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Geopolitical Risk and Country-Level CO_2 Emissions: A Deep Learning Approach Comparing LSTM, CNN and ConvLSTM

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ABSTRACT

The investigation in this research employs advanced deep learning methods to analyze the bidirectional relationship between geopolitical risks and CO_2 emissions in China, India, and the USA across the timeframe of 1990 to 2019. Data sourced from the Recent GPR Index and CO_2 emissions was utilized. The exploration of how geopolitical risks influence climate change provides valuable insights for decision-makers in policymaking roles. The study's outcomes indicate a positive correlation between geopolitical risks and CO_2 emissions across all three nations, with both variables exhibiting an ascending trend throughout the studied period. Noteworthy is the consistent superior performance of the Long Short-Term Memory (LSTM) model when compared to the Convolutional Neural Network (CNN) and Convolutional Long Short-Term Memory (ConvLSTM) models in short term prediction. This consistent effectiveness in CO_2 emission prediction showcases the strength of the LSTM model. The divergence in model efficacy among the different nations highlights the significance of tailoring CO_2 emission prediction models to each country's unique attributes. These insights should significantly influence policymakers as they strategize approaches to mitigate geopolitical risks, curtail CO_2 emissions, and to adopt well-informed strategies in combating climate change.

Keywords: Geopolitical Risks, CO_2 Emissions, Deep Learning, LSTM Model, Climate Change, Environmental Sustainability
JEL Classifications: Q54, Q56, C63, G18

1. INTRODUCTION AND LITERATURE REVIEW

Geopolitical risks encompass potential disruptions in political, social, or economic realms triggered by geopolitical events like wars, political transitions, and international conflicts. These risks wield substantial influence over businesses, economies, and investment portfolios (Jiang et al., 2022, Abbass et al., 2022, Mitsas et al., 2022). To measure geopolitical risks, several indices have been developed that considers various factors such as political stability, government effectiveness, rule of law, and corruption. These indices provide a numerical representation of the level of geopolitical risk in a given country or region, allowing for comparison and analysis.

One of the most widely used indices for measuring geopolitical risk is the Political Risk Services (PRS) Country Risk Index, which provides a comprehensive evaluation of a country's political, economic, and operational risk environment. Another popular index is the Euromoney Country Risk Index, which uses a combination of quantitative and qualitative factors to assess geopolitical risk.

While there are several indices available to measure geopolitical risk, we prefer to use the Geopolitical Risk (GPR) index developed by Caldara and Iacoviello (2022) which provides a measure of adverse geopolitical events and associated risks based on a tally of newspaper articles covering geopolitical tensions. The GPR index has been shown to be a useful predictor of economic outcomes, such as investment, stock prices, employment, and the probability of economic disasters, and has been used in a variety of studies examining the relationship between geopolitical risk and economic activity. In our analysis of the predictability of CO_2 emissions using GPR, the index provides a valuable measure of geopolitical risk, which is an important factor to consider when forecasting future emissions trends (Caldara and Iacoviello, 2022).

Exploring the predictability of environmental deterioration, particularly concerning CO_2 emissions, through the utilization of a geopolitical risk index offers valuable insights into the interplay between political stability and ecological sustainability. The examination of the connection between the geopolitical risk index and CO_2 emissions enables researchers to discern patterns where nations displaying greater political stability and security tend to exhibit decreased emissions, and conversely, where the opposite relationship exists (Wang et al., 2022). Moreover, this scrutiny pinpoints specific countries or regions that exhibit heightened vulnerability to environmental degradation due to geopolitical factors. It emphasizes the necessity of addressing these factors to realize sustainable developmental objectives.

The uniqueness of our investigation lies in the application of advanced deep learning techniques to explore the association between geopolitical risks and CO_2 emissions in three pivotal countries: China, India, and the USA. Diverging from prior studies, our research employs an array of neural networks, encompassing Convolution Neural Network (CNN), Long Short-Term Memory (LSTM), and ConvLSTM models, to meticulously analyse this interrelationship. The outcomes divulge a noteworthy positive connection between geopolitical risks and CO_2 emissions across all three nations, underscoring that amplified geopolitical risks tend to coincide with increased CO_2 emissions across timeframes.

The predictability of environmental degradation (CO_2 emissions) is a complex issue that is influenced by various factors, including geopolitical risk, economic conditions, technological advancements, and policy decisions (Wang et al., 2021, Su et al., 2019, Gupta et al., 2019). As a result, incorporating measures of geopolitical risk such as the Geopolitical Risk (GPR) index developed by Caldara and Iacoviello (2022) can provide valuable insights into understanding the potential risks and uncertainties associated with environmental degradation. Specifically, the GPR index can be used to identify periods of heightened geopolitical tensions and associated risks that may affect the predictability of CO_2 emissions, and to examine the economic effects of these risks on energy markets and carbon-intensive industries. By analysing the relationship between GPR and CO_2 emissions, policymakers and investors can make more informed decisions that account for the potential impacts of geopolitical risk on environmental sustainability. The analysis of relationship between geopolitical risk and CO_2 emissions would provide a better understanding of the predictability of environmental degradation.

