close'])
```

```
[65]: # Shift features to simulate real-time prediction
      df_model.loc[:, features] = df_model[features].shift(1)

      # Drop rows with NaNs again (caused by shift above)
      df_model = df_model.dropna().copy()
```

```
[67]: features = ['Open', 'High', 'Low', 'Close', 'Volume', 'Market_Cap',
                  'Daily_Return', 'Price_Range', 'Volatility']
      X = df_model[features]
      y = df_model['Target_Close']

      # Train-test split (no shuffling for time series)
      X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, shuffle=False)

      lr = LinearRegression()
      lr.fit(X_train, y_train)

      y_pred = lr.predict(X_test)
```

Code to Implement Time-series forecasting using Prophet

```
•[252]: # Filter from mid-2022 onwards
        df = df[df['Date'] >= '2022-06-01'].copy()

        df = df[['Date', 'Close']]
        df.rename(columns={'Date': 'ds', 'Close': 'y'}, inplace=True)

        # Log-transform the price to avoid negative forecasts
        df['y'] = np.log(df['y'])

        # Build the model
        model = Prophet()
        model.fit(df)

        future = model.make_future_dataframe(periods=30)
        forecast = model.predict(future)
```

[256]:
```python
# Train Prophet model
model = Prophet()
model.fit(df)

# Forecast
future = model.make_future_dataframe(periods=30)
forecast = model.predict(future)

# Inverse log transformation for comparison
forecast['yhat'] = np.exp(forecast['yhat'])

# Merge only the overlapping (actual) part
merged = forecast[['ds', 'yhat']].merge(df[['ds', 'y']], on='ds', how='inner')
merged['y_actual'] = np.exp(merged['y'])  # Back to original scale
```

Code to Implement XGBoost

•[298]:
```python
#XGBOOST model
# Load dataset (assumes df has 'Date' and 'Close' columns)
df = df.sort_values('Date').copy()

# Add lag features
df['lag_1'] = df['Close'].shift(1)
df['lag_2'] = df['Close'].shift(2)
df['lag_3'] = df['Close'].shift(3)

# Drop rows with NaNs caused by shifting
df.dropna(inplace=True)

# Feature set and target
X = df[['lag_1', 'lag_2', 'lag_3']]
y = df['Close']

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, shuffle=False, test_size=0.2)

# Train XGBoost model
model = XGBRegressor(objective='reg:squarederror', n_estimators=100)
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
```

Proforma 4

Undertaking from the PG student while submitting his/her final dissertation to his respective institute

Ref. No. _________

I , the following student

Sr. No.	**Sequence of students names on a dissertation**	**Students name**	**Name of the Institute & Place**	**Email & Mobile**
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