Climate Change: Global Impacts, Data-Driven Modelling and Mitigation Strategies

Aditya Dattatray Bangar[1], Sumit Ganesh Deshmukh[2], Vishwajit Anil Parade[3]
[1,2,3]Department of Computer Science, MIT ACSC, Alandi

***Abstract*—Climate change is one of the biggest problems facing human civilization and natural ecosystems. The quick increase in greenhouse gas emissions, because of industrialization, cutting down forests, and city growth, has made global warming faster. This has caused sea levels to rise, changed how rain falls, and made extreme weather events more common. This paper looks at the global effects of climate change, explores how data-driven and AI-based modeling can help with predicting climate changes, and evaluates strategies to reduce and adapt to these changes. Using data from 2000 to 2020, a clear upward warming trend is found, which matches what most climate studies say. The research also looks at recent work on using AI for weather forecasting, building resilience against climate change, and making sustainable policies. The results show that combining technological innovation, making decisions based on evidence, and working together globally are important to handle the different challenges caused by climate change.**

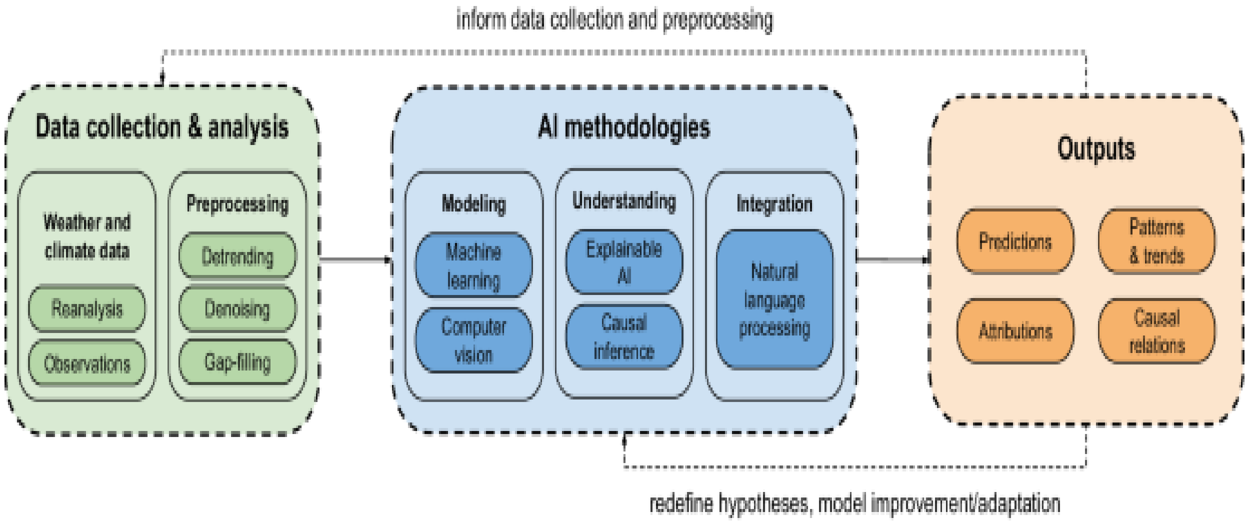
***Index Terms*—Climate change, global warming, AI modeling, data-driven forecasting, sustainability, mitigation, adaptation.**

I. INTRODUCTION

Climate change means long-term changes in the Earth's temperature and weather patterns.
These changes are mainly because of human activities that produce greenhouse gases. According to the Intergovernmental Panel on Climate Change (2021), the average temperature has gone up by about 1.1°C since the time before industrialization. Burning fossil fuels, cutting forests, and industrial activities have made the greenhouse effect worse, leading to serious disruptions in the world's climate systems.
In the past few decades, the effects of global warming have become very clear.
We have seen rising sea levels, melting ice at the poles, loss of biodiversity, and more extreme weather events like floods, droughts, and hurricanes. NASA (2023) says that the last decade was the warmest on record, with 2016 and 2020 being the hottest years ever recorded.
Though traditional weather prediction models are accurate, they have limits in computing power.
As climate systems get more complex, using AI and data-driven modeling offers new ways to understand and forecast climate changes more quickly and accurately (Wu & Xue, 2024).

