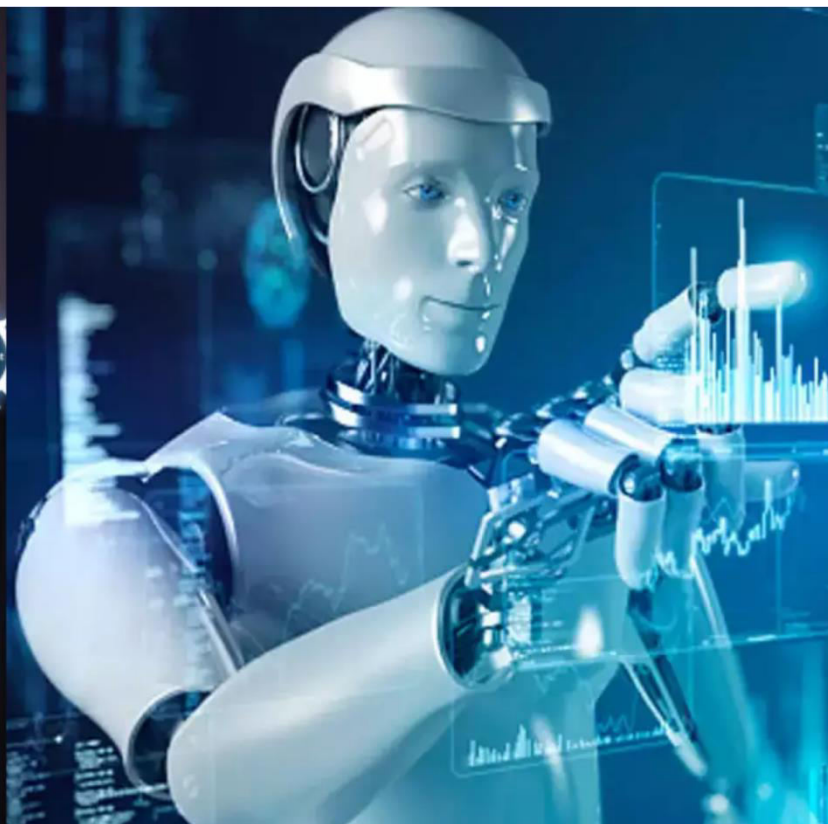




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Forecasting Global Mean Sea Level Rise from Temperature and CO₂ Historical Trends using LSTM Model

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ABSTRACT: To understand the impacts of climate change and help adapt to the coastline, proper prognosis of the Global Mean Sea Level (GMSL) is essential. The article develops forecasting algorithms using the Long short-term memory (LSTM) neural networks applied to historical data of GMSL, global surface temperature variations, and the CO₂ levels in the atmosphere between 1880 and 2023. Univariate models (through the application of GMSL only) and multivariate models (by incorporating temperature and CO₂) were constructed and optimized to capture complex time trends. Results indicate that the univariate models have the ability to provide the base forecast but the multivariate LSTMs can significantly enhance the accuracy of the forecast as they include the nonlinear interaction between climatic drivers. Multivariate model is more likely to forecast in the long run and may offer valuable information to decision-makers, planners, and environmental researchers in terms of predicting future sea level rise. The paper determines the utility of incorporating historical climatic data into advanced approaches of deep learning to avert assist in guiding evidence-based mitigation and adaption programs along vulnerable coasts.

KEYWORDS: Global Mean Sea Level, LSTM, Climate Forecasting

I. INTRODUCTION

The rise in global mean sea level (GMSL) is considered one of the biggest consequences of climate change and poses a serious threat to ecosystem and infrastructure and human populations in the coastal areas. According to Intergovernmental Panel on Climate Change (IPCC), the sea level rose by about 20 cm since 1900, and the pace of these changes is growing at an ever-growing pace during the past several decades (Hamdan et al., 2023). This is primarily because the ocean water is expanding due to global warming and melting glaciers and ice sheets that have a very close correlation with the amount of carbon dioxide (CO₂) in the atmosphere and the increasing global temperature. In order to come up with the adaptive strategies, the GMSL must be accurately forecasted in the case of the vulnerable areas in the coastlines (Tumse and Alcansoy, 2025).