However, it is important to note that the relationship between geopolitical risk and CO_2 emissions is not straightforward and can be influenced by other factors such as economic growth, technological advancements, energy policy, and public attitudes towards the environment (Li et al., 2022, Flouros et al., 2022, Syed et al., 2022). Additionally, geopolitical risk can also have a direct impact on the energy sector (Sweidan, 2021), potentially leading to changes in energy consumption patterns and greenhouse gas emissions.

Changes in government policies and regulations, such as environmental protection measures, can also impact CO_2 emissions. Economic conditions, such as recessions or booms, can affect energy production and consumption, which in turn affects CO_2 emissions (Doda, 2014 and Wang et al., 2018). Additionally, geopolitical events, such as trade disputes or sanctions, can affect the energy sector and CO_2 emissions. Therefore, geopolitical risks can have both direct and indirect impacts on CO_2 emissions (Syed et al., 2022).

In recent years, there has been a growing interest in predicting CO_2 emissions, as this is a critical issue that affects global sustainability. In response, researchers have developed a variety of models and used multiple variables to make predictions about future CO_2 emissions.

The study of the predictability of environmental degradation, specifically CO_2 emissions, has been the focus of numerous research studies in the past decade. Researchers have explored the relationship between political and economic factors, including geopolitical risks, and CO_2 emissions. Kahn (2010) highlights the role of geopolitical risks in affecting energy production and consumption, and its impact on CO_2 emissions. Similarly, Anser et al. (2021) and Zhao et al. (2021) investigate the relationship between geopolitical risks and energy investments and find that geopolitical risks can impact energy production, consumption, and CO_2 emissions.

Iqbal et al. (2023) examine the impact of economic policy uncertainty on CO_2 emissions in developed and developing countries and find that political instability can have short-run and long-run effects on CO_2 emissions. Similarly, Gani (2012) used geopolitical risk indices to assess the relationship between geopolitical risks and carbon emissions in developing nations and found that geopolitical risks can have a significant negative impact on carbon emissions.

The impact of government policies on CO_2 emissions has also been investigated. Halkos and Paizanos (2016) use VAR methods to show that government policies can have a significant impact on CO_2 emissions in the short-run. The analysis in this study further sheds light on the impact of geopolitical risks on climate change and emphasizes the need for policymakers to consider these risks when developing strategies to mitigate emissions. By recognizing the importance of geopolitical factors in climate change, policymakers can make more informed decisions and implement effective measures to address this issue. Our study's unique approach using deep learning techniques provides valuable insights into the complex relationship between geopolitical risks and CO_2 emissions, making it a significant contribution to the field.

The predictability of environmental degradation (CO_2 emission) using geopolitical risk index can be analyzed using deep learning techniques. The big three countries (China, India, and the United States) are good candidates for this analysis due to their large CO_2 emissions and varying levels of geopolitical risk. Deep learning models such as recurrent neural networks (RNNs) or long-short term memory (LSTM) networks can be used to analyze the time-series data of CO_2 emissions and geopolitical risk indices for these countries. The goal would be to train the model to identify patterns and relationships between the two variables and make predictions about future CO_2 emissions based on changes in geopolitical risk. Sharma et al. (2022) employed long-term memory to forecast energy consumption using weather data. Their results show that the approach of long short-term memory outperforms other competing deep learning method and traditional econometrics methods. Ashin Nishan and Muhammed Ashiq (2020) used the Artificial Neural Network (ANN) to predict carbon dioxide emissions and growth using energy use as the input variable. The findings suggest that the accuracy of predicting the relationship between CO_2 emission and growth can be improved using machine learning techniques. Furthermore, Han et al. (2023) applied the residual neural network (RESNET) to analyse energy structures of different countries or regions, their results show that the RESNET model outperforms traditional models such as the convolutional neural network (CNN), radial basis function (RBF), extreme learning machine (ELM), and back propagation (BP) in terms of correctness and functionality.

It is important to note that while deep learning models have shown promising results in many areas, they may not be a guarantee of accuracy. It will be crucial to validate the model using appropriate metrics such as mean absolute error or mean squared error and compare its performance with other traditional statistical models.

The short-run and long-run relationships between geopolitical risks and CO_2 emissions can vary depending on the specific circumstances. In the short-run, geopolitical risks, such as political instability or conflict, can result in disruptions to energy production and consumption (Flouros et al., 2022), leading to changes in CO_2 emissions. In the long-run, changes in government policies aimed at reducing CO_2 emissions, increased investment in renewable energy, and advances in technology can result in a decrease in CO_2 emissions.

Hence, it is important to consider the time horizon of the analysis when examining the relationship between geopolitical risks and CO_2 emissions. The short-run relationship may reflect the immediate impact of geopolitical risks on energy production and consumption (Chu et al., 2023), while the long-run relationship may reflect the impact of broader economic, technological, and policy changes (Hashmi et al., 2022, Anser et al., 2021, Su et al., 2019). To fully understand the relationship between geopolitical risks and CO_2 emissions, it is necessary to consider both the short-run and long-run dynamics.

In addition to these studies, some researchers have applied deep learning techniques to predict CO_2 emissions. Wang et al. (2019) compare the performance of different deep learning models. Ahmed et al. (2022) use deep learning techniques to predict CO_2 emissions from energy consumption. Some of the most commonly used deep learning methods for forecasting include Recurrent Neural Networks (RNNs), Convolutional Neural Networks (CNNs), and Artificial Neural Network (ANNs) and Long Short-Term Memory (LSTM) networks. Studies have shown that deep learning methods can produce accurate and reliable forecasts of CO_2 emissions. For example, LSTMs have been shown to outperform traditional time-series models such as ARIMA and ETS in forecasting. This is due to their ability to handle large datasets and recognize complex patterns in data.

The remainder of the study is organized as follows: Section 2 presents the methodology, Section 3 covers the results and discussion, Section 4 outlines the implications of the study, and Section 5 provides recommendations and concludes the research.

2. METHODOLOGY AND DATA

To investigate the relationship between the geopolitical risk index and CO_2 emissions in USA, India, and China, we aim to answer the following research questions using deep learning approaches:

1. How does geopolitical risk impact CO_2 emissions in these countries?
2. What is the effect of the geopolitical risk on the predictability of CO_2 emissions using deep learning algorithms?
3. How do different deep learning models perform in predicting environmental degradation as measured by CO_2 emissions in these countries with the geopolitical risk index?

These questions aim to provide some valuable insights into the connection between geopolitical risk and environmental degradation, as well as the potential of deep learning algorithms in predicting environmental degradation. Additionally, focusing on the big three countries will allow us to explore similarities and differences in environmental degradation patterns across these countries and identify common factors that contributes to environmental degradation.

This study uses the Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), and ConvLSTM for the deep learning analysis as they offer several benefits amongst which include:

i. Capturing temporal dependencies: Time series data often exhibits temporal dependencies, where past observations influence future predictions. CNN, LSTM, and ConvLSTM models are specifically designed to capture and model these dependencies effectively. They can learn intricate patterns and long-term dependencies in the data, making them suitable for forecasting tasks.
ii. Automatic feature extraction: Deep learning models, including CNN, LSTM, and ConvLSTM, have the ability to automatically learn and extract relevant features from raw input data. This eliminates the need for manual feature engineering, saving time and effort. These models can identify important temporal features and representations that are critical for accurate time series forecasting.
iii. Handling high-dimensional data: Time series data can often be high-dimensional, with multiple variables or channels involved. CNN, LSTM, and ConvLSTM models are

well-suited for handling such data as they can process input tensors of arbitrary shape. CNNs are effective in capturing spatial relationships, while LSTM and ConvLSTM models excel at modeling sequential information across multiple time steps.

iv. Non-linear modeling capability: Deep learning models offer powerful non-linear modeling capabilities, enabling them to capture complex relationships within time series data. CNN, LSTM, and ConvLSTM architectures consist of multiple layers with non-linear activation functions, allowing them to learn and represent intricate patterns and dynamics in the data.

v. Transfer learning and pre-trained models: Deep learning models, including CNN, LSTM, and ConvLSTM, benefit from transfer learning. Pre-trained models trained on large datasets or similar tasks can be fine-tuned or used as feature extractors for time series forecasting. This leverages the knowledge and representations learned from other domains or tasks, enhancing the model's performance on time series data with limited training samples.

vi. Scalability and parallelization: Deep learning models can be efficiently trained and executed on modern computational hardware, including GPUs and TPUs. CNN, LSTM, and ConvLSTM models can be parallelized and trained on large-scale datasets, making them suitable for handling extensive time series data with substantial computational power.

vii. State-of-the-art performance: CNN, LSTM, and ConvLSTM models have achieved state-of-the-art performance in various time series forecasting tasks. They have been successfully applied in diverse domains such as finance, weather prediction, energy load forecasting, and traffic prediction, among others.

Their success and widespread adoption indicate their effectiveness in addressing time series forecasting challenges.

2.1. Data Sources

The analysis in question relies on a monthly data sequence of GPR Index, which provides insight into the degree of geopolitical risk present in a given month. This index was created by Caldara and Lacoviello (2022) using information gathered from the electronic archives of 10 prominent newspapers. Covering the time period from 1985 to 2019, the GPR Index offers a measurement of adverse geopolitical events and related risks, based on the frequency of newspaper articles covering geopolitical tensions.

Information on CO_2 emissions (metric tons per capita) for the USA, China, and India, which encompasses a period from 1990 to 2019, was obtained from the World Bank's website. The annual CO_2 emission data was converted to a monthly data sequence for analysis in this study. The graphical illustration of the GPR Index and the CO_2 emission is given in Figures 1-3.

The graph in Figure 1 shows the relationship between China's GPR Index and its CO_2 emissions from 1990 to 2019. The graph depicts an upward trend in both variables over time, which suggests a positive correlation between geopolitical risk and CO_2 emissions. It can be observed that China's GPR index and CO_2 emissions have increased sharply since 2005. This suggests that the geopolitical risks have increased significantly in China since then, which has been accompanied by an increase in carbon emissions.

Figure 1: China's GPR versus CO_2 emission

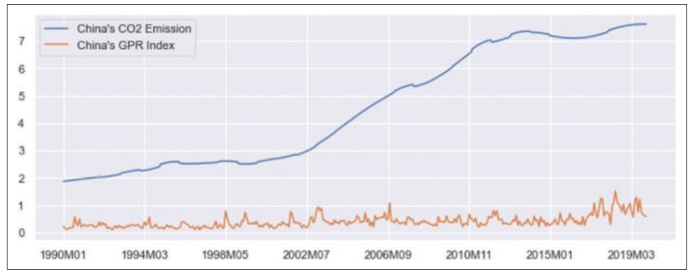


Figure 2: USA GPR versus CO_2 emission

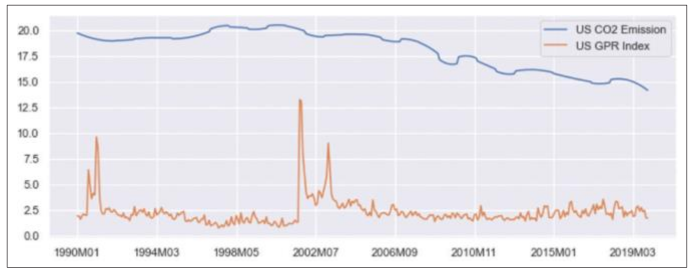
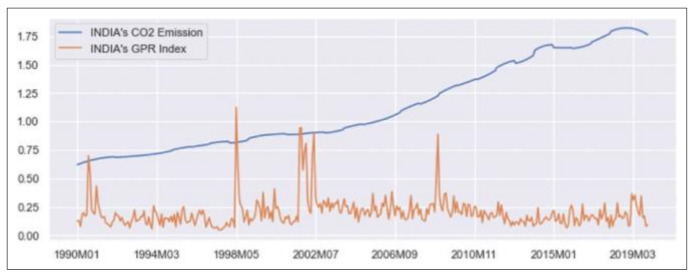


Figure 3: India's GPR versus CO_2 emission



In Figure 2, The graph shows the relationship between the GPR Index and CO_2 emissions for the USA from 1990 to 2019. The graph depicts a positive correlation between geopolitical risk and CO_2 emissions, with both variables increasing over time. However, unlike China, the USA's GPR index remained relatively stable until 2001 and began to show an upward trend after the 9/11 terrorist attacks. It can be observed that the CO_2 emissions have gradually increased over time, however, with a decline in the trend after the 9/11 attacks. This indicates a negative association after 9/11.

Figure 3 shows the relationship between India's GPR Index and its CO_2 emissions from 1990 to 2019. The graph depicts an upward trend in both variables, suggesting a positive correlation between geopolitical risk and CO_2 emissions in India. It can be observed that India's GPR index has remained relatively stable, with a few fluctuations, while CO_2 emissions have steadily increased over time. The graph shows that India's CO_2 emissions surpassed its GPR index, implying that India's CO_2 emissions increased at a faster rate compared to its geopolitical risks during this period.

2.2. Data Description/Input Model

The monthly CO_2 emission and GPR Index were divided into training dataset and testing dataset. Out of a total of the 360

Table 1: Data description

Country	Dataset	Sample	Size	Statistical Indicator			
				Max	**Min**	**Mean**	**Standard**
China	GPR Index	All Dataset	360	1.52	0.09	0.40	0.23
		Train Data	240	1.08	0.09	0.33	0.15
		Test Data	120	1.52	0.20	0.55	0.27
	CO_2 Emission	All Dataset	360	7.62	1.87	4.55	2.10
		Train Data	240	6.08	1.87	3.26	1.23
		Test Data	120	7.62	6.01	7.13	0.35
	Dataset	**Sample**	**Size**	**Statistical Indicator**			
				Max	**Min**	**Mean**	**Std.**
India	GPR Index	All Dataset	360	1.12	0.04	0.20	0.13
		Train Data	240	1.12	0.04	0.21	0.15
		Test Data	120	0.36	0.06	0.16	0.06
	CO_2 Emission	All Dataset	360	1.82	0.62	1.12	0.38
		Train Data	240	1.31	0.62	0.88	0.17
		Test Data	120	1.82	1.31	1.60	0.15
	Dataset	**Sample**	**Size**	**Statistical Indicator**			
				Max	**Min**	**Mean**	**Std.**
USA	GPR Index	All Dataset	360	13.22	0.75	2.29	1.35
		Train Data	240	13.22	0.75	2.37	1.61
		Test Data	120	3.55	1.43	2.13	0.48
	CO_2 Emission	All Dataset	360	20.49	14.14	18.15	1.88
		Train Data	240	20.49	16.67	19.34	0.81
		Test Data	120	17.49	14.26	15.79	0.81

data points, 240 data points from 1990 to 2009 (19 years) was used as the training dataset while the remaining 120 data points from 2010 to 2019 (9 years) was used as the testing dataset. The statistical description for the train/test dataset is as depicted in Table 1 while Table 2 describes the structure of the deep learning input/output model.

Table 1 presents statistical data related to GPR Index and CO_2 Emission for China, India, and the USA. The table is divided into three sections based on the country. Each section has columns: the dataset name, the sample size, the maximum value, the minimum value, the mean, and the standard deviation. For each country, the data is divided into three subsets: All Dataset, Train Data, and Test Data. The Train Data set is used to train the model, and the Test Data set is used to test the model's accuracy. The data was split into 240 and 120 for Train and Test Data sets, respectively, for all the countries. The standard deviation is a measure of how much the data deviates from the mean value. The standard deviation for the CO_2 Emission is higher than that of the GPR Index for all the countries, indicating that the data is more spread out for CO_2 Emission values than for GPR Index values.

Table 2 represents an Input/Output Model that relates GPR Index and CO_2 Emission. The model is used for prediction purposes and takes the form of a linear regression model where GPR Index serves as the input variable (X) and CO_2 Emission serves as the output variable (Y). The table includes two sets of data: Train and Test. Train data consists of 240 observations and Test data consists of 120 observations. Each observation in the dataset contains four input variables (X1 to X4) and one output variable (Y1 to Y4). The model was created by analysing the relationship between GPR Index and CO_2 Emission using the training data and can be used to predict CO_2 Emission for new values of GPR Index.

Table 2: Input/output model

	GPR index-CO_2 emission model						Output (CO_2 Emission)
	Input (GPR Index - CO_2 Emission variable)						
Train	X_1	X_2	X_3	Y_1	Y_2	Y_3	Y_4
	X_2	X_3	X_4	Y_2	Y_3	Y_4	Y_5
	…						…
	X_{237}	X_{238}	X_{239}	Y_{237}	Y_{238}	Y_{239}	Y_{240}
Test	X_{238}	X_{239}	X_{240}	Y_{238}	Y_{239}	Y_{240}	Y_{241}
							…
	X_{357}	X_{358}	X_{359}	Y_{357}	Y_{358}	Y_{359}	Y_{360}

In the table, Y represents the CO_2 Emission and X represents the GPR Index

3. RESULTS AND DISCUSSION

The results obtained from the experiment as depicted in Table 3 and illustrated in Figure 4a-c suggest that deep learning models, specifically CNN, LSTM, and ConvLSTM, can be used to accurately predict carbon emissions for China, India, and the USA. The models were able to predict carbon emissions with reasonable accuracies, as indicated by the RMSE, MAE, R^2, and MAPE values.

In general, the lower the values for RMSE and MAE the better the model's predictive power. A higher R^2 value indicates a stronger correlation between the predicted and actual carbon emissions, and a lower MAPE value suggests that the model's predictions are closer to the actual values. The following discusses the results obtained by country base on the evaluation metrics:

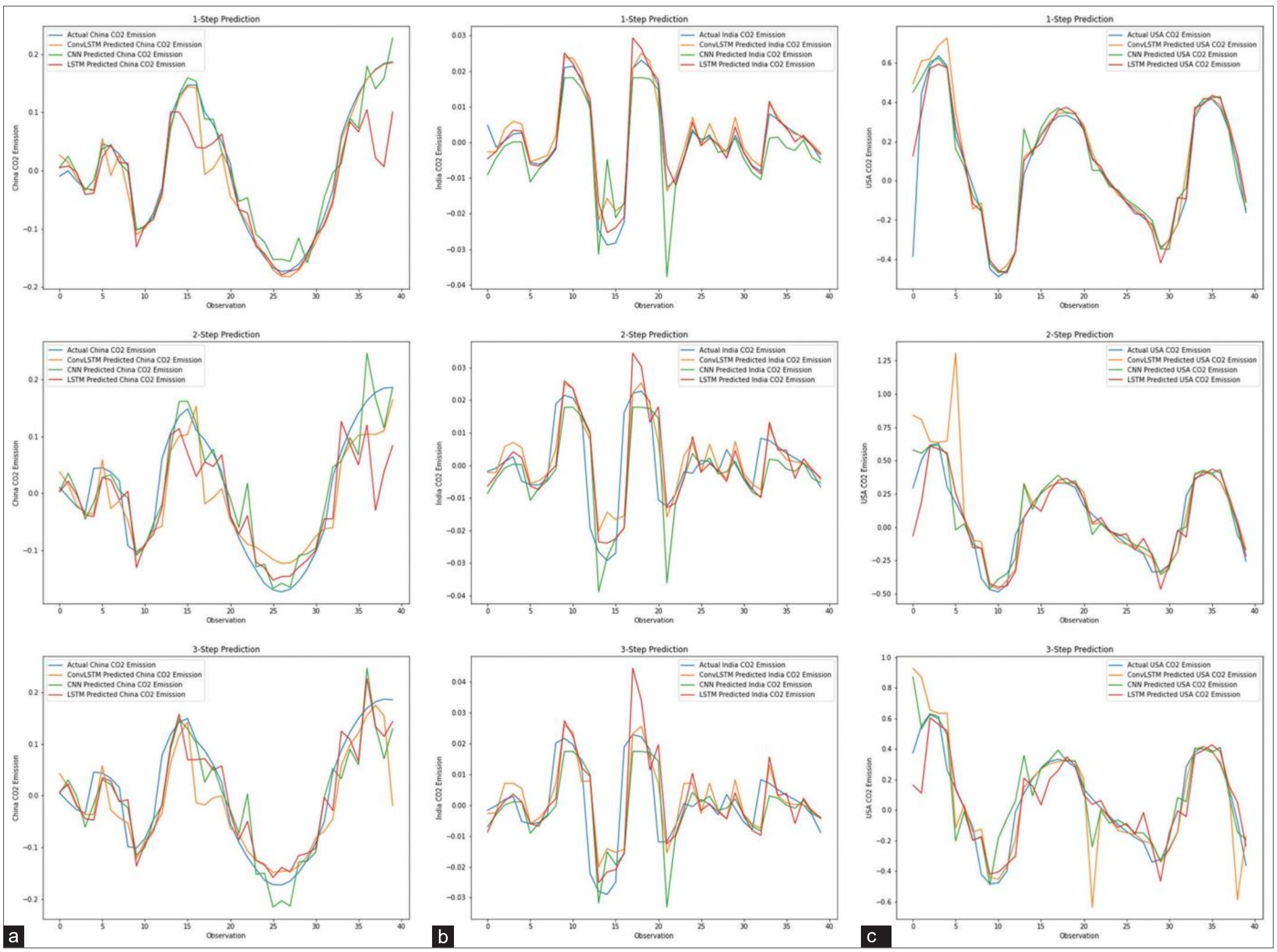
3.1. China

The CNN model performs the best on the 1-step prediction with RMSE of 0.0237, offering the most accurate short-term forecasts. However, accuracy decreases as the prediction horizon extends to 2-step and 3-step predictions with RMSE of 0.0405 and 0.0474

