Unveiling the Future of Carbon Emissions Trading: A Deep Learning Perspective on Regional Markets.

GROUP - 07

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Problem Statement

The COVID-19 pandemic has disrupted carbon emission trading, causing short-term fluctuations and potentially reshaping long-term market dynamics. This has introduced uncertainty for stakeholders, requiring effective risk management strategies. Furthermore, the pandemic's influence on emission reduction policies and sustainable recovery efforts remains unclear. Current predictive models for carbon emission trading lack the sophistication to accurately forecast market behavior, hindering informed decision-making.In this project we will be focusing on how can we leverage advanced predictive models integrating machine learning and deep learning techniques and comprehensive datasets to enhance forecasting accuracy, thereby empowering market participants and policymakers with actionable insights amidst the dynamic landscape of global challenges.

Background

According to a study and the reports from the webpage of Carbon Credits (2022), "The average American generates 16 tons of CO2e a year through driving, shopping, using electricity and gas at home, and generally going through the motions of everyday life". They have also mentioned what are the alternative ways that companies can follow to reduce their carbon emissions, the use of renewable sources of energy like they can install solar panels or windmills to reduce their electricity so which will directly affect the carbon footprints. The next step that could be followed is capturing the carbon from the air which is done by creating carbon-neutral fuel like biofuel. Lastly, supporting and promoting reforestation by donations or creating awareness by doing plantations.

The advent of the Covid-19 pandemic prompted widespread lockdowns and economic slowdowns resulting in a sudden and sharp decrease in industrial activity, transportation, and energy consumption. This resulted in a temporary reduction in carbon emissions as factories shut down, flights were grounded, and people stayed home. The pandemic had a significant impact on carbon emission trading, with both short-term disruptions and potential long-term implications for the market. As a short term effect the pandemic introduced significant uncertainty into carbon markets, as stakeholders grappled with unpredictable economic conditions and shifting regulatory landscapes. This heightened the importance of effective risk management strategies for market participants.

The experience of reduced emissions during lockdowns may have influenced discussions around climate policy and emissions reduction targets in the post-pandemic world. There could be increased emphasis on sustainable recovery efforts and policies that promote resilience to future crises.Hence, it is crucial to create cutting-edge predictive models capable of accurately and reliably forecasting carbon emission trading. These models should incorporate advanced machine learning methods and utilize comprehensive datasets covering environmental, economic, and regulatory factors while accommodating temporal and spatial variations in emission markets. Moreover, overcoming the shortcomings of existing models, like their inability to capture nonlinear patterns and failure to incorporate real-time data, is vital for improving the accuracy of carbon emission trading forecasts.

Literature Review

Alshatri and Hussain (2023) in their research, surveyed different papers published in IEEE, SpringerLink, and other journals, and also they took data from the past from 1st January 2005 to 1st July 2023. After a detailed study, they have listed 20 factors and 13 target variables to predict the market and the prices in the auction and also how it will impact the GDP of the country. The selection criteria for each paper are also mentioned as to why it is selected and the years that they have kept in mind are between 2005 to 2023 reputed journal and conference papers also, they have followed the backward citation method has been used and implemented so, none of the important papers or data is been lost. So, the 20 main factors affecting carbon credit prices are related to non-renewable fossil fuels such as coal, natural gas, petroleum, and other electricity markets. Apart from this, it is also dependent on the air quality and the AQI of the country. The credit also depends on macroeconomics such as the raw material import and export, the stock market, and the currency of the dealing countries. They have also, described that public awareness is also an important factor that could affect the prices because the web search index will analyze the works and if it has some words related to the climate, air quality, and so on then the analysis will tell that the awareness is growing and from the government, support will directly affect demand for carbon credits and increasing the value for those carbon credits.

Guðbrandsdóttir (2011) tells about predicting the prices of carbon credits in the European Union Emission Trading Scheme also, called EU ETS. The description of the dataset used tells us that the data is huge and has many features so to reduce the number of features the process used PCA for feature reduction and to select the important features and later they matched the features with the data from the British energy market and global equity indices. So, the start of the project is done with an analysis of time series to calculate gross return in the one-time frame in between certain intervals and keeping track of how a random variable changes with respect to time and so after that the correlation between the variable is taken into consideration and the basic building block of principal components analysis and after selecting the features in the presence of multicollinearity the OLS estimation parameters where not good so, the next topic or the method used is Latent Root Regression (LRR) which is modified version of OLS and is good with synonyms so, the features with high relation can be easily combined and the implementation of a dumpy variable to decrease the number of dependent variables and to generate the test and train data set so the parameters can be adjusted for non - predictive near singularities.

The data in this project also has the same features that were the outcome of the study from Alshatri N. and Hussain F. K. (2023) and there is also great overlap in the features and the data selected for the thesis in the current research. The last stage is the prediction phase and the algorithm used were base-line regressions and also, the implementation of PCA using backward elimination and forward selection regression results were compared. This thesis investigates the impact of market relationships on the evolution of carbon prices in the EU ETS, aiming to determine their role as significant driving forces. The study also explores the possibility of making predictions about carbon prices based on these identified relationships.

Lasse et al. (2020), suggested a beautiful paper regarding the carbon footprint for training a deep learning model. As we all know that know-a-days machine learning and artificial intelligence are taking a huge place in the world and to make the model efficient we need to train it on huge data so, the authors of this project have focused on and have predicted the carbon footprint for training a deep learning model. If we take the example of a Chatgpt it has billions of nodes and the data used to train is the whole world wide web and the training time for the modal is nearly a year. So, back in 2020, the authors thought of building a performance matrix using their tool called "*carbontracker*" so, the outcome could not only build good models but also build an efficient one. The conclusion of the paper focuses on the operational region of low carbon intensity region, hyperparameters can be improved by substitution in grid search, and last energy and efficiency of hardware and setting can help to reduce carbon emissions.

Huang & He (2020) in the research paper predicted the carbon prices by using the unstructured data. With the growing development of the carbon emission trading market, carbon assets now have financial attributes that can effectively reduce excess carbon emissions. Precisely projecting the price of carbon is crucial for well-informed policymaking. This research provides a unique approach to combinatorial optimization using unstructured data to improve prediction accuracy. It utilizes unstructured data screened by the Baidu engine and structured data filtered by factor evaluation and the gray correlation approach as one input for prediction. Furthermore, the other input—volatile carbon prices—is decomposed by the mean value approach. The study creates the scaling cooperation factor model to estimate China's carbon trading prices, The model's efficacy is confirmed by simulation trials carried out in eight pilot regions in China. This method helps to better understand market dynamics and gives policymakers an important tool to help them decide on carbon emissions and trading with more knowledge.

Mao & Yu (2024) in a recent paper researched a hybrid forecasting approach for carbon emissions and how the economy of China is being impacted. The National Carbon Emission Trading Market's formal debut is a major accomplishment for China. Accurately predicting carbon pricing in this market is crucial for businesses to actively engage in the market as well as for the government to create wise laws. Predicting these prices, however, is not an easy task because of the inherent complexity of the market, which includes volatility and instability brought on by a variety of complicated elements. This research proposes a new method for carbon price predictions. It considers a number of variables that affect national carbon pricing. It presents a framework that integrates many methods, including feature selection, machine learning predictions, and data breakdown and reconstruction. The objective is to improve efficiency, accuracy and comprehensibility of carbon price estimates, particularly in light of the intricate and unpredictable nature of the carbon markets. The results of this study are rather intriguing: (1) the novel forecasting framework outperforms existing models in terms of accuracy, and (2) the variables influencing national carbon pricing vary with time. High-frequency series are influenced by short-term energy markets and economic indicators, but medium- and low-frequency series are more heavily influenced by financial markets and long-term economic situations. In addition to improving our knowledge of the factors influencing China's domestic carbon market pricing, this research offers governments and businesses insightful information they can use to develop efficient carbon price prediction tools. It's similar to having a plan in a market that is dynamic and always evolving.

Kenton (2023) said in his article, that the carbon market is very big and the prediction of the tonnes of carbon dioxide that the country will release should be equal to or less than the carbon credit that the country has. By the word carbon credit, the reader may think that it is only related to carbon dioxide but it is the the amount of all the greenhouse gasses including carbon dioxide. Also, the countries that have their credit sell them in the auction, and the countries whose emission amount is higher than their score so, they will bid in the auction to get those credits. Companies can release a certain quantity of carbon dioxide thanks to carbon credits. One ton of carbon dioxide or its equivalent in other greenhouse gasses is equal to one credit. It is a component of the cap-and-trade scheme. Businesses are granted credits for pollution up to a certain amount, which gradually drops. If a business has excess credits, it can sell it to another business that needs them. Companies have two incentives to cut emissions thanks to this approach. If they exceed the limit, they must first purchase extra credits. Secondly, they may generate revenue by reducing emissions and selling surplus credits. Proponents of carbon credits claim that they reduce emissions. Certified projects contribute to the battle against climate change by reducing, eliminating, or avoiding greenhouse gas emissions.

Kunda & Phiri (2017) in their research try to analyze CO2 emissions trends across different sectors in Zambia from 1971-2014, using time series analysis. The main goal was to understand the sources contributing to rising CO2 levels. The findings showed transport, including cars and trucks, caused the highest growth in emissions over the period. Overall, CO2 emissions have substantially increased in Zambia, driven by the transport sector growth as well as manufacturing.The forecast indicates emissions will likely continue rising, especially in the transport and manufacturing industries. Older vehicles were found to be a major factor in transport emissions.The research highlights the specific industries like transport and manufacturing that have disproportionately contributed to rising CO2 levels in Zambia over the past decades. The authors suggest policy interventions targeting cleaner vehicles and sustainable transport, as well as emissions regulations for industry, are needed to curb this trajectory.

Liu et al. (2015) explores how the policy and development state of China's carbon trade market are emerging and issues affecting the market trade development.In 2013, China started testing a carbon-trading market with five pilot schemes. This was a big step for China to reduce greenhouse gas emissions and show its interest in global carbon trading. However, there are challenges, like not having a clear plan for China's carbon market, mistakes in setting emission limits, and an underdeveloped market system. The Chinese government is more focused on changing companies' behavior than doing a lot of trading in the carbon market. Expanding the market quickly might be hard, and the prices of carbon are a big concern for the Chinese government. China's carbon market is still uncertain. There's a need for more studies to understand how it works, improve the market system, and set clear rules. The government also has to work on making sure companies follow the rules and have a department overseeing everything.

Lu et al. (2020) tells us about China who has the largest carbon emissions globally, trends in their carbon pricing and trading volumes across markets which are impactful. However, there has been little previous research comprehensively modeling and predicting carbon price and trading volume trends across all of China's carbon markets. Hybrid models achieved the highest accuracy levels, with prediction accuracies of 98.40% and 97.89% respectively on the testing data sets. However, high prediction accuracy alone does not guarantee stability and reliability of model predictions over longer time periods. Notably, the authors did claim that in addition to accuracy.

Mardani et al. (2020) in their paper succeeded in an efficient multi-stage methodology for predicting carbon dioxide (CO_2) emissions in Group of 20 (G20) countries. The methodology utilizes a self-organizing map (SOM) clustering to group countries based on similarities in factors related to CO_2 emissions. Adaptive neuro-fuzzy inference systems (ANFIS) and artificial neural network (ANN) models are then constructed for each SOM cluster to predict emissions. Additionally, singular value decomposition (SVD) is employed for dimensionality reduction and handling missing values. The results, based on real-world data, demonstrate the effectiveness of the approach for predicting G20 CO_2 emissions, with the SOM-ANFIS-SVD combination providing the highest accuracy (0.065 mean average error). Comparison with other methods shows the superiority of the proposed technique. The analysis stresses the importance of understanding the relationship between economic development, CO_2 emissions, and energy consumption for energy and economic policy-making in G20 countries.