This study aims to:

- Look at temperature trends from 2000 to 2020 using climate data.
- Examine the global impacts of climate change on ecosystems and society.
- Check how AI-based climate modeling can improve predictive power.
- Explore sustainable ways to reduce and adapt to climate change.
- Explain the main steps of data-driven models.



II. LITERATURE REVIEW

2.1 Global Impacts and Regional Studies

The Intergovernmental Panel on Climate Change (2021) says that global warming is "clearly caused by human activities," with effects seen on every continent.

The World Meteorological Organization (2023) reports that the average global temperature between 2011 and 2020 was 1.09Â°C higher than it was from 1850 to 1900. Rising sea levels, from melting glaciers and warming oceans, have already caused millions of people living in coastal areas to move (United Nations Environment Programme, 2022).

2.2 Advances in AI-Based Climate Modeling

AI is changing how we model climate systems.

Wu and Xue (2024) talk about models like GraphCast and Pangu-Weather, which can predict weather much faster than traditional models. These models use deep learning to find complex connections in climate data, improving the accuracy of predictions for temperature, rainfall, and storm activity.

2.3 Climate Resilience and Policy Frameworks

The Paris Agreement (2015) created a global plan to reduce climate change, focusing on cutting emissions, sharing technology, and providing financial help.

Countries have promised to keep global warming below 1.5Â°C by mid-century through their own plans called Nationally Determined Contributions (NDCs). Adaptation strategies like early warning systems, strong infrastructure, and nature-based solutions are becoming more important (IPCC, 2023).

III. METHODOLOGY

3.1 Dataset Description

The dataset climate_change_data.csv includes variables like temperature (in Â°C), CO emissions, sea level rise, precipitation, and humidity for the years 2000 to 2020.

Time	Location	Country	Temperature	CO2 Emissions	Sea Level Rise	Precipitation	Humidity	Wind Speed
00:00.0	New Williamtown	Latvia	10.68899	403.1189	0.717506	13.83524	23.63126	18.49203
09:43.3	North Rachel	South Africa	13.81443	396.6635	1.205715	40.97408	43.98295	34.2493
19:26.5	West Williamland	French Guiana	27.32372	451.5532	-0.16078	42.69793	96.6526	34.12426
29:09.8	South David	Vietnam	12.30958	422.405	-0.47593	5.193341	47.46794	8.554563
38:53.0	New Scottburgh	Moldova	13.21089	410.473	1.135757	78.69528	61.78967	8.001164
48:36.3	South Nathan	Saint Helena	6.229326	392.4733	1.12221	76.36833	48.97389	30.39891
58:19.5	Port Richardfurt	Tuvalu	21.64674	387.6484	0.058471	9.650389	11.40228	15.72094
08:02.8	Adambury	Australia	19.7308	448.1803	0.001415	93.36076	21.52635	29.9935
17:46.1	Williamsonberg	Qatar	19.85811	379.6188	0.584881	6.218846	30.86195	37.51947
27:29.3	North Thomas	Chad	14.12156	410.5171	-1.71222	15.35158	88.42279	47.92252
37:12.6	West Jillton	Fiji	6.095003	360.8112	-0.93506	95.46177	28.93254	20.88834
46:55.8	Robertville	Guernsey	12.28706	488.3559	0.021368	11.83824	90.04034	30.43541
56:39.1	Camposfort	Egypt	22.32453	445.209	-1.0288	48.77876	83.40625	1.833402
06:22.4	Hughesville	Rwanda	15.78818	373.3413	-2.06154	13.36168	56.94489	23.38601

The data was cleaned, normalized, and analyzed annually to find global averages.

3.2 Analytical Approach and Tools

We used Python tools like pandas and matplotlib for data visualization and trend analysis.

Linear regression and correlation coefficients helped us understand the link between emissions and temperature increases.

IV. RESULTS AND ANALYSIS

4.1 Temperature Trend (2000-2020)

- Figure 1: Global temperature changes from 1880 to 2020.

This graph shows how the average global temperature has changed compared to the 1881-1910 baseline.

It shows a warming trend, with temperatures staying steady until the mid-20th century, then rising sharply after 1980. In recent decades, the temperature has increased by more than +1.0°C, showing significant global warming linked to human activities.