Table 3: Error measures of predicted CO_2 emission versus actual CO_2 emission

Country	Model	RMSE			MAE			R^2			MAPE		
		1-step	2-step	3-step	1-step	2-step	3-step	1-step	2-step	3-step	1-step	2-step	3-step
China	CNN	0.0237	0.0405	0.0474	0.0188	0.0286	0.0358	0.9535	0.8679	0.8225	160.4499	53.2605	50.9189
	LSTM	0.0493	0.0607	0.0441	0.0294	0.0427	0.0348	0.7977	0.7026	0.8466	80.8653	62.9549	52.3238
	ConvLSTM	0.0267	0.0492	0.0555	0.0151	0.0395	0.0381	0.9406	0.8045	0.7567	129.4119	66.2540	78.4026
	Model	**RMSE**			**MAE**			**R^2**			**MAPE**		
		1-step	**2-step**	**3-step**	**1-step**	**2-step**	**3-step**	**1-step**	**2-step**	**3-step**	**1-step**	**2-step**	**3-step**
India	CNN	0.0067	0.0107	0.0108	0.0041	0.0064	0.0065	0.7181	0.3138	0.3075	80.6431	101.6879	249.4981
	LSTM	0.0031	0.0105	0.0113	0.0019	0.0063	0.0070	0.9424	0.3376	0.2390	34.5713	118.3902	320.3497
	ConvLSTM	0.0037	0.0092	0.0098	0.0026	0.0058	0.0066	0.9160	0.4881	0.4263	73.9808	139.0925	248.8894
	Model	**RMSE**			**MAE**			**R^2**			**MAPE**		
		1-step	**2-step**	**3-step**	**1-step**	**2-step**	**3-step**	**1-step**	**2-step**	**3-step**	**1-step**	**2-step**	**3-step**
USA	CNN	0.1426	0.1129	0.1621	0.0558	0.0797	0.1074	0.7844	0.8567	0.7166	61.5085	71.4954	79.2637
	LSTM	0.0916	0.1280	0.1425	0.0437	0.0834	0.1015	0.9110	0.8158	0.7809	39.0519	59.3578	114.3787
	ConvLSTM	0.1497	0.2262	0.1984	0.0569	0.1013	0.1039	0.7625	0.4242	0.5751	41.9768	72.5494	111.1880

Figure 4: (a) China's predicted CO_2 versus actual CO_2 emission, (b) India predicted CO_2 versus actual CO_2, (c) USA predicted CO_2 emission versus actual CO_2



respectively. LSTM performs worse than CNN for the 1-step and 2-step predictions, with the highest RMSE for the 2-step prediction, indicating poor mid-term performance. However, it slightly improves for the 3-step prediction, outperforming CNN for the longest forecast horizon. ConvLSTM is in between CNN and LSTM, performing well for the 1-step prediction, though not as well as CNN. However, its RMSE increases substantially for 2- and 3-step predictions, indicating a decline in accuracy as the prediction range expands.

For the MAE which provides insight into the average prediction error, with lower values indicating better performance. The CNN model performs well for the 1-step prediction with a value of 0.0188, showing small errors in the short term. However, as the prediction horizon increases, the MAE increases steadily, indicating a growing average error for 2-step and 3-step predictions. The LSTM model has higher errors in the 1-step and 2-step predictions compared to CNN, indicating poorer short-term and mid-term accuracy. However, the MAE for the 3-step prediction is lower than CNN's, suggesting LSTM handles longer-term predictions slightly better. ConvLSTM performs the best for the 1-step prediction, with the smallest MAE of 0.0151. However, it shows increased errors for the 2-step and 3-step predictions, where its performance worsens relative to CNN and LSTM.

In terms of R^2, The CNN model performs exceptionally well for 1-step predictions, capturing over 95% of the variance. However, R^2 declines as the prediction horizon increases, indicating the model's decreasing predictive power over longer time steps. LSTM has a lower R^2 for 1-step and 2-step predictions, implying less accuracy in short-term predictions compared to CNN. However, for the 3-step prediction, LSTM performs better than CNN, showing stronger long-term predictive power. The ConvLSTM model exhibits high predictive accuracy in short-term (1-step) with an R^2 value of 0.9406, but the performance drops for longer-term predictions (2-step and 3-step) with R^2 values of 0.8045 and 0.7567.

For MAPE, which expresses prediction accuracy as a percentage, the CNN has an unusually high MAPE of 160.4499 for the 1-step prediction, indicating large relative errors. The 2-step and 3-step predictions are significantly better but still suggest room for improvement. LSTM's MAPE values show a steady improvement with longer prediction steps. While not perfect, the MAPE indicates relatively better performance than CNN for 1-step and similar performance for longer steps. The ConvLSTM model has better 1-step performance than CNN but worse performance than LSTM. Its error rate increases more than expected for longer-term predictions (especially 3-step), making it less reliable for those scenarios.

3.2. India

The CNN model performs well for the 1-step prediction with an RMSE of 0.0067, but the error increases slightly as the forecast horizon expands (0.0107 for 2-step, 0.0108 for 3-step). The LSTM model outperforms CNN in the short-term (1-step RMSE = 0.0031), but its performance declines as the steps increase (slightly worse at 3-step: 0.0113). ConvLSTM balances performance well across all steps. While not the best for 1-step prediction (0.0037), it has a more consistent performance for the 2-step and 3-step predictions (0.0092 and 0.0098), outperforming both CNN and LSTM in mid-term and long-term forecasts. So, while the LSTM has the lowest error for 1-step prediction, showing its strength in short-term forecasting. ConvLSTM has a more balanced performance across all steps, which suggests it handles long-term forecasting slightly better than the other models.

In terms of MAE, the CNN model in its 1-step prediction error is 0.0041, but increases for 2-step (0.0064) and stays relatively stable for 3-step (0.0065). LSTM has the lowest MAE for the 1-step prediction (0.0019), suggesting it captures short-term trends well. Its error slightly increases over the 2-step and 3-step predictions (0.0070 for 3-step). ConvLSTM produces the best overall performance for 2-step prediction (0.0058), slightly trailing LSTM for 1-step but keeping errors relatively low for longer-term forecasts. So, the LSTM model is superior for short-term predictions (1-step), while ConvLSTM strikes a better balance for longer forecasts.

In terms of R^2, the CNN model is strong for 1-step (0.7181) but loses predictive power significantly for 2-step and 3-step forecasts (R^2 drops below 0.32). The LSTM model is best fit for 1-step (0.9424), but it suffers a similar drop-off for longer-term predictions, where the R^2 values are considerably lower (0.2390 for 3-step). ConvLSTM, the second-best for short-term (0.9160 for 1-step) and performs better than CNN and LSTM for mid-term predictions (2- and 3-step), maintains a higher R^2. Hence, the LSTM model provides the best fit for short-term predictions, while ConvLSTM maintains a better fit over longer time horizons.

For Mean Absolute Percentage Error (MAPE), the CNN model resulted in a high value for the 1-step prediction (80.6431) and escalates dramatically for the 3-step prediction (249.4981), indicating poor accuracy in longer-term forecasts. While the LSTM model performs much better in the short term with a MAPE of 34.5713 but struggles more as the forecast horizon expands (320.3497 for 3-step). The ConvLSTM model struggles less than CNN and LSTM in terms of relative error growth but still shows high MAPE values for 2- and 3-step predictions (248.8894 for 3-step). Hence, the LSTM has the lowest MAPE for the short-term forecast, suggesting better relative accuracy for 1-step predictions. However, the errors escalate rapidly for all models in the long term, making it challenging to rely on these models for precise longer-term predictions.

3.3. USA

The CNN performs well in 2-step predictions (0.1129), but its RMSE increases for both 1-step and 3-step predictions. The increase in RMSE from 2-step to 3-step (from 0.1129 to 0.1621) shows that CNN struggles with longer-term predictions, becoming less accurate over time. The LSTM model achieves the lowest RMSE across all steps, especially for 1-step (0.0916) and 3-step predictions (0.1425), meaning LSTM is the most accurate model overall. The slightly higher RMSE in the 2-step prediction (0.1280) indicates a slight dip in mid-term accuracy but still outperforms CNN and ConvLSTM across all steps. ConvLSTM performs worse than both CNN and LSTM across all steps, with the highest RMSE values in 2-step (0.2262) and 3-step (0.1984). This suggests that ConvLSTM struggles more with longer-term forecasts compared to the other models. Hence, the LSTM provides the most accurate predictions overall, while ConvLSTM's increasing RMSE for 2-step and 3-step predictions reflects poorer performance in medium and long-term forecasts. CNN shows a balance for 2-step but weakens for 3-step predictions.

In terms of MAE, the CNN model performs moderately well in 1-step (0.0558) and 2-step predictions (0.0797), but its error increases significantly in the 3-step prediction (0.1074), which shows CNN's declining accuracy as prediction horizons extend. The LSTM achieves the lowest MAE for 1-step predictions (0.0437), indicating superior short-term accuracy. While, LSTM shows an increase in MAE for the 2-step and 3-step predictions, it still performs slightly better than CNN in the 3-step prediction (0.1015 vs. 0.1074). ConvLSTM's MAE for 1-step (0.0569) and 3-step predictions (0.1039) is higher than both CNN and LSTM, indicating that ConvLSTM struggles more with maintaining accuracy across different horizons. Hence, the LSTM is the most reliable model for minimizing error across all prediction horizons, particularly excelling in short-term (1-step) predictions. CNN performs well for mid-term forecasts, but its errors increase in longer-term forecasts, and ConvLSTM consistently underperforms.

The R^2 obtained from the CNN model is strongest in the 2-step prediction (0.8567), indicating a good fit for mid-term forecasts. However, it drops for 1-step (0.7844) and 3-step predictions (0.7166), showing declining accuracy in short- and long-term forecasting. The LSTM model outperforms CNN and ConvLSTM with the highest R^2 for 1-step predictions (0.9110), meaning it captures most of the variance in short-term forecasts. For the 2-step predictions, LSTM's R^2 (0.8158) is lower than CNN's, still indicating strong performance, and 3-step (0.7809) showing that LSTM handles long-term predictions better than CNN. The ConvLSTM shows the lowest R^2 for 2-step predictions (0.4242), indicating poor mid-term forecasting accuracy. While, it performs reasonably in 1-step predictions (0.7625), ConvLSTM's performance deteriorates quickly as the prediction horizon extends. Hence, the LSTM is the most consistent performer, with the highest R^2 for short-term predictions and strong long-term performance. CNN is better suited for mid-term predictions, but its overall predictive power diminishes for longer-term forecasts. ConvLSTM struggles to explain the variance in the data, particularly for mid- to long-term predictions.

As for the MAPE, the CNN exhibits high MAPE for 1-step predictions (61.5085), indicating poor relative accuracy in short-term predictions. Although it improves for 2-step (71.4954) and 3-step predictions (79.2637), these values are still high, reflecting relatively large errors. The LSTM has the lowest MAPE for 1-step predictions (39.0519), suggesting that it performs best in terms of relative accuracy for short-term forecasts. However, for 3-step predictions, LSTM's MAPE rises dramatically to 114.3787, indicating poor relative accuracy in long-term forecasting despite its lower RMSE and MAE. The ConvLSTM's MAPE values show poor relative performance in 2-step (72.5494) and 3-step predictions (111.1880), suggesting that its predictions have significant relative errors as the prediction horizon extends. Hence, the LSTM provides the most accurate short-term predictions in terms of relative error (MAPE), but it struggles with long-term accuracy. CNN shows consistently high MAPE values across all horizons, and ConvLSTM shows a steep decline in accuracy for longer-term predictions.

4. DISCCUSSION AND IMPLICATIONS

This study reveals the following key insights about the implications of geopolitical risk on environmental forecasting and the effectiveness of deep learning models in this domain.

a) Impact of Geopolitical Risk on CO_2 Emissions: Geopolitical risk significantly impacts CO_2 emissions in all three countries: China, India, and the USA, but in different ways based on the economic, energy, and policy frameworks of each country. For China, its heavy reliance on fossil fuels leads to more unpredictable emission patterns, particularly over longer-term predictions. In India, the growing renewable energy sector helps mitigate some of the risks, but longer-term forecasts still show higher errors. In the USA, shifts in energy policy and international relations due to geopolitical risks make future emissions harder to predict, especially for multi-step forecasts, as indicated by increased prediction errors.
b) Deep Learning Models' Predictability under Geopolitical Risk: The performance of deep learning models (CNN, LSTM, ConvLSTM) in predicting CO_2 emissions under the influence of GPR indices varies across countries. Short-term predictability is highest with LSTM models across all countries, capturing immediate responses to geopolitical events. However, long-term predictability decreases for 2-step and 3-step predictions due to the increasing complexity of geopolitical risks, as reflected by higher error metrics. LSTM consistently outperforms CNN and ConvLSTM, especially for short-term forecasts, while ConvLSTM struggles with long-term predictions, suggesting that temporal dynamics are more crucial than spatial factors in predicting CO_2 emissions driven by geopolitical risk.
c) Country-Specific Implications: China's higher RMSE and MAPE values for longer-term predictions indicate that its CO_2 emissions are highly sensitive to geopolitical risks due to its global trade reliance and industrial activities. In contrast, India shows resilience in short-term predictions with lower error rates, but increasing errors in long-term forecasts highlight uncertainty around future energy policies. The USA exhibits strong short-term emission predictability through the LSTM model, but declining accuracy in longer-term predictions suggests that geopolitical risks create significant uncertainty in its future emissions, driven by complex energy policies and global influence.
d) General Implications for Policy and Forecasting: The studies suggest that while AI and deep learning models can effectively predict CO_2 emissions in the short term, geopolitical risks add significant uncertainty to long-term predictions. Policymakers should be cautious when relying on long-term forecasts for environmental planning, particularly in geopolitically volatile regions. Additionally, deep learning models like LSTM, which excel in temporal prediction, may be more appropriate for short-term environmental policy and decision-making, whereas more robust and hybrid models may need to be developed for longer-term predictions under geopolitical risks.

5. CONCLUSION AND RECOMMENDATION

In conclusion, geopolitical risk indices play a critical role in the predictability of CO_2 emissions, with the ability to disrupt short-term and long-term emission patterns. The variability in model performance across China, India, and the USA highlights the need for tailored prediction approaches that account for each country's geopolitical landscape, energy policies, and economic activities.

Although, the LSTM model consistently outperforms the CNN and the ConvLSTM models for short term CO_2 emission prediction, its performance continues to decline as the steps increases for medium and long-term forecasts.

Policymakers should take these insights into account when formulating strategies to mitigate geopolitical risks and reduce CO_2 emissions. As future work, further research can explore additional contextual factors that impact CO_2 emissions, enabling more comprehensive and accurate prediction models tailored to individual countries. Additionally, expanding this study to include more countries and exploring the temporal evolution of the relationship between geopolitical risks and CO_2 emissions can provide deeper insights into the global dynamics of this critical issue.

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