Wang & Ye (2017) in their research developed a non-linear grey multivariable model (NGM) to forecast China's carbon emissions from fossil energy consumption, incorporating power exponential terms as exogenous variables to capture complex non-linear relationships with economic growth. Two non-linear programming models are constructed to optimize unknown parameters, minimizing mean absolute percentage error. Empirical analysis of Chinese GDP and emissions data (1953-2013) shows the NGM(1,N) model significantly outperforms traditional gray and autoregressive integrated moving average approaches in accuracy. The model adapts to large sample sizes by dividing data into stages. Scenario analysis applies the NGM(1,N) to quantify China's future emissions under varying economic growth, offering insights into energy and environmental policymaking. Expanding upon the standard GM(1,N) through power exponential terms better describes variable non-linearity. Results emphasize optimizing industrial structure, developing non-fossil energy, and improving efficiency as critical for China's low-carbon economic development. Proposed future work leverages big data technology to enable real-time emissions feedback and proactive energy structure adjustments aligned with China's carbon reduction goals. This study contributes an advanced non-linear modeling approach with policy insights for sustainable growth pathways.

Boateng et al. (2020) developed models to forecast China's carbon emissions stemming specifically from buildings. They used 5 predictive factors: urbanization, R&D spending, GDP, energy consumption, and population. Six machine learning algorithms. The models were trained on 140 observations and validated on 36 observations. The random forest algorithm achieved the highest prediction accuracy at 99.88%, followed by KNN, XGBoost, decision tree, AdaBoost, and SVR. The decision tree was the most time-efficient. Random forest was the top-performing model for accurately forecasting building-related emissions. However, KNN also produced accurate predictions quickly and promptly. The authors recommend random forest, K-nearest neighbors, and decision tree models to policymakers to enable quality, real-time forecasts of China's building emissions patterns. This can inform policy interventions on time.

Li et al. (2022) compared a number of machine learning algorithms which are used to predict monetary value of carbon in the HBEA and GDEA provinces of China. The study used historical data on carbon prices and three energy prices (coal, natural gas, and petroleum) in these provinces from May 2014 to July 2021. The three energy prices were considered because the fluctuations in their costs can readily impact the carbon price. The models tested for this prediction are Multivariate machine learning models. During this study, the findings revealed that Multivariate LSTM performed best with minimum values in evaluation metrics for both HBEA and GDEA provinces. Based on this evaluation, they are convinced that Multivariate LSTM has predicted the carbon prices better than the other models used in the study.

Wu et al. (2015) carried out a research to estimate the BRICS Countries carbon dioxide emissions and also to establish a relationship between socioeconomic factors like urban population, growth of economy, consumption of energy and emissions of carbon dioxide with an innovative multivariable grey model called GOM (1, N). They chose these BRICS countries because they are major contributors to global emissions. These grey prediction models are useful when analyzing systems with complex and uncertain data. The data was obtained from the World Bank website for the 2004-2010 timeframe which has variables like GDP data, Energy use, Urban population, and emissions of carbon dioxide. Results suggest that China had the highest growth rate in terms of carbon emissions followed by India, Brazil, Russia, and South Africa. Increased population in urban areas and energy use directly contributed to higher CO2 emissions. Growth in the economy has led to more carbon emissions in countries like China, India, and South Africa but less in Brazil and Russia. Overall, the GOM (1, N) model has effectively estimated the BRICS nations carbon dioxide emissions based on the mentioned socioeconomic factors.

Acheampong & Boateng (2019) in their research used an artificial neural network (ANN) model to forecast each nation's(Australia, Brazil, China, India, and the USA) level of carbon emissions. Carbon emission intensity measures the amount of Carbon dioxide released per one unit of GDP. These countries were selected for research because they rank among the highest in the world for carbon dioxide emissions globally. The models used socioeconomic parameters like growth of the economy, energy use, research and development (R&D), financial development, urbanization, FDI, industrialisation, and trade openness as input. Data for the parameters except financial development were collected from the World Bank website for 1980-2015. Data for the Financial Development index came from the IMF (International Monetary Fund) website for the period 1980Q1-2015Q4. The team used a multilayer perceptron (MLP) algorithm with backpropagation in ANN for better performance. Input data was normalized and then standardized before training. Sensitivity analysis with partial rank correlation coefficient (PRCC) is used to determine which input parameter mostly contributes to the carbon emissions of each country. Results showed that R&D had the largest effect on carbon emissions in Australia, urbanization in Brazil and USA, energy use in India, and population size in China. The team also suggests that the ANN models were highly accurate in predicting carbon emission intensity with negligible errors.

Zhu et al. (2023) proposed using the XGBOOST machine learning algorithm to forecast domestic carbon prices in China. Government organizations allocate specific carbon emission quotas to companies based on their previous carbon emissions data. By predicting prices, companies with surplus carbon credits can sell them to higher emitting companies to achieve emission reductions cost-effectively. The research utilized carbon trading data from 2013-2021 for major Chinese cities- Beijing, Fujian, Guangdong, Hubei, Shanghai, Shenzhen, Tianjin, Chongqing from China Research Data Service Platform (CNRDS). The 10615 total samples were divided into 80% training (10508) and 20% testing (107) sets. The data was then standardized and Pearson correlation coefficient is calculated to identify and remove highly correlated features via Principal Component Analysis. After that, XGBOOST was applied to make predictions and it is further optimized with Bayes Optimization. The accuracy is then evaluated using MAE and RMSE metrics. Using this, the final prediction results are evaluated, and the team concludes that Bayes Optimized XGBOOST model is much better than traditional XGBOOST in both accuracy and stability. The research demonstrates the value of machine learning algorithms to predict carbon pricing accurately.

Bhatt et al. (2023) addressed the critical problem of increasing carbon dioxide (CO_2) emissions and how they impact climate change in this research. They highlighted the need to accurately predict when Earth's atmospheric carbon dioxide concentration will likely reach 500 ppm, leading to irreparable environmental damage. For this research, they used a historical US dataset with 38 features related to emissions in the US, they then pre-processed the data and applied PCA to reduce it to 17 input parameters. Multiple machine learning models were tested, with the Decision Tree Regressor having the best prediction accuracy at 99%. The study estimated that by 2047, the 500 ppm threshold will have been reached based on current trends. To return to safer levels (316 ppm), they calculated a required CO_2 emissions reduction rate of 6.37% and a reversal rate of about 23.38%. The team also mentioned that a 0.75 ppm increase in

CO_2 causes a 0.05°C temperature rise, meaning a projected total of 5.6°C atmospheric temperature increase by 2047. Overall, the study demonstrates using machine learning to accurately predict the timeline for reaching critical carbon emission thresholds, informing urgent climate action needs.

Lei & Yang (2020) address the pressing issue of growing residential energy use and the resulting CO_2 emissions in China, the world's largest emitter of carbon dioxide. Given the critical importance of transitioning to a low-carbon economy, understanding the driving forces behind residential CO_2 emissions is essential for informing policy decisions aimed at mitigating climate change. In this research, a comprehensive analysis of influencing elements affecting CO_2 emissions associated with residential energy use is conducted, offering valuable insights for policymakers and stakeholders. To begin with, the study selects 18 preliminary indicators related to residential energy-related CO_2 emissions and employs gray relational analysis to identify their correlations. This approach allows for the identification of key factors strongly associated with CO_2 emissions in the residential sector. Subsequently, these influencing factors are classified into four categories based on their characteristics, and PCA is used to simplify the dataset. This process results in the extraction of four components, which serve as input data for the forecasting model. Innovatively, the study proposes a hybrid ICSO-SVM model for the prediction of CO_2 emissions, marking the first application of this approach in the field. The model integrates the improved chicken swarm algorithm with support vector machine (SVM) optimization techniques. Through a testing case focused on Shanghai's residential sector, the forecasting results of the ICSO-SVM model are compared with those of other models. The study draws several conclusions based on these comparisons: (a) By considering local electricity and heat emissions coefficients, the study yields a more precise measurement of CO_2 emissions related to residential energy use at the city level. (b) Utilizing grey relational analysis and principal component analysis to analyze influencing factors enhances prediction accuracy significantly. (c) The improved chicken swarm algorithm proves effective in optimizing SVM, contributing to the practicality and effectiveness of the ICSO-SVM model. (d) Compared to alternative methods, the newly established ICSO-SVM model demonstrates practicality and promise in forecasting CO_2 emissions.Despite the impressive results achieved by this study, several issues remain to be addressed in future research. For instance, there may be additional influencing factors yet to be uncovered, and efforts should be made to minimize information loss during the dimensional reduction process. Additionally, further investigation into prediction models employing more advanced intelligent algorithms is warranted to improve forecasting precision.

Methodology

We estimate the CO_2 emissions from energy use in different states based on the types of fuels they consume. These fuels include coal, natural gas, and various petroleum products like gasoline and diesel. For each fuel type, we calculate emissions from two sources: combustion and non-combustion. Combustion emissions come from burning the fuel for energy, while non-combustion emissions occur when the fuel is used for non-energy purposes, like in industrial processes. To calculate combustion emissions, we multiply the amount of fuel consumed by its CO_2 emissions factor. For fuels used solely for energy purposes, like in residential heating or electricity generation, we assume all of it is combusted. For non-combustion emissions, we consider the portion of the fuel that's not burned for energy. Some of this non-energy use captures carbon instead of releasing it into the atmosphere. We calculate non-combustion emissions based on the remaining fuel quantity and its emissions factors. We use data from various sources and the EPA's emissions factors to make these estimates. For certain fuels like hydrocarbon gas liquids (HGL), we break down the emissions by individual components like propane or butane, using consumption data from surveys. If detailed consumption data is not available, we estimate it based on the shares observed in later years.

The government agency known as the U.S. Energy Information Administration, or EIA, igathers and studies data on energy use and production. Although part of the Department of Energy, EIA conducts independent analyses. The dataset we are utilizing comes from EIA and looks at carbon dioxide emissions from energy consumption in each U.S. state from 1970-2021. The data is measured in million metric tons of CO_2 per year. This information can show differences between states based on climate, what energy sources they use, economic factors, building codes, and energy policies. Analyzing the data allows us to compare and understand variations in state-level carbon emissions related to energy over time.

Table 1. State energy-related carbon dioxide emissions by year (1970–2021)

million metric tons of energy-related carbon dioxide

State	1970	1971	1972	1973	1974	1975	1976	1977	1978	1979	1980	1981	1982	1983
Alabama	102.6	98.5	104.9	109.6	108.8	107.8	108.1	111.7	106.6	111.6	107.1	103.8	90.9	89.9
Alaska	11.3	12.6	13.4	12.5	12.8	14.5	16.0	18.0	19.5	17.5	17.4	17.0	23.9	25.9
Arizona	24.9	27.0	30.2	34.4	36.7	38.2	43.8	50.5	49.3	56.1	52.9	59.9	58.5	54.2
Arkansas	36.2	35.1	37.2	40.8	39.1	36.4	38.9	41.6	42.4	40.2	37.5	42.9	42.7	47.1
California	294.4	305.8	312.7	329.3	304.5	311.5	326.9	354.5	345.2	362.1	344.4	334.2	298.8	293.5
Colorado	43.0	43.6	47.5	51.1	50.5	51.8	55.1	58.3	58.4	58.9	58.9	57.8	59.0	57.2
Connecticut	47.8	45.9	47.2	48.6	45.4	41.7	43.4	43.1	44.0	42.0	40.1	35.4	35.4	34.8
Delaware	16.1	15.9	16.0	17.2	16.7	15.5	16.2	16.1	16.2	17.1	17.5	16.3	14.7	17.7
District of Columbia	13.6	11.9	11.3	11.9	9.8	7.9	7.7	7.9	7.5	6.0	5.2	4.7	5.2	5.0
Florida	104.4	111.5	121.7	132.2	124.3	125.9	134.5	138.2	146.1	153.4	155.8	156.1	140.0	146.1
Georgia	73.5	79.6	86.8	93.1	91.7	91.4	96.2	104.7	106.5	111.4	113.0	113.5	110.1	117.3
Hawaii	13.9	15.1	15.5	16.0	15.1	15.2	15.6	16.7	17.0	18.4	18.1	16.3	14.9	14.9
Idaho	10.2	11.1	11.6	12.0	12.1	13.1	12.9	12.9	13.3	13.3	11.2	10.2	9.7	9.6
Illinois	247.2	243.7	253.3	257.0	252.0	245.4	254.2	256.3	258.8	248.6	232.4	214.2	203.8	210.5
Indiana	171.9	169.1	184.0	188.4	181.5	179.0	181.4	186.3	185.6	192.8	184.1	179.4	162.2	168.4
Iowa	53.5	53.4	56.4	59.5	56.1	55.1	58.5	58.8	58.1	63.3	59.2	58.5	57.4	56.3
Kansas	51.1	52.8	56.1	57.1	57.4	57.6	60.5	61.9	67.7	73.0	67.9	64.6	63.2	62.9
Kentucky	86.3	88.5	94.1	94.5	95.2	91.3	101.0	101.6	102.9	102.7	103.9	103.2	98.5	100.5
Louisiana	144.1	146.7	155.4	168.9	172.2	159.8	182.7	204.9	212.4	204.0	192.9	192.7	176.8	168.0
Maine	16.8	20.6	22.2	21.3	18.7	16.1	18.7	19.0	17.7	16.2	14.6	14.4	17.4	13.3
Maryland	74.2	75.4	76.3	81.7	76.3	67.1	72.6	67.6	70.2	73.3	67.5	63.2	61.2	62.4
Massachusetts	99.6	100.0	103.9	103.2	94.4	91.8	96.5	95.3	93.5	80.2	77.6	73.4	76.3	73.3
Michigan	186.8	192.7	199.4	200.0	190.4	191.8	193.6	185.0	188.7	188.7	179.4	170.0	158.2	155.0
Minnesota	69.3	68.5	72.7	76.0	74.6	72.8	77.8	79.4	80.7	76.8	71.4	67.0	65.2	63.3
Mississippi	38.7	40.5	43.3	44.1	43.3	40.9	43.4	47.3	50.1	50.4	47.7	45.1	45.4	42.8
Missouri	86.6	89.1	94.7	99.9	97.7	100.9	107.2	111.4	110.9	110.0	104.5	101.8	101.2	102.7
Montana	14.4	14.9	15.7	17.0	16.6	16.8	19.4	20.6	21.3	22.7	20.3	18.7	16.4	16.6
Nebraska	27.5	27.5	29.5	30.2	29.1	28.7	31.2	31.2	30.8	31.6	30.2	28.4	28.8	29.9
Nevada	10.8	13.8	18.9	20.1	20.4	21.0	22.2	23.7	22.5	23.5	22.4	23.9	25.4	25.2
New Hampshire	12.8	13.4	14.1	13.6	12.6	12.6	13.6	14.1	13.6	12.9	12.8	11.5	11.2	11.2
New Jersey	129.5	125.0	127.9	131.5	119.9	106.0	117.2	113.2	111.1	109.9	111.0	107.6	109.6	111.1
New Mexico	35.0	37.2	39.7	40.1	40.6	39.2	42.0	41.7	40.1	40.6	44.9	44.1	45.2	48.7
New York	284.9	277.1	274.1	280.4	258.8	244.5	262.6	259.8	254.5	233.2	221.9	205.8	195.6	178.0
North Carolina	97.3	99.2	104.5	109.0	104.3	95.2	106.0	108.2	103.1	110.7	112.7	112.6	108.3	107.7
North Dakota	14.8	15.9	16.9	16.4	16.9	16.2	18.6	19.9	22.4	24.9	25.5	27.0	28.8	30.1
Ohio	275.3	269.9	284.9	291.6	291.7	284.3	296.5	293.6	294.5	293.0	274.5	267.9	246.2	234.9
Oklahoma	55.6	56.4	59.3	59.8	61.9	62.5	69.0	72.2	77.1	80.1	77.3	80.1	84.8	85.4
Oregon	25.6	27.0	29.3	29.6	27.3	26.8	26.7	27.5	29.6	30.2	28.3	29.8	28.9	25.7
Pennsylvania	306.7	303.4	315.0	325.6	305.0	291.3	308.6	303.0	302.7	316.1	294.4	271.5	240.9	246.2
Rhode Island	13.1	13.6	13.5	12.5	11.5	10.5	10.6	11.0	10.1	9.3	8.4	7.8	7.4	7.7
South Carolina	42.2	44.1	46.9	48.8	45.7	42.6	50.6	54.1	53.2	52.8	55.1	55.7	52.4	49.7
South Dakota	9.4	9.3	9.7	9.4	9.2	10.9	12.5	12.3	12.9	12.7	11.6	10.9	11.4	10.4
Tennessee	77.9	76.3	87.0	98.6	90.3	89.7	102.0	102.5	104.2	101.8	100.8	99.4	88.2	94.8
Texas	358.9	375.8	398.2	434.7	427.4	406.6	422.1	461.1	492.5	512.3	516.6	511.6	485.8	488.2
Utah	24.4	25.5	25.8	28.2	29.6	31.0	30.8	32.0	34.1	36.7	35.9	33.8	32.2	33.5
Vermont	5.5	5.5	5.8	5.9	5.3	5.2	5.9	5.8	5.8	5.4	4.6	4.5	4.1	4.4
Virginia	86.6	87.4	88.7	89.6	85.0	81.2	86.1	87.4	84.7	89.5	81.9	78.3	74.8	77.3
Washington	44.8	46.1	52.3	57.4	53.1	54.9	54.9	60.1	58.9	61.8	58.1	59.0	54.9	50.3
West Virginia	77.0	78.0	89.0	97.6	100.3	97.8	104.2	102.9	96.7	100.9	102.5	104.0	95.8	97.4

Fig1. CO2 emission by year based on State energy

Total Emissions by State (Table 1), This table details total CO2 emissions by state, reflecting all fossil fuel combustion and non fuel uses of petroleum products within state boundaries. For fuel combustion, emissions are attributed to the state where the fuels are burned. For non fuel uses like plastics production, emissions from petrochemical feedstocks are allocated to states based on location of production facilities.

Table 2. 2021 State energy-related carbon dioxide emissions by fuel

	million metric tons of carbon dioxide				shares		
State	Coal	Petroleum	Natural Gas	Total	Coal	Petroleum	Natural Gas
Alabama	29.6	40.2	38.6	108.4	27.3%	37.1%	35.6%
Alaska	1.8	17.5	19.6	38.9	4.6%	44.9%	50.5%
Arizona	15.4	42.1	25.6	83.0	18.5%	50.7%	30.8%
Arkansas	20.7	22.5	18.8	62.0	33.4%	36.3%	30.4%
California	2.7	208.1	113.3	324.0	0.8%	64.2%	35.0%
Colorado	24.2	33.5	27.7	85.4	28.3%	39.3%	32.4%
Connecticut	0.3	20.1	16.2	36.6	0.8%	55.0%	44.2%
Delaware	0.4	8.0	4.6	13.0	3.4%	61.4%	35.2%
District of Columbia	0.0	1.0	1.5	2.5	0.0%	40.5%	59.5%
Florida	19.2	123.3	83.9	226.3	8.5%	54.5%	37.1%
Georgia	19.5	64.0	40.6	124.1	15.7%	51.6%	32.7%
Hawaii	1.2	16.0	0.1	17.3	6.9%	92.3%	0.8%
Idaho	0.3	13.2	7.1	20.5	1.4%	64.2%	34.4%
Illinois	49.9	77.0	57.4	184.2	27.1%	41.8%	31.1%
Indiana	71.7	49.4	45.3	166.4	43.1%	29.7%	27.2%
Iowa	25.3	26.3	21.6	73.1	34.6%	35.9%	29.5%
Kansas	21.0	23.7	15.1	59.8	35.1%	39.6%	25.3%
Kentucky	52.5	39.7	19.1	111.3	47.2%	35.7%	17.1%
Louisiana	9.2	83.7	95.7	188.6	4.9%	44.4%	50.7%
Maine	0.2	11.3	3.0	14.4	1.1%	78.3%	20.7%
Maryland	6.6	30.0	16.0	52.6	12.6%	57.0%	30.4%
Massachusetts	0.0	34.8	21.3	56.1	0.0%	62.1%	37.9%
Michigan	41.6	56.3	49.9	147.8	28.2%	38.1%	33.7%
Minnesota	17.2	38.6	27.4	83.2	20.6%	46.5%	32.9%
Mississippi	6.2	26.7	30.2	63.1	9.8%	42.3%	47.9%
Missouri	59.1	42.5	15.4	117.0	50.5%	36.3%	13.2%
Montana	11.8	12.2	4.5	28.5	41.2%	42.8%	15.9%
Nebraska	20.7	16.6	9.9	47.2	43.9%	35.2%	21.0%
Nevada	3.4	19.9	16.1	39.4	8.7%	50.4%	40.9%
New Hampshire	0.3	9.8	3.2	13.3	2.3%	73.9%	23.8%
New Jersey	1.2	51.2	36.7	89.1	1.4%	57.4%	41.2%
New Mexico	12.8	18.3	14.8	45.9	27.8%	39.9%	32.2%
New York	0.5	83.7	71.8	156.0	0.3%	53.7%	46.0%
North Carolina	21.3	60.8	33.4	115.6	18.4%	52.6%	28.9%
North Dakota	34.7	11.8	10.1	56.5	61.3%	20.8%	17.9%
Ohio	54.8	71.4	67.8	194.0	28.3%	36.8%	34.9%
Oklahoma	12.6	36.5	38.7	87.8	14.4%	41.5%	44.1%
Oregon	0.1	22.4	16.0	38.5	0.3%	58.1%	41.6%
Pennsylvania	45.9	70.0	97.6	213.5	21.5%	32.8%	45.7%
Rhode Island	0.0	5.1	5.6	10.6	0.0%	47.7%	52.3%
South Carolina	15.6	35.5	18.3	69.3	22.5%	51.2%	26.4%
South Dakota	2.1	8.1	5.0	15.2	13.6%	53.4%	33.0%
Tennessee	21.6	49.5	21.5	92.7	23.3%	53.4%	23.2%
Texas	92.8	325.4	245.3	663.5	14.0%	49.0%	37.0%
Utah	26.5	21.2	14.4	62.1	42.6%	34.2%	23.2%
Vermont	0.0	4.8	0.7	5.6	0.0%	87.0%	13.0%
Virginia	6.5	54.7	36.8	98.0	6.6%	55.9%	37.5%

Fig2. CO2 emissions by fuel based on State energy

Emissions by Fuel Type (Table 2), The fuel mix and electricity generation portfolios cause emissions profiles to vary drastically across states. Some rely heavily on coal and have high per capita emissions, while others use more renewable sources and natural gas. Each state has personalized total and per capita emissions broken down across coal, natural gas, petroleum, wood/biomass, and other categories.

Table 3. 2021 State energy-related carbon dioxide emissions by sector

	million metric tons of energy-related carbon dioxide						shares				
State	Commercial	Electric Power	Residential	Industrial	Transportation	Total	Commercial	Electric Power	Residential	Industrial	Transportation
Alabama	2.3	47.2	2.1	19.6	37.2	108.4	2.2%	43.5%	1.9%	18.1%	34.3%
Alaska	2.3	2.8	1.7	18.4	13.7	38.9	5.9%	7.2%	4.5%	47.3%	35.1%
Arizona	3.1	34.3	2.5	4.6	38.5	83.0	3.8%	41.3%	3.0%	5.6%	46.3%
Arkansas	3.6	28.5	2.1	8.3	19.5	62.0	5.8%	46.0%	3.3%	13.4%	31.5%
California	19.4	35.3	26.2	63.9	179.1	324.0	6.0%	10.9%	8.1%	19.7%	55.3%
Colorado	4.4	30.6	8.3	13.2	28.9	85.4	5.2%	35.8%	9.7%	15.4%	33.8%
Connecticut	4.3	9.2	7.2	1.6	14.3	36.6	11.7%	25.2%	19.6%	4.4%	39.0%
Delaware	1.1	1.8	1.0	3.8	5.4	13.0	8.2%	13.6%	7.5%	29.4%	41.3%
District of Columbia	0.9	0.0	0.7	0.0	0.9	2.5	34.9%	0.0%	26.8%	1.0%	37.4%
Florida	6.8	91.2	1.5	12.3	114.6	226.3	3.0%	40.3%	0.6%	5.4%	50.6%
Georgia	4.6	40.9	7.4	12.7	58.6	124.1	3.7%	32.9%	5.9%	10.2%	47.2%
Hawaii	0.5	5.8	0.1	1.0	10.0	17.3	3.1%	33.3%	0.4%	5.6%	57.6%
Idaho	1.5	2.0	2.0	3.4	11.6	20.5	7.2%	9.8%	9.9%	16.5%	56.7%
Illinois	14.2	52.4	23.0	34.5	60.1	184.2	7.7%	28.5%	12.5%	18.8%	32.6%
Indiana	6.1	68.8	8.2	43.4	39.8	166.4	3.7%	41.4%	4.9%	26.1%	23.9%
Iowa	3.8	24.1	4.8	20.5	19.8	73.1	5.2%	33.0%	6.6%	28.1%	27.1%
Kansas	2.7	22.2	3.8	13.5	17.5	59.8	4.5%	37.2%	6.3%	22.6%	29.3%
Kentucky	2.7	56.9	3.1	14.9	33.7	111.3	2.4%	51.1%	2.8%	13.4%	30.3%
Louisiana	2.4	30.4	2.1	108.9	44.8	188.6	1.3%	16.1%	1.1%	57.7%	23.8%
Maine	1.8	1.3	2.7	1.6	7.1	14.4	12.2%	8.8%	18.5%	11.2%	49.3%
Maryland	5.2	11.2	5.7	2.8	27.6	52.6	9.9%	21.4%	10.8%	5.4%	52.5%
Massachusetts	7.4	6.1	12.5	3.3	26.7	56.1	13.2%	10.9%	22.3%	5.9%	47.6%
Michigan	10.8	52.9	19.0	17.6	47.5	147.8	7.3%	35.8%	12.8%	11.9%	32.2%
Minnesota	6.8	21.2	9.3	16.7	29.1	83.2	8.2%	25.5%	11.2%	20.1%	35.0%
Mississippi	1.6	25.2	1.5	11.3	23.4	63.1	2.5%	40.0%	2.4%	18.0%	37.2%
Missouri	4.6	60.2	6.3	8.6	37.2	117.0	4.0%	51.5%	5.4%	7.3%	31.8%
Montana	1.6	12.5	1.7	4.5	8.2	28.5	5.7%	43.7%	6.0%	15.9%	28.7%
Nebraska	2.1	19.8	2.4	9.1	13.8	47.2	4.5%	41.9%	5.2%	19.3%	29.1%
Nevada	2.3	13.7	2.6	3.1	17.8	39.4	5.8%	34.7%	6.6%	7.8%	45.1%
New Hampshire	1.4	2.1	2.5	0.7	6.6	13.3	10.6%	15.8%	18.5%	5.5%	49.6%
New Jersey	9.9	13.3	14.8	8.4	42.7	89.1	11.1%	15.0%	16.6%	9.4%	47.9%
New Mexico	1.8	17.1	2.3	8.4	16.3	45.9	4.0%	37.3%	4.9%	18.3%	35.5%
New York	21.8	25.0	33.7	8.3	67.3	156.0	13.9%	16.0%	21.6%	5.3%	43.1%
North Carolina	5.2	40.1	5.4	10.1	54.8	115.6	4.5%	34.7%	4.7%	8.7%	47.4%
North Dakota	1.2	27.4	1.1	17.9	8.8	56.5	2.2%	48.5%	1.9%	31.7%	15.7%
Ohio	12.0	68.5	17.3	37.5	58.8	194.0	6.2%	35.3%	8.9%	19.3%	30.3%
Oklahoma	3.2	26.7	4.0	23.1	30.8	87.8	3.6%	30.5%	4.5%	26.3%	35.1%
Oregon	2.4	8.2	2.9	4.7	20.2	38.5	6.4%	21.4%	7.6%	12.1%	52.5%
Pennsylvania	11.4	77.5	19.3	49.3	56.0	213.5	5.4%	36.3%	9.0%	23.1%	26.2%
Rhode Island	0.9	3.4	2.1	0.6	3.6	10.6	8.8%	31.7%	20.0%	5.6%	33.9%
South Carolina	2.3	25.0	2.1	7.3	32.6	69.3	3.3%	36.1%	3.1%	10.5%	47.0%
South Dakota	0.8	2.4	1.0	4.0	7.0	15.2	5.4%	15.8%	6.7%	26.2%	45.9%
Tennessee	4.3	24.0	4.4	14.3	45.7	92.7	4.6%	25.9%	4.7%	15.4%	49.3%
Texas	14.2	180.3	12.2	241.6	215.2	663.5	2.1%	27.2%	1.8%	36.4%	32.4%
Utah	3.0	29.9	4.1	6.8	18.2	62.1	4.8%	48.2%	6.6%	11.0%	29.3%
Vermont	0.9	0.0	1.4	0.4	2.9	5.6	16.6%	0.1%	24.3%	7.4%	51.6%
Virginia	6.0	24.4	6.2	11.6	49.8	98.0	6.1%	24.9%	6.4%	11.8%	50.8%

Fig3. Carbon dioxide emissions by sector based on State energy

Emissions by End-Use Sector (Table 3), Total and per capita CO2 emissions are shown for the residential, commercial, industrial, and transportation sectors within each state. This facilitates analysis of trends and variances based on structural economic differences, climate and weather demands on sectors like residential and commercial, and other drivers.

Table 4. Per capita energy-related carbon dioxide emissions by state (1970–2021)

metric tons of energy-related carbon dioxide per person

State	1970	1971	1972	1973	1974	1975	1976	1977	1978	1979	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991
Alabama	29.7	28.2	29.7	30.6	30.0	29.3	28.9	29.5	27.8	28.9	27.5	26.5	23.2	22.9	24.1	25.6	25.5	25.8	26.1	27.3	27.1	27.8
Alaska	37.3	40.0	41.4	37.7	37.5	38.6	39.8	44.5	48.1	43.4	42.9	40.8	53.1	53.1	55.7	54.5	57.7	55.2	55.8	60.9	61.4	60.4
Arizona	13.9	14.2	15.0	16.2	16.5	16.7	18.7	20.8	19.6	21.3	19.3	21.3	20.2	18.2	19.1	19.2	17.0	16.4	16.9	18.1	17.1	16.9
Arkansas	18.7	17.8	18.4	19.8	18.6	16.8	17.9	18.9	18.9	17.7	16.4	18.7	18.6	20.4	19.4	21.1	21.4	20.1	21.8	21.9	21.5	20.9
California	14.7	15.0	15.2	15.8	14.4	14.5	14.9	15.9	15.1	15.6	14.5	13.8	12.0	11.6	12.2	12.1	11.3	12.1	12.1	12.3	12.0	11.4
Colorado	19.4	18.9	19.7	20.5	19.9	20.0	20.9	21.6	21.1	20.7	20.2	19.4	19.3	18.2	19.2	19.2	18.8	18.8	19.5	19.8	20.1	20.0
Connecticut	15.7	15.0	15.4	15.8	14.8	13.5	14.1	14.0	14.2	13.6	12.9	11.3	11.3	11.0	11.9	11.8	12.3	12.2	12.9	13.3	12.3	12.0
Delaware	29.2	28.2	27.9	29.8	28.7	26.5	27.4	27.3	27.2	28.7	29.4	27.4	24.5	29.2	30.1	28.1	27.3	28.1	28.6	27.0	26.9	26.2
District of Columbia	18.0	15.8	15.2	16.2	13.7	11.2	11.1	11.7	11.2	9.3	8.2	7.4	8.2	8.0	8.3	7.5	8.2	7.8	7.8	8.1	7.3	7.3
Florida	15.2	15.6	16.2	16.7	15.0	14.8	15.5	15.6	16.1	16.3	15.8	15.3	13.4	13.6	13.0	13.4	14.0	14.5	14.9	14.9	14.4	14.1
Georgia	16.0	16.9	18.0	19.0	18.3	18.1	18.7	20.1	20.1	20.6	20.6	20.4	19.5	20.5	22.3	22.9	21.6	22.0	22.0	20.9	21.3	19.7
Hawaii	18.0	18.8	18.7	18.7	17.4	17.2	17.3	18.2	18.2	19.3	18.7	16.6	15.0	14.7	15.4	16.4	15.8	15.7	18.2	18.7	19.2	17.1
Idaho	14.3	15.0	15.3	15.3	14.9	15.8	15.1	14.6	14.6	14.3	11.8	10.6	10.0	9.8	9.8	10.0	9.9	10.2	10.7	11.2	11.2	11.5
Illinois	22.2	21.8	22.5	22.8	22.4	21.7	22.4	22.5	22.7	21.8	20.3	18.7	17.8	18.4	18.1	17.4	17.2	16.9	17.3	17.0	16.8	16.6
Indiana	33.1	32.2	34.7	35.3	33.9	33.4	33.7	34.3	33.9	35.0	33.5	32.7	29.7	30.9	33.9	33.5	32.7	33.7	35.5	36.1	37.1	36.0
Iowa	18.9	18.7	19.7	20.8	19.6	19.1	20.2	20.2	19.9	21.7	20.3	20.1	19.9	19.6	19.9	20.4	20.3	21.1	22.6	22.6	22.8	23.4
Kansas	22.7	23.5	24.9	25.2	25.3	25.2	26.3	26.7	29.0	31.1	28.7	27.1	26.3	26.1	29.2	28.0	26.8	28.0	28.7	27.8	27.7	27.1
Kentucky	26.7	26.8	28.2	28.0	27.9	26.3	28.6	28.4	28.5	28.2	28.3	28.1	26.7	27.2	28.4	29.2	30.1	30.6	33.4	32.4	32.6	32.2
Louisiana	39.5	39.5	41.3	44.6	45.1	41.1	46.2	51.0	52.2	49.3	45.7	45.0	40.6	38.2	39.8	37.4	39.5	40.5	42.7	44.1	45.4	44.8
Maine	16.9	20.3	21.4	20.4	17.7	15.0	17.1	17.2	15.9	14.4	13.0	12.7	15.3	11.6	13.1	12.7	15.9	14.7	17.0	15.7	15.3	14.9
Maryland	18.8	18.8	18.7	19.9	18.5	16.2	17.5	16.2	16.8	17.5	16.0	14.8	14.3	14.5	15.7	14.7	14.8	15.6	15.9	16.4	14.7	14.2
Massachusetts	17.5	17.4	18.0	17.9	16.4	15.9	16.8	16.6	16.3	14.0	13.5	12.7	13.2	12.6	13.7	13.5	14.4	14.4	14.3	14.8	13.8	13.6
Michigan	21.0	21.5	22.1	22.0	20.9	21.0	21.2	20.2	20.5	20.4	19.4	18.5	17.4	17.1	17.9	18.4	18.7	18.9	19.6	19.2	19.3	19.0
Minnesota	18.2	17.8	18.8	19.5	19.1	18.5	19.6	19.9	20.1	19.0	17.5	16.3	15.8	15.3	16.3	15.9	15.3	16.2	17.9	18.4	18.0	17.7
Mississippi	17.4	17.9	18.8	18.8	18.2	17.0	17.8	19.2	20.1	20.1	18.9	17.8	17.8	16.7	17.3	16.9	17.3	17.9	19.1	17.9	18.8	18.5
Missouri	18.5	18.8	19.9	20.9	20.4	21.0	22.2	22.9	22.7	22.4	21.2	20.6	20.5	20.8	21.4	20.1	19.7	20.1	20.7	20.7	20.1	20.0
Montana	20.6	20.9	21.8	23.4	22.5	22.5	25.7	26.8	27.2	28.9	25.7	23.5	20.3	20.4	25.1	26.9	28.9	29.3	35.8	36.3	34.9	36.0
Nebraska	18.5	18.3	19.4	19.7	18.9	18.6	20.1	20.0	19.7	20.2	19.2	18.0	18.2	18.9	19.9	19.3	18.4	19.2	21.7	20.6	20.8	21.1
Nevada	21.9	26.5	34.6	35.3	34.2	33.8	34.4	35.0	31.3	30.7	27.6	28.2	28.8	28.0	28.6	24.7	27.6	26.8	29.2	27.6	25.2	25.2
New Hampshire	17.3	17.5	18.0	17.0	15.4	15.2	16.2	16.2	15.2	14.2	13.8	12.3	11.8	11.7	13.3	13.3	13.6	14.4	14.5	14.4	13.1	12.9
New Jersey	18.0	17.2	17.4	17.9	16.3	14.4	16.0	15.4	15.1	14.9	15.0	14.5	14.8	14.9	15.6	14.8	15.0	15.5	15.2	15.7	14.2	14.1
New Mexico	34.2	35.3	36.8	36.2	35.9	33.8	35.3	34.3	32.4	31.6	34.3	33.1	33.1	34.9	32.5	32.4	29.5	31.3	32.3	33.5	34.7	31.0
New York	15.6	15.1	14.9	15.4	14.3	13.6	14.6	14.6	14.4	13.3	12.6	11.7	11.1	10.1	10.3	10.6	10.7	11.3	11.6	11.9	11.5	11.0
North Carolina	19.1	19.1	19.7	20.2	19.1	17.2	18.9	19.0	17.9	19.0	19.1	18.9	18.0	17.7	17.7	17.1	17.8	16.8	17.3	17.6	16.7	16.3
North Dakota	23.8	25.4	26.7	25.9	26.6	25.4	28.8	30.6	34.4	38.1	39.0	40.8	43.1	44.5	50.6	56.5	58.2	59.8	67.9	68.4	70.4	72.1
Ohio	25.8	25.1	26.5	27.1	27.1	26.4	27.6	27.3	27.3	27.1	25.4	24.8	22.9	21.9	22.5	22.5	22.9	23.0	23.8	23.8	22.7	22.4
Oklahoma	21.6	21.5	22.3	22.2	22.6	22.5	24.4	25.2	26.4	26.9	25.4	25.9	26.4	26.0	26.6	25.7	23.9	25.7	27.1	27.7	27.9	28.1
Oregon	12.2	12.6	13.4	13.2	12.0	11.5	11.2	11.2	11.8	11.7	10.7	11.2	10.9	9.7	10.2	10.1	9.8	10.2	10.8	11.0	10.8	11.7
Pennsylvania	26.0	25.5	26.4	27.4	25.7	24.5	25.9	25.5	25.5	26.6	24.8	22.9	20.3	20.8	22.2	21.3	20.9	21.8	22.7	22.9	22.2	21.5
Rhode Island	13.8	14.1	13.8	12.9	12.1	11.1	11.2	11.6	10.6	9.8	8.8	8.1	7.8	8.0	8.8	8.7	9.7	9.9	10.4	9.2	8.8	10.6
South Carolina	16.2	16.5	17.2	17.6	16.1	14.7	17.2	18.1	17.5	17.1	17.6	17.5	16.3	15.4	16.2	16.4	16.3	17.2	18.0	17.6	17.4	17.4
South Dakota	14.0	13.9	14.3	13.9	13.5	16.0	18.2	17.9	18.7	18.4	16.8	15.8	16.5	15.0	15.5	15.8	15.3	13.5	16.4	16.8	16.9	16.4
Tennessee	19.8	19.0	21.2	23.8	21.4	21.0	23.5	23.2	23.2	22.3	21.9	21.5	19.0	20.3	21.1	21.9	22.1	21.7	22.1	21.2	21.5	20.2
Texas	31.9	32.6	33.9	36.2	34.8	32.4	32.7	35.0	36.5	36.9	36.0	34.7	31.7	31.0	31.7	31.5	30.7	31.0	32.8	33.7	33.4	32.4
Utah	22.9	23.2	22.7	24.1	24.7	25.1	24.1	24.2	24.9	25.8	24.4	22.3	20.7	21.0	22.1	22.4	21.6	26.5	30.6	30.6	31.5	30.0

Fig4. Energy-related carbon dioxide emissions by state with respect to Per capita

Per Capita CO2 Emissions (Table 4), By dividing total CO2 emissions by state population, per capita emissions provide a normalized basis for comparison. Many factors influence a state’s per capita emissions, including predominant economic activities, energy sources, building standards, weather variations, and policy measures.

Table 5. Energy intensity by state (2000–2021)
thousand Btu per chained 2012 dollar of GDP

State	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Alabama	13.3	12.1	12.2	11.8	11.7	11.2	11.1	11.0	10.7	10.0	10.5	10.2	10.0	10.1	10.4	10.0
Alaska	18.8	18.0	17.1	17.3	17.6	17.5	15.2	14.0	12.7	11.4	11.7	11.6	10.8	10.8	11.0	11.2
Arizona	6.4	6.3	6.1	5.8	5.8	5.5	5.4	5.3	5.2	5.4	5.5	5.5	5.3	5.3	5.3	5.3
Arkansas	12.7	12.2	12.0	11.4	10.7	10.5	10.3	10.5	10.4	10.1	10.7	10.5	9.9	10.0	10.0	9.5
California	4.7	4.7	4.6	4.4	4.4	4.2	4.1	4.1	3.9	3.9	3.8	3.7	3.5	3.5	3.3	3.2
Colorado	5.5	5.8	5.8	5.8	5.8	5.7	5.6	5.6	5.5	5.5	5.7	5.4	5.2	5.2	5.0	4.8
Connecticut	3.9	3.8	3.8	4.1	3.9	3.7	3.3	3.3	3.0	3.1	3.2	3.1	3.0	3.2	3.2	3.1
Delaware	5.4	5.0	5.5	5.3	4.8	5.1	4.8	4.9	5.0	4.2	4.4	4.5	4.5	4.7	4.3	4.3
District of Columbia	2.3	2.2	2.2	2.1	2.1	2.0	1.9	1.9	1.7	1.8	1.7	1.6	1.5	1.6	1.6	1.5
Florida	6.3	6.2	6.1	5.8	5.7	5.4	5.3	5.2	5.2	5.4	5.6	5.4	5.2	5.2	5.1	5.1
Georgia	7.5	7.2	7.4	7.2	7.2	7.0	6.8	6.8	6.6	6.8	7.3	6.9	6.4	6.4	6.3	6.1
Hawaii	4.9	4.9	5.0	5.0	5.0	4.8	4.8	4.8	3.9	4.1	4.3	4.3	4.1	4.1	4.0	4.0
Idaho	11.5	10.9	10.6	9.7	9.7	9.2	9.1	9.2	8.9	8.8	9.0	8.9	8.8	8.7	8.4	8.5
Illinois	6.3	6.1	6.1	6.0	5.9	6.0	5.7	5.7	5.8	5.6	5.7	5.6	5.3	5.5	5.5	5.2
Indiana	10.9	10.7	10.8	10.6	10.2	10.1	9.7	9.7	9.7	9.7	9.6	9.4	9.1	9.3	9.2	9.0
Iowa	9.8	9.7	9.7	9.3	8.9	8.8	8.9	9.0	9.6	9.9	10.0	9.9	9.1	9.6	9.3	8.8
Kansas	9.8	9.3	9.5	9.7	9.4	8.6	8.4	8.4	8.0	8.1	8.2	7.9	7.5	7.7	7.8	7.4
Kentucky	11.9	12.1	12.8	12.0	12.1	11.8	11.4	11.7	11.6	11.6	11.5	11.0	10.7	10.1	9.8	9.5
Louisiana	21.1	18.3	18.6	17.2	17.2	15.6	16.4	18.6	18.2	17.1	16.7	17.6	17.0	17.2	16.7	16.8
Maine	9.6	8.6	8.5	8.2	8.2	8.2	7.7	8.1	8.3	7.7	7.7	7.8	7.5	7.8	7.7	7.8
Maryland	5.8	5.6	5.7	5.7	5.4	5.3	4.9	4.9	4.7	4.7	4.6	4.3	4.2	4.2	4.2	4.1
Massachusetts	4.3	4.2	4.2	4.1	4.0	3.9	3.6	3.6	3.5	3.4	3.4	3.2	3.1	3.2	3.2	3.1
Michigan	7.4	7.3	7.2	7.2	7.1	7.0	6.8	6.8	6.9	7.0	6.9	6.8	6.4	6.7	6.7	6.4
Minnesota	7.1	7.0	7.0	7.1	6.8	6.6	6.5	6.6	6.6	6.4	6.5	6.3	6.1	6.2	6.2	5.7
Mississippi	14.1	13.0	13.3	13.1	12.8	12.1	12.2	12.2	11.5	11.3	11.7	11.5	11.1	10.9	11.0	10.8
Missouri	7.5	7.7	7.6	7.5	7.3	7.5	7.4	7.4	7.1	6.9	7.1	7.0	6.6	6.7	6.9	6.6
Montana	13.1	11.4	11.7	11.2	11.3	11.3	11.5	11.6	11.3	10.8	9.9	9.6	9.4	9.4	9.2	8.9
Nebraska	8.8	8.5	8.5	8.2	8.1	7.9	7.9	8.1	8.5	8.3	8.9	8.4	8.3	8.3	8.1	7.7
Nevada	5.9	5.9	5.7	5.7	5.4	5.1	5.2	5.1	5.0	5.1	5.4	5.3	5.3	5.4	5.4	5.1
New Hampshire	5.5	5.3	5.3	5.3	5.2	5.0	4.6	4.6	4.6	4.6	4.5	4.4	4.2	4.4	4.5	4.4
New Jersey	5.3	5.2	5.1	5.1	5.2	5.2	4.9	5.1	4.9	4.7	4.5	4.5	4.2	4.2	4.3	4.1
New Mexico	9.3	9.2	8.9	8.6	8.3	8.2	8.1	8.3	7.8	7.3	7.5	7.7	7.6	7.7	7.7	7.6
New York	3.8	3.6	3.6	3.8	3.7	3.6	3.2	3.3	3.3	3.0	3.0	2.9	2.7	2.8	2.8	2.8
North Carolina	7.3	7.1	7.1	6.9	6.9	6.6	6.1	6.1	6.0	5.9	6.3	5.9	5.7	5.7	5.6	5.5
North Dakota	15.4	16.4	15.3	14.4	14.3	13.9	13.6	13.7	13.0	12.4	12.5	12.4	10.6	11.2	11.1	10.8
Ohio	8.4	8.0	7.7	7.7	7.6	7.5	7.2	7.4	7.5	7.2	7.2	6.9	6.6	6.6	6.6	6.4
Oklahoma	12.0	11.7	11.1	11.2	10.7	10.6	10.3	10.1	9.7	9.3	9.8	9.5	8.9	9.1	8.9	8.2
Oregon	8.3	7.7	7.5	7.0	6.7	6.6	6.5	6.3	6.0	6.1	5.8	5.8	5.6	5.7	5.5	5.1
Pennsylvania	7.3	7.0	7.1	7.0	6.9	6.8	6.6	6.4	6.3	5.9	6.0	5.9	5.6	5.9	6.0	5.7
Rhode Island	4.6	4.5	4.3	4.5	4.3	4.1	3.8	3.9	3.8	3.9	3.8	3.6	3.6	3.8	3.9	3.8
South Carolina	10.8	10.4	10.3	10.0	10.4	9.9	9.8	9.4	9.3	9.3	9.7	9.2	8.9	8.9	8.8	8.7
South Dakota	9.0	8.7	8.4	8.5	8.4	8.6	8.6	8.8	9.1	9.1	9.4	8.8	8.6	8.9	8.8	8.5
Tennessee	9.4	9.5	9.3	9.1	8.8	8.7	8.5	8.6	8.3	7.9	8.4	7.9	7.3	7.4	7.5	7.2
Texas	12.2	11.7	11.7	11.5	10.9	10.1	9.5	9.2	8.8	8.5	8.9	8.7	8.4	8.5	8.3	7.9
Utah	8.1	7.6	7.3	7.3	7.2	6.9	6.6	6.3	6.2	6.1	6.1	6.2	6.1	6.2	5.8	5.6
Vermont	6.5	6.3	6.1	6.0	6.1	6.0	5.8	5.8	5.3	5.8	5.5	5.2	4.4	4.8	4.9	4.8
Virginia	6.9	6.5	6.5	6.5	6.5	6.4	6.2	6.2	5.9	5.7	5.7	5.5	5.3	5.4	5.5	5.4
Washington	7.2	6.7	6.1	6.0	6.1	5.8	5.9	5.5	5.4	5.5	5.3	5.3	5.0	5.0	4.7	4.5
West Virginia	12.0	11.8	12.0	11.3	11.5	11.2	11.4	11.8	11.3	10.4	10.9	10.5	10.4	10.6	11.1	10.9

Fig5. Energy intensity by state

Energy Intensity Metrics (Table 5), Energy intensity reflects energy consumption per dollar of economic output. High energy intensity typically corresponds with high per capita emissions, since more energy is used to power economic activities. States with cold climates or those producing energy-intensive industrial goods tend to have higher energy intensities.

Table 6. Carbon intensity of the energy supply by State (1970–2021)

kilograms of energy-related carbon dioxide per million Btu

State	1970	1971	1972	1973	1974	1975	1976	1977
Alabama	69.9	68.2	68.7	68.3	66.0	66.8	67.3	60.8
Alaska	62.3	62.9	62.6	63.4	63.4	62.6	62.7	61.2
Arizona	50.3	50.9	51.6	53.7	55.6	59.3	61.5	64.5
Arkansas	52.7	53.4	54.5	53.4	53.4	50.2	52.7	52.8
California	54.9	55.2	55.9	56.3	54.8	55.5	58.0	59.3
Colorado	62.8	62.2	62.9	63.6	64.0	65.4	66.4	67.9
Connecticut	65.7	61.4	60.5	63.7	59.8	58.7	55.5	55.0
Delaware	71.4	70.7	69.5	69.7	69.4	69.3	68.8	69.0
District of Columbia	74.0	72.2	71.5	71.9	71.2	70.2	68.8	69.2
Florida	65.9	66.1	66.9	65.6	64.2	64.7	64.9	62.1
Georgia	61.9	62.2	63.3	63.1	63.7	62.6	63.1	64.6
Hawaii	70.7	71.1	71.1	71.1	71.2	70.9	71.0	71.4
Idaho	41.3	42.2	42.0	41.9	40.5	41.0	40.8	45.8
Illinois	67.2	66.2	64.7	63.8	63.7	63.3	62.3	62.0
Indiana	74.3	73.2	74.0	74.4	74.0	75.2	75.7	75.9
Iowa	63.3	63.1	63.8	63.9	61.8	61.5	62.5	63.1
Kansas	57.3	56.9	57.3	58.2	58.7	61.1	61.3	61.8
Kentucky	72.3	72.4	72.5	72.2	73.2	73.0	73.2	73.7
Louisiana	50.8	50.6	50.4	51.0	51.1	51.5	51.5	52.2
Maine	56.8	59.6	59.3	52.2	50.0	47.2	46.1	46.9
Maryland	70.6	70.1	68.5	69.0	68.3	64.8	64.3	60.4
Massachusetts	66.9	66.7	66.9	65.2	65.9	65.6	65.3	65.1
Michigan	70.1	70.0	69.2	68.1	67.9	67.3	66.1	66.2
Minnesota	64.9	63.1	62.1	62.5	62.1	59.4	60.5	61.1
Mississippi	56.2	56.0	56.7	58.5	59.5	60.3	61.8	62.6
Missouri	65.8	66.4	67.5	67.3	67.4	69.3	69.9	70.6
Montana	43.9	43.3	44.7	48.6	45.8	45.9	46.2	52.8
Nebraska	59.6	59.4	60.4	59.7	55.2	53.3	55.6	54.3
Nevada	58.9	61.8	67.6	67.7	69.2	69.5	70.5	70.6
New Hampshire	64.4	64.5	64.6	62.5	62.5	63.8	62.2	63.0
New Jersey	66.1	65.3	64.3	65.0	64.7	64.3	64.1	62.7
New Mexico	63.2	64.8	64.6	66.2	66.2	66.0	65.4	67.7
New York	65.5	64.2	63.3	63.0	62.3	61.4	61.6	61.2
North Carolina	70.7	69.6	69.4	69.6	69.9	68.7	69.8	68.3
North Dakota	62.1	61.6	63.4	64.7	64.1	62.1	65.3	71.2
Ohio	73.1	72.6	72.5	72.7	73.1	74.0	73.7	74.3
Oklahoma	55.4	55.2	55.3	54.5	54.2	54.6	55.6	55.9
Oregon	33.4	32.2	32.8	36.5	31.9	31.8	30.6	33.7
Pennsylvania	74.8	74.5	74.2	75.0	73.6	72.2	71.8	71.2
Rhode Island	66.2	66.1	66.9	65.3	64.8	63.8	63.9	63.0
South Carolina	63.0	60.3	59.8	58.3	53.9	47.1	51.1	53.2
South Dakota	43.3	41.0	42.2	47.3	45.3	44.6	49.1	52.7
Tennessee	65.3	63.8	64.7	65.9	65.1	65.7	68.4	67.4
Texas	52.0	51.9	52.1	52.7	52.7	53.9	53.7	54.2
Utah	66.1	66.2	65.2	67.2	68.1	68.6	66.5	69.9

State	1978	1979	1980	1981	1982	1983	1984	1985	1986
Alabama	59.3	59.2	56.8	56.7	51.2	51.8	53.2	59.7	62.2
Alaska	60.1	58.3	58.8	60.9	58.5	59.2	59.3	61.1	62.3
Arizona	62.9	65.6	62.9	67.4	68.6	61.5	61.4	62.3	55.4
Arkansas	53.1	52.4	49.0	52.1	53.8	55.2	52.9	54.8	57.1
California	57.3	56.9	56.6	57.9	54.8	53.5	54.0	54.2	53.1
Colorado	67.6	67.3	68.8	70.6	70.3	69.2	69.7	70.0	70.2
Connecticut	54.4	54.5	53.6	50.8	50.1	51.2	50.8	52.1	48.9
Delaware	68.9	68.2	71.1	73.3	72.9	75.6	74.1	73.3	74.3
District of Columbia	68.5	66.6	64.2	63.0	63.1	63.6	63.3	62.6	63.0
Florida	62.8	63.3	62.9	63.4	60.5	63.2	60.1	61.8	62.5
Georgia	64.2	64.0	63.7	65.5	64.8	64.8	66.9	66.9	67.3
Hawaii	71.7	71.6	69.0	68.7	68.4	67.4	68.2	68.5	67.9
Idaho	41.4	41.9	39.0	37.3	34.0	32.2	32.1	34.9	33.3
Illinois	61.0	61.3	61.7	60.5	60.7	61.3	59.2	58.0	57.3
Indiana	74.7	74.9	75.5	75.4	74.5	75.3	75.9	75.9	75.7
Iowa	65.5	64.1	62.8	63.4	62.8	63.0	62.6	66.2	64.6
Kansas	62.9	62.6	64.4	66.0	65.8	67.5	66.8	64.1	62.3
Kentucky	73.4	72.6	75.1	76.2	74.7	75.5	75.0	76.3	76.9
Louisiana	52.1	51.3	50.9	50.9	51.3	52.3	52.8	52.6	51.2
Maine	45.5	44.7	37.9	36.1	40.8	32.8	35.4	35.8	40.8
Maryland	61.4	61.5	61.5	59.8	60.3	59.7	60.4	61.3	60.0
Massachusetts	63.8	62.0	64.1	63.2	64.5	62.3	66.6	62.5	65.3
Michigan	64.8	64.7	63.3	63.0	63.2	62.8	64.2	64.9	65.7
Minnesota	59.7	58.4	59.9	59.4	58.4	57.0	59.7	57.1	56.0
Mississippi	62.8	62.3	62.2	62.2	61.7	61.7	59.7	57.9	59.1
Missouri	69.7	70.2	72.3	73.3	72.6	73.4	73.0	67.6	68.4
Montana	49.0	51.8	50.7	47.9	45.7	44.6	50.5	52.8	53.2
Nebraska	54.1	54.3	57.4	57.7	54.0	58.3	60.0	61.8	56.6
Nevada	69.1	68.3	67.8	69.5	73.9	68.0	66.3	66.4	69.3
New Hampshire	62.2	61.8	62.7	59.7	60.4	59.0	61.0	61.1	59.9
New Jersey	62.0	62.4	62.0	59.4	59.2	61.5	62.2	58.8	60.2
New Mexico	67.5	67.6	70.0	70.6	71.2	73.1	72.5	74.0	73.7
New York	60.3	59.2	57.8	56.5	56.5	54.0	53.9	53.8	54.3
North Carolina	64.7	65.3	68.8	70.4	67.1	64.9	61.0	62.1	63.1
North Dakota	68.1	70.4	72.4	72.7	72.8	72.9	76.9	79.3	80.6
Ohio	72.9	71.8	72.2	72.1	71.6	70.8	71.1	71.8	72.9
Oklahoma	57.0	56.5	58.9	61.1	61.6	62.0	62.5	62.0	62.5
Oregon	33.6	33.4	31.8	31.8	27.8	25.6	25.8	26.0	26.1
Pennsylvania	70.2	71.1	71.3	69.8	68.4	69.3	68.7	67.7	65.3
Rhode Island	62.4	61.6	60.5	60.6	59.8	59.2	60.5	55.7	62.2
South Carolina	51.8	52.3	54.9	56.5	58.4	48.9	51.3	48.6	45.9
South Dakota	50.2	51.3	51.3	52.0	51.8	49.9	49.9	51.0	49.2
Tennessee	68.2	65.6	68.2	67.4	60.3	60.5	60.8	64.4	69.5
Texas	54.9	54.7	54.5	55.3	56.9	57.9	56.9	57.3	57.1
Utah	70.2	70.7	71.0	72.4	71.0	70.3	70.6	71.5	71.8

Fig6. Carbon emission intensity of each state

Carbon Intensity of Energy Supply (Table 6), This examines the carbon dioxide emitted per unit of overall energy supply in each state, providing a supply-side emission efficiency perspective. It is influenced most significantly by the reliance on carbon-intensive coal versus cleaner natural gas and renewable sources for electricity generation.

Table 7. Carbon Intensity of the economy by state (1997–2021)

metric tons of energy-related carbon dioxide per chained 2012 million dollars of GDP

State	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
Alabama	776.1	763.9	756.4	782.3	704.7	708.7	686.0	670.1	650.5	649.0	647.9	604.6	517.9	569.1	535.3	503.7
Alaska	976.7	1028.0	1056.0	1,105.8	1,038.7	994.2	1,012.9	1,048.6	1,040.0	923.1	843.8	762.4	663.2	680.4	670.7	620.3
Arizona	364.1	355.8	347.9	354.2	354.8	334.1	327.2	326.0	316.1	316.9	302.4	293.1	295.2	309.5	306.7	290.7
Arkansas	688.2	702.9	691.0	723.8	689.1	657.3	626.5	597.1	589.1	570.9	578.8	583.2	547.3	585.5	581.3	544.3
California	289.5	275.7	259.9	246.3	252.7	248.7	232.4	239.1	224.9	219.4	219.4	211.3	208.3	196.8	187.4	185.4
Colorado	433.9	410.3	395.1	382.7	403.5	407.0	398.6	402.3	393.2	388.7	376.9	366.8	363.4	373.3	355.0	341.7
Connecticut	266.5	238.6	211.5	195.3	197.0	192.1	209.9	197.7	189.0	163.5	160.8	149.2	144.7	145.5	140.6	135.4
Delaware	437.4	394.3	373.0	386.6	347.8	377.5	377.9	344.2	362.2	338.7	348.7	350.9	282.5	295.1	283.4	278.4
District of Columbia	145.8	141.3	138.1	142.2	136.3	133.5	127.9	127.4	124.9	112.7	113.4	101.6	96.9	94.4	89.0	81.8
Florida	423.6	414.2	398.8	401.5	391.9	379.9	369.0	358.1	344.1	331.9	324.7	315.1	314.9	335.7	320.3	307.3
Georgia	492.7	464.6	443.1	451.5	429.6	435.0	435.3	437.1	431.1	421.5	419.0	407.8	403.7	429.3	397.3	344.7
Hawaii	334.9	344.1	335.7	335.1	344.2	358.3	358.7	354.6	343.4	337.9	342.4	273.7	276.9	293.1	291.7	282.0
Idaho	465.4	465.4	451.3	454.9	481.6	445.8	424.8	424.3	390.0	361.4	391.8	359.4	353.3	376.9	333.7	341.7
Illinois	399.1	373.2	352.4	339.9	323.0	320.5	317.7	319.1	326.5	306.0	309.3	308.7	293.4	298.8	291.5	270.4
Indiana	886.1	842.9	847.0	848.1	839.7	838.5	824.8	798.4	786.9	761.5	760.7	750.5	739.4	723.4	698.4	665.9
Iowa	687.4	697.2	695.5	665.0	667.7	656.8	633.3	585.2	570.3	567.5	571.2	589.2	570.7	573.4	551.7	493.7
Kansas	667.9	623.8	631.7	633.6	594.6	614.6	629.8	608.2	574.5	551.4	540.1	518.1	514.8	510.6	496.9	459.9
Kentucky	942.6	901.2	918.2	939.7	953.9	999.4	939.9	951.9	921.8	903.5	922.9	911.1	901.1	891.7	848.9	814.7
Louisiana	1108.5	996.4	970.1	1,067.1	941.2	946.0	893.5	877.7	803.3	847.7	946.2	906.4	845.8	843.3	901.1	855.2
Maine	453.7	423.6	415.8	431.0	391.1	394.8	402.1	387.9	373.1	345.9	357.6	335.0	322.1	308.3	305.0	284.0
Maryland	377.1	367.6	367.5	357.9	352.0	362.3	360.6	340.6	333.8	301.8	301.9	281.8	278.4	271.8	250.1	238.6
Massachusetts	296.3	278.0	269.4	262.5	259.9	261.3	253.6	244.4	242.3	219.4	220.1	207.4	196.2	192.9	181.6	171.5
Michigan	485.0	493.6	485.6	465.3	451.4	436.3	441.6	427.1	421.6	412.5	409.7	415.1	430.3	411.0	393.3	370.7
Minnesota	459.8	431.4	426.3	416.0	409.8	415.8	429.7	402.9	385.8	376.9	380.2	372.5	351.8	345.2	336.5	315.8
Mississippi	750.3	758.5	803.4	787.1	768.1	759.9	766.0	748.6	699.4	706.1	705.8	667.0	634.6	648.9	610.5	594.4
Missouri	560.3	571.5	564.3	532.9	550.1	545.3	541.6	531.2	541.8	534.0	532.9	506.0	485.9	505.8	496.0	466.3
Montana	703.1	772.8	735.1	794.4	745.7	717.2	721.1	727.0	712.6	703.4	732.2	702.4	654.0	615.0	546.1	540.2
Nebraska	550.4	566.8	526.4	528.9	520.5	508.5	506.9	480.8	479.1	472.6	461.8	487.8	480.2	485.5	486.6	487.9
Nevada	425.7	410.3	401.0	400.9	401.2	379.3	382.5	362.4	344.0	321.6	315.7	305.7	304.5	324.2	309.5	304.6
New Hampshire	267.0	250.8	251.6	260.7	254.0	254.4	260.1	249.1	236.5	217.0	207.0	204.5	198.3	180.9	185.4	170.5
New Jersey	341.7	308.8	306.6	290.2	281.1	276.2	282.5	290.9	293.3	269.7	281.0	266.4	242.3	225.9	225.6	207.3
New Mexico	688.2	683.7	656.7	668.2	671.2	647.5	632.4	602.9	591.1	578.6	575.9	542.5	519.4	515.9	530.5	520.8
New York	211.7	206.0	200.6	200.9	190.7	189.5	200.8	197.7	187.1	164.3	167.1	161.3	145.3	149.7	140.0	127.4
North Carolina	464.6	445.3	429.7	440.0	426.5	422.3	406.4	410.2	397.9	365.0	373.5	355.6	336.8	363.2	330.6	307.9
North Dakota	1278.7	1206.5	1274.4	1,266.5	1,337.2	1,256.0	1,195.2	1,169.5	1,144.8	1,107.8	1,108.6	1,036.6	958.7	929.9	889.4	769.6
Ohio	609.2	581.6	583.0	576.0	555.3	547.8	554.0	532.5	528.5	506.4	524.3	519.9	500.1	503.2	475.3	436.9
Oklahoma	836.6	808.5	789.4	806.4	785.4	750.6	756.0	703.5	698.8	671.1	649.4	630.0	599.6	621.6	604.3	551.5
Oregon	306.8	338.0	329.0	315.7	316.5	286.9	277.7	261.2	265.8	243.0	252.8	235.1	235.4	227.6	195.8	190.1

Fig7. Carbon emission intensity of economy by each state

Carbon Intensity of the Economy (Table 7), By multiplying the intensity of energy and carbon intensity, the dataset arrives at the carbon intensity of the entire economy for each state. This accounts for both demand-side energy needed per unit of economic output and supply-side emissions per unit of energy.

Table 8. Net electricity trade index and primary electricity source for selected States (2000–2021)

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Most CO_2 per capita																	
Wyoming	3.3	3.1	3.1	3.0	2.9	2.9	2.7	2.6	2.4	2.5	2.5	2.4	2.6	2.7	2.5	2.5	2.4
North Dakota	2.9	2.7	2.6	2.5	2.4	2.7	2.4	2.5	2.4	2.5	2.5	2.4	2.3	2.1	1.9	2.0	2.0
Alaska	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
West Virginia	3.0	2.7	3.0	3.0	2.8	2.8	2.6	2.5	2.4	2.2	2.3	2.3	2.2	2.2	2.3	2.1	2.2
Louisiana	1.0	1.1	1.1	1.1	1.1	1.1	1.1	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9
Montana	1.6	1.9	1.8	1.8	1.8	1.9	1.8	1.7	1.7	1.7	2.0	2.0	1.8	1.8	1.9	1.9	1.8
Kentucky	1.1	1.1	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.9	1.0	1.1	1.0	1.0
Indiana	1.2	1.1	1.1	1.1	1.1	1.1	1.1	1.0	1.1	1.0	1.0	1.0	1.0	0.9	1.0	0.9	0.9
Nebraska	1.1	1.1	1.1	1.1	1.1	1.1	1.0	1.1	1.0	1.1	1.1	1.1	1.0	1.1	1.2	1.3	1.1
Iowa	1.0	0.9	0.9	0.9	0.9	0.9	0.9	1.0	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.0
Least CO_2 per capita																	
Rhode Island	0.9	1.0	0.9	0.7	0.6	0.7	0.7	0.9	0.9	1.0	1.0	1.1	1.0	0.8	0.8	0.9	0.8
New Jersey	0.7	0.7	0.7	0.7	0.6	0.7	0.7	0.7	0.7	0.8	0.8	0.8	0.8	0.8	0.9	0.9	1.0
New Hampshire	1.4	1.4	1.4	1.8	2.0	2.0	1.8	1.9	2.0	1.8	1.9	1.8	1.6	1.7	1.7	1.7	1.7
Washington	1.0	0.9	1.2	1.1	1.1	1.1	1.1	1.1	1.1	1.0	1.0	1.1	1.1	1.1	1.1	1.1	1.2
Oregon	0.9	0.9	1.0	1.0	1.1	1.0	1.0	1.0	1.1	1.1	1.1	1.2	1.2	1.2	1.2	1.2	1.2
Vermont	1.6	1.4	1.3	1.3	1.2	1.2	1.5	1.3	1.5	1.7	1.5	1.6	3.1	3.1	3.1	2.2	1.9
Maryland	0.8	0.7	0.6	0.7	0.7	0.7	0.7	0.7	0.7	0.6	0.6	0.6	0.6	0.5	0.6	0.6	0.6
California	0.8	0.7	0.7	0.7	0.7	0.7	0.8	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7
Massachusetts	0.7	0.7	0.7	0.8	0.8	0.8	0.7	0.8	0.8	0.7	0.8	0.7	0.6	0.6	0.6	0.6	0.6
New York	0.9	1.0	0.9	0.9	0.9	0.9	1.0	1.0	1.0	0.9	0.9	1.0	1.0	1.0	1.0	1.0	1.0

Net electricity trade index is defined as Total Supply / (Total Disposition - Net Interstate Trade)
Index values greater than 1.0 indicate a net export of electricity, and values less than 1.0 indicate a net import of electricity
Source: U.S. Energy Information Administration, State Electricity Profiles, Supply and Disposition of Electricity, 2000 through 2021
http://www.eia.gov/electricity/state/
Note: The District of Columbia is not considered in this table, as it is not a state.

Fig8. Net electricity trade index and primary source of electricity for selected states.

Treatment of Electricity Trade (Table 8), For consistency, CO2 emissions are attributed to the states where electricity generation occurs rather than where power is consumed. So major electricity exporting states, especially those reliant on coal, tend to show much higher total and per capita CO2 emissions.

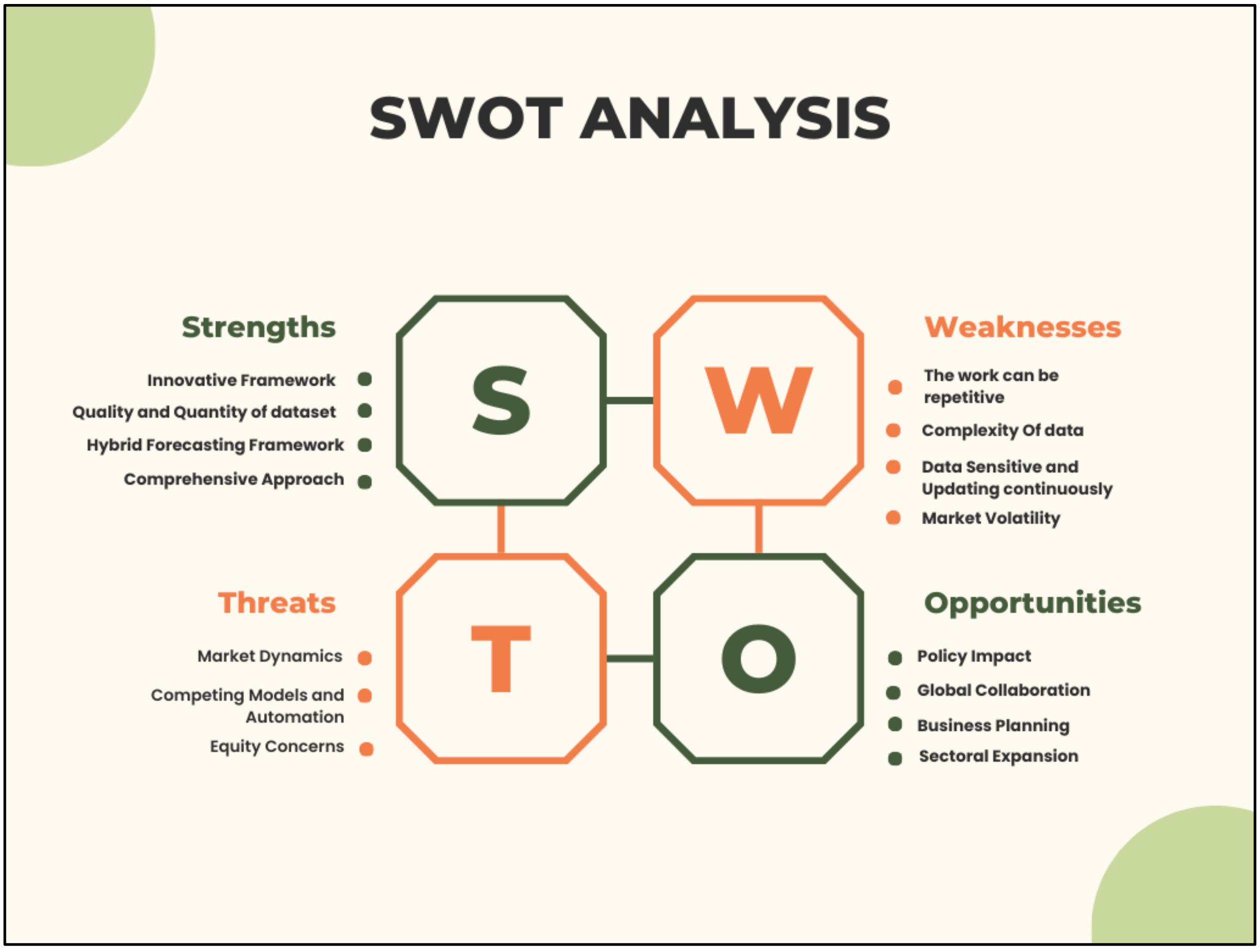
Proposed Model:

According to the research papers, we have observed that certain algorithms have high accuracy when predicting future carbon emissions, hence we are going to use Random Forest, MultiVariate data model. In case, if any of the above models do not work for our datasets we are planning to use some classification algorithm which ever fits the best for our dataset. The summarizing approach for predicting carbon emission trading prices using the XGBOOST involves predicting carbon emission trading price as a problem which can be solved using the XGBoost machine learning algorithm. Careful data preprocessing is undertaken on the dataset which involves dealing with missing values, removing outliers, and datatype correction. The XGBoost model requires careful configurations and hyperparameter tuning techniques like cross-validation during the training process using the historical data. Performance metrics such as MAE and MSE are used to evaluate the models, and then these metrics are used to refine and improve the model iteratively. Once satisfactory levels of predictive performance are reached, the model is then deployed for real-time carbon emission price predictions, with periodic updates to make sure that the model is updated with the most recent data. If the accuracy is not up to the mark, we may use Bayes optimization to further optimize it.

Here is a summary paragraph of using a recurrent neural network to predict carbon emission trading prices: The key method involves formulating the prediction problem as a sequence-to-sequence regression task to be solved by an RNN model. Relevant time-sensitive features are selected from the historical preprocessed data for the RNN to learn temporal patterns and dependencies. The RNN architecture configuration and hyperparameter tuning plays an important role and employs methods like grid/random search with cross-validation. Training occurs on historical data before the deployment for real-time forecasting. Also, acknowledging the uncertainties in financial forecasting is critical despite RNN capabilities. Additional enhancements are always done based on the performance metrics we take. Once the predictive performance of the model is as expected, we then use it to predict the real time carbon emission price. To summarize, the RNN methodology leverages sequence modeling to tackle the carbon price prediction challenge.

Here is a summary paragraph of using a convolutional network (CNN) in combination with other models to predict carbon emission trading prices: CNN-IBFA, an innovative solution set to transform carbon emission trading predictions. By combining Convolutional Neural Networks with Iterative Bayesian Filter Adaptation (CNN-IBFA).We want to explore more into combinatorial algorithms. Our method starts with data preparation, where we carefully choose features and clean data to ensure our models work effectively. We then bring together CNN-IBFA to train our models thoroughly. We start by gathering data covering various factors influencing carbon emission trading prices, from historical trading patterns to economic and environmental indicators, even taking into account geopolitical events. Then, we clean the data for any missing pieces and outliers, and get everything into a standardized format. Followed by selecting the most important features that will drive our predictions. These carefully chosen features then go into our CNN-IBFA model, where they undergo extensive training and fine-tuning, ensuring our model works well. As we evaluate our model's performance, we use metrics like MAE and MSE to make sure it's up to scratch.

SWOT Analysis



Strength:

Innovative Frame: This project will be a one-stop show for all the people looking for the conclusion for any carbon dioxide-related data with different types of graphs to enhance their readability. Quality and Quantity of dataset: The data will be used are taken from the US government website, it contains data on the emission of carbon dioxide from all the different sources including industries and, traffic and then we are planning to combine it with USA climatic data to see how it is affecting the weather and then we will be predicting the carbon credit score required in future and compare it with the past to get the clear idea about the relationship with the factors affecting the rate other features.

Weakness:

Market Volatility: Carbon markets can experience volatility due to factors such as changing regulatory environments, economic conditions, and political uncertainties, leading to fluctuations in carbon prices. Leakage and Displacement: Emissions trading may lead to carbon leakage, where emissions are displaced to regions with weaker regulations, potentially undermining the effectiveness of emission reduction efforts. Complexity: The design and implementation of emissions trading schemes can be complex, requiring coordination among stakeholders, robust monitoring and enforcement mechanisms, and accurate carbon accounting systems. Equity Concerns: There are concerns about the distributional impacts of emissions trading, as the costs and benefits may not be evenly distributed among participants, potentially exacerbating social inequalities. Market Manipulation: Carbon markets are susceptible to market manipulation, such as speculative trading or fraudulent activities, which can undermine market integrity and trust.

Threats:

Market dynamics: nowadays the market is not stable and the things which have just been introduced can be outdated within a few years and that’s very common in the computer field and according to us that will be one of the greatest threats of our project. Computation Models and Automation: In the end, all that matters for the project is the accuracy of the model that we will be building for the prediction of the data. Also, the main problem is that LLM already present in the world because the amount of data and the time they have been getting for training will definitely have a great impact on their accuracy and that could be one of the threats.

Opportunities:

Global Collaboration: There is an opportunity for international cooperation to harmonize emissions trading schemes and create a more integrated global carbon market, facilitating cost-effective emission reductions and promoting climate action. Carbon Offsetting: Emissions trading can support carbon offset projects, such as reforestation or renewable energy initiatives, which can generate additional revenue streams and contribute to broader sustainable development goals. Technological Innovation: Advances in data analytics, blockchain technology, and carbon accounting tools present opportunities to enhance the transparency, efficiency, and integrity of carbon markets. Sectoral Expansion: Emissions trading can be expanded to cover additional sectors beyond energy and industry, such as transportation, agriculture, and land use, providing opportunities to address emissions from a wider range of sources. Climate Finance: Emissions trading can mobilize climate finance by channeling investments into low-carbon projects and technologies, stimulating economic growth while reducing greenhouse gas emissions.

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Possible Datasets Link:

https://www.eia.gov/environment/emissions/state/

https://data.world/rhubarbarosa/eex-data-exploration/workspace/file?datasetid=carbon-allocation-trade-data-eex&filename=eex_data_sellers.csv

https://data.world/opensnippets/weather-details/workspace/file?filename=weather_dataset_19-01-2020.csv

https://data.world/gymprathap/world-weather-dataset/workspace/file?filename=World-Weather-Dataset.zip