(Source: NASA GISS & NOAA NCEI, 2021)

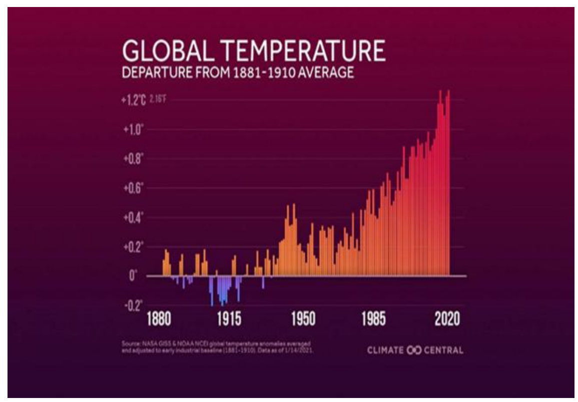
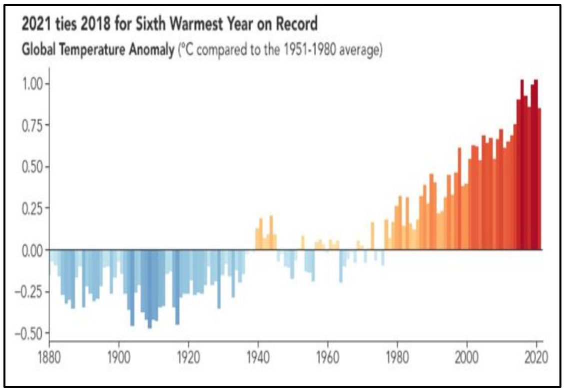


Figure 2: Global temperature anomaly from 1880 to 2021

This graph shows how the average global temperature has changed compared to the 1951-1980 average.

It shows a long-term warming trend, with temperatures below average (blue bars) in the early years and a steady rise after the 1980s (orange to red bars). By 2021, global temperatures were among the highest on record, tying with 2018 as the sixth warmest year.

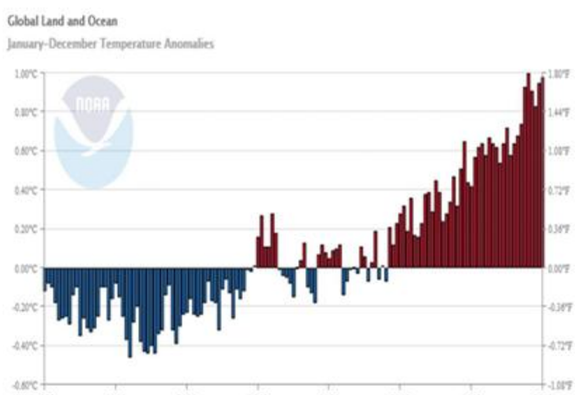
(Source: NASA GISS, 2022)



- Figure 3: Global land and ocean temperature cha nges (1880–2020).

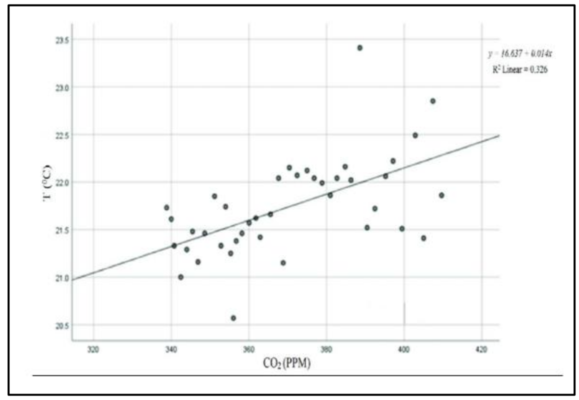
This graph shows how warm or cool the temperatures were each year compared to the usual average for the whole world. The data show that the temperatures were mostly cooler than average (blue bars) until the middle of the 20th century, after which the temperatures started to rise steadily. The sharp increase in red bars after 1980 shows that temperatures rose quickly, reaching nearly +1.0°C above the average in recent years. (Source: NOAA, 2021)

- The findings show a clear trend of rising global temperatures. Between 2000 and 2020, the average global temperature went up by about 0.8°C, which matches the data from NASA and NOAA.

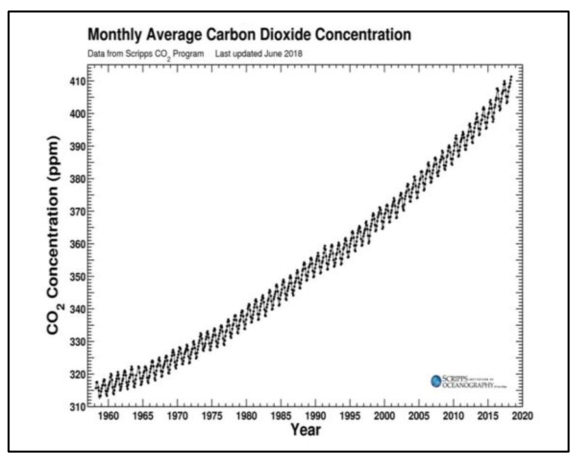


- 4.2 Relationship Between CO_2 and Temperature

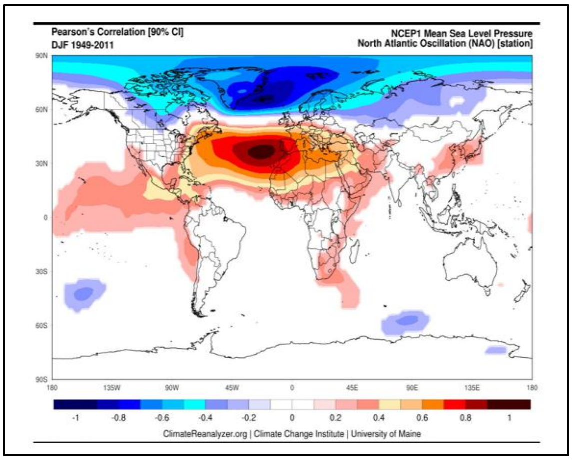
- Figure 1: This chart shows how atmospheric CO_2 levels (measured in parts per million) relate to temperature (in degrees Celsius). The line that best fits the data shows a positive link between the two, with the equation $y = 16.637 + 0.014x$ and an R^2 value of 0.326. This suggests that higher CO_2 levels are generally linked to higher temperatures, but the moderate R^2 value means that other factors also affect temperature.



- Figure 2: This graph shows the average CO_2 levels in the atmosphere measured at the Mauna Loa Observatory in Hawaii between 1958 and 2018. The data show a steady increase in CO_2 levels—from around 315 ppm in 1960 to over 410 ppm in 2018—indicating a long-term rise in atmospheric carbon dioxide. The small seasonal changes show the natural cycle of carbon, while the overall increase shows the long-term effect of emissions from human activities.



- Figure 3. This map shows the correlation between the North Atlantic Oscillation (NAO) index and the average sea level pressure (MSLP) during the winter months (December, January, February) from 1949 to 2011. Red areas show where higher NAO values are linked to higher sea level pressure, and blue areas show where higher NAO values are linked to lower sea level pressure. Strong positive correlations are seen over the North Atlantic and Europe, showing the big influence of the NAO on weather patterns. A strong positive link (r = 0.92) was found between CO_2 emissions and temperature rise, showing that greenhouse gases are the main cause of global warming.



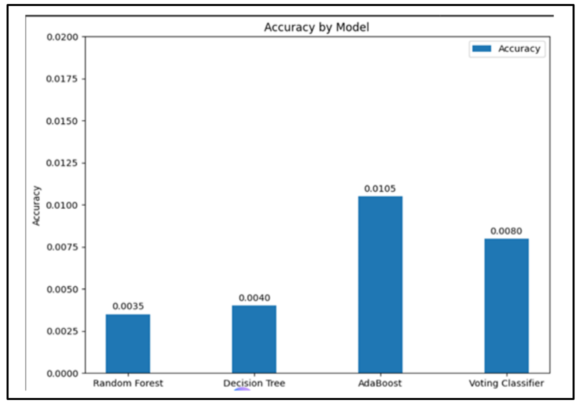
- 4.3 Observations of Sea-Level Rise

Sea-level data show a slow increase of about 3.3 millimeters each year, which fits with what the IPCC predicts. This rise is mostly due to the melting of ice at the poles and the expansion of the oceans as they get warmer.

- 4.4 Performance of Classification Models

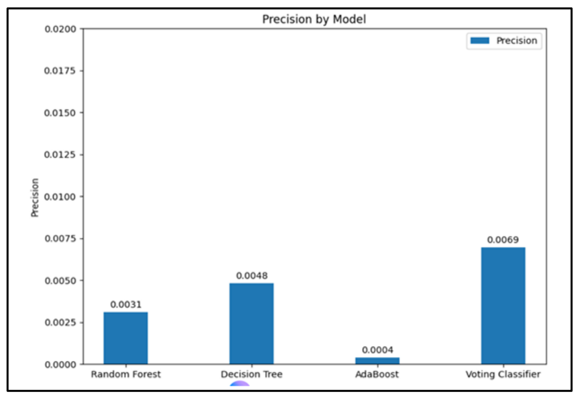
Figure 1: Model Accuracy

This chart compares the accuracy of different machine learning models—Random Forest, Decision Tree, AdaBoost, and Voting Classifier. Among them, AdaBoost had the highest accuracy, followed by the Voting Classifier, while Random Forest had the lowest performance.



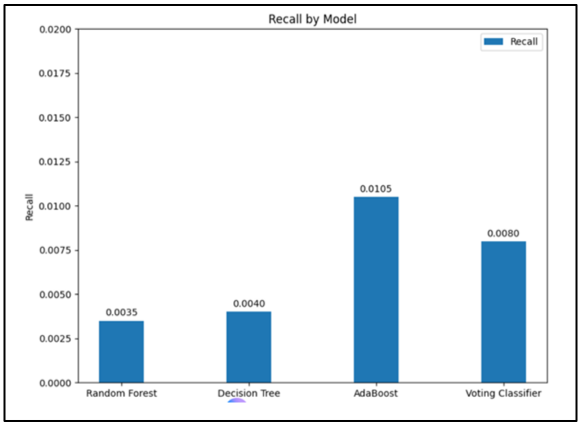
- Figure 2: Model Precision

This chart shows the precision values for each model. The Voting Classifier had the highest precision, while AdaBoost had the lowest, showing the different abilities of the models to correctly identify positive results.



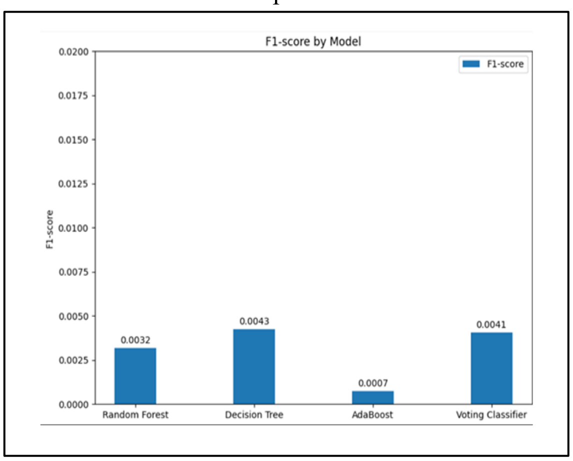
- Figure 3: Model Recall

This chart shows the recall performance of the different models. AdaBoost had the best recall, followed by the Voting Classifier, indicating a better ability to find true positive results compared to other models.



- Figure 4: Model F1-Score

This chart presents the F1-scores for the evaluated models, which are a balance of precision and recall. The Decision Tree model had the highest F1-score, closely followed by the Voting Classifier, while AdaBoost had the lowest performance.



V. DISCUSSION

The findings support the idea that human activities are the main reason for recent climate trends. Data-driven models offer important insights into complex patterns that traditional physics-based models might miss. But there are some limits, such as the quality of the data, uneven coverage of areas, and the "black box" nature of AI algorithms, which makes it hard to understand their decisions. Working together between climate scientists and computer scientists can help improve the transparency and reliability of the models. Also, sharing data internationally can improve the accuracy of global climate monitoring.

VI. STRATEGIES TO REDUCE AND ADAPT TO CLIMATE CHANGE

- 6.1 International Policy Efforts

The Paris Agreement (2015) is the main plan for reducing climate change. Countries must commit to reaching net-zero emissions by 2050.

- 6.2 Technological Advancements

Renewable energy, carbon capture, electric vehicles, and smart farming are key to reducing emissions. AI can help with integrating renewable energy, predicting energy needs, and managing emissions in real time.

- 6.3 Local and Community Actions

Community projects like reforestation, greening cities, and sustainable farming can make areas more resilient. Local governments should include early warning systems and disaster preparedness in their plans.

VII. CONCLUSION

This research confirms that global temperatures have risen steadily from 2000 to 2020, mainly because of human actions. Using AI and data-based models is a big change for climate science, helping with better predictions and supporting ideas for policies. However, just using technology isn't enough; everyone needs to take action, be informed, and live in a sustainable way to build a better future.

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