The traditional statistical/physical models have been helpful in some cases, but generally cannot well describe the nonlinear, dynamic interactions among two or more climatic variables. The recent advancements of deep learning and Long Short-Term Memory (LSTM) neural networks give prospects to predict time series in climatic science (Balogun and Adebisi, 2021). The latter are very useful in GMSL prediction, as lasting dependence and non-linear relationship LSTM models can address both of these properties. The data presented in historical records of the sea level, the earth surface temperature, and atmospheric carbon dioxide in this paper allow creating univariate and multivariate LSTM models that can contribute to enhancing the precision of the prediction and supporting climate adaptation planning with evidence (Song et al., 2023).

II. RATIONALE AND OBJECTIVE

Sea level (GMSL) rise is not only a scientific concern but also a policy focus, where any small rises in sea level may raise flooding or coastal erosion and socio-economic vulnerability (Elneel et al., 2024). Past records show that the rise in sea levels is largely influenced by the temperature anomalies worldwide and the level of carbon dioxide (CO₂) in the atmosphere that continues to rise at an unprecedented rate. Even though the traditional statistical and process based models have been useful in the study of these dynamics, it could also be constrained in predicting them because of the

linear assumption and complication in modeling non-linear interaction over time of various climate variables (Uluocak, 2025).

The second successful alternative is Long Short-Term Memory (LSTM) neural networks alternative also referred to as deep learning. The LSTMs are a big asset regarding sequential data and being able to capture time-based dependencies including hidden connections hence they are very relevant in the model of the sea level rise complexities (Hilal et al., 2024). The study is motivated to develop sound and solid models of data which does not only use the past GMSL records but also adds the relationship of temperature and CO₂ to improve the accuracy of the forecast.

The key objectives of this research are:

1. To develop univariate and multivariate LSTM models for GMSL forecasting.
2. To compare the predictive performance of models using only GMSL with those incorporating CO₂ and temperature.
3. To provide insights that can inform climate adaptation and coastal risk management strategies.

III. METHODOLOGY

The research study is carried out as a quantitative study based only on secondary data that are publicly accessible and credible databases on climate. The database was based on historical data of Global Mean Sea Level (GMSL), global surface temperature changes, and carbon dioxide (CO₂) concentration levels in the atmosphere between 1880 and 2023. The fact that secondary data are standard, generally accepted and updated by reputable institutions of climate research make them credible (Cheng, 2023).

Prior to the training of the model, all the variables were normalized to normalize the data before modeling. Any holes or inaccurate values were filled and the data were normalized into time-series sequences that can be inputted into deep learning. The following forecasting models have been built on the basis of Long short term memory (LSTM) neural networks, which are more suitable in sequential data. Two were performed, including univariate processing (only GMSL applied) and multivariate processing (GMSL applied, in combination with temperature and CO₂). The parameters such as learning rate, a batch size, and the number of epochs were adjusted to give the model optimization. Measures of performance were Mean Absolute Error (MAE) and Root Mean SquareError (RMSE).

The ethical considerations were taken in the form of utilizing non-personal and exclusively open access data, openness of the methodology of research and avoidance of bias and manipulations in data selection and report (Ranasinghe, 2025).

IV. LITERATURE REVIEW

Theme 1: Historical Trends in Global Mean Sea Level (GMSL)

Sadhukhan et al. (2022) state that Global Mean Sea Level (GMSL) has been rising continuously since the late 19th century because of the major causes of human-induced climate change and natural variability. Observational record of tide gauges and satellite altimetry records indicate that GMSL has been increasing at a rate of approximately 20 centimeters over the past 140 years, and has been gaining momentum over the past decades (Reich et al., 2020). The increases have been relatively low in the beginning, 1-2 millimeters/year in the 20th century. Later measurements, however, show higher levels of rates of more than 3 millimeters per year, an indication that the factors which are involved are still further propagated.

Chin, S. and Lloyd (2024) postulated that the reduction in ice and the expansion of sea water on land is the primary contributor of the rise in GMSL. This increase can be attributed in part to the warming of surface water as the world temperature increases hence taking on the heat and causing the water to swell. Meanwhile, the melting of glaciers and ice sheets in Greenland, Antarctica, and other regions has also occurred very fast supplying oceans with significant quantities of freshwater. These mechanisms cannot be universal everywhere in the world and it is why the sea level changes not everywhere due to several factors such as ocean circulation, land gravity influence, and land subsidence.

Wen et al. (2023) suggest that historical datasets play a critical role in studying and forecasting the change of sea level. Long-term records of tide gauges and satellite altimetry are part of continuous measurements of coastal and nearshore heights since the beginning of the 1990s which is an accurate measure of the global elevation of the sea surface

(Accarino et al., 2021). Combining such data sets, scientists are able to reproduce the past variations of the GMSL, trend variations, and test predictive models. The current records play a crucial role in the training of the advanced forecasting techniques, including machine learning and LSTM, since it operates with the linear and nonlinear time dynamics. Knowing these trends, scientists will have more possibilities to forecast future sea levels and help planning of the coastal zone and the adaptation of climate changes.

To recap it all, proper forecasting is anchored on historical trends of GMSL knowledge, of changes processes as well as the significance of quality datasets. This will be critical in predicting the increased sea level in future and mitigating the extent of its impacts on the endangered communities and ecosystems.

Theme 2: Climate Drivers – Temperature and Atmospheric CO₂

Global sea level rise has been described by Ayinde et al. (2024) to be linked directly to climate changes on Earth, which refers to surface temperature and the concentration of carbon dioxide (CO₂) in the air. Surface temperatures deviation as a kind of deviation of long-term average temperatures has direct consequences on sea level because it leads to the thermal expansion of the ocean water. Ocean warming also causes the water molecules to move faster and occupy a larger area that contributes to the noticeable increase in Global Mean Sea Level (GMSL). It has been demonstrated that even minor warming of the world temperature can lead to devastating effects on sea level in the long-term, which is why oceanic processes are sensitive to climate changes (Tebaldi et al., 2021).

Elabd et al. (2025) using their findings indicate that Atmospheric CO₂ is among the leading of the greenhouse gases, which trap the heat in the earth atmosphere. Increase in CO₂ concentrations enhances the greenhouse effect which leads to increment in world temperatures and consequently rise in sea level. There are also higher levels of CO₂ leading to the melting of glaciers and ice sheets that add freshwater to the seas and boost GMSL. The CO₂ present in the atmosphere has surged in the past century by over 420 parts per million (ppm) and has been linked strongly to temperature and sea level.

As Ayaz (2024) has mentioned, the relationship between CO₂ and the sea level is nonlinear and complicated in most circumstances. It is the process of sea level change that creates dynamic and unpredictable patterns through the interaction such as ice-albedo processes, ocean- atmosphere interactions etc. One such example is that warming may result in some regions melting ice faster than others, or that ocean currents in a region or near a region can distribute heat unevenly, affecting that region more than the rest of the planet (Vignudelli et al., 2019). It is necessary to observe that such nonlinear interactions must be taken into account when the appropriate forecasting models are developed as linear models may either underestimate or over simplify the potential future changes.

Another idea is that the combined effect of temperature variations and CO₂ levels can contribute to the creation of a more precise, comprehensive, and efficient projection of the sea level, as Elneel et al. (2023) assume. With these climate drivers incorporated in the predictive modeling, such as Long Short-Term Memory (LSTM) networks, researchers can predict the complicated dependence between the variables and improve the accuracy of the predictions (Sweeney et al., 2020). Finally, the knowledge affects the climate change adaptation and policymaking in managing the coastal and marine risks.

Theme 3: Traditional Approaches to Sea Level Forecasting

According to Taylor and Feng (2022), Forecasting Global Mean Sea Level (GMSL) was traditionally founded on both models based on statistics and models that also have advantages and weaknesses. Autoregressive Integrated Moving Average (ARIMA) and linear regression, time-series decomposition are some of the most common statistical models used to analyze historical records about the sea level. These models set trends, seasonal changes and cyclical changes and may be applied to forecast in the short run or medium run the outcome of a dependent variable on the basis of previous data. They are simple to operate and apply and are useful in settings where it is probable that the relations between the variables will be linear in nature.

Nieves et al. (2021) on their part added that Process-based models are founded on the physical principles of oceanography and glaciology. These models are used to simulate climatic drivers such as temperature increases and CO₂ levels on oceans and ice sheets. Process based models provide a mechanistic explanation of how the sea level changes as they incorporate such processes as thermal expansion, melting ice and also change in ocean circulation. They can be

particularly used to predict long-term forecasting and analyze the situation within the framework of different climatic change scenarios (Kamran et al., 2025).

The conventional models, despite their usefulness, have major disadvantages, according to Ahmed et al. (2023). The complex and nonlinear interactions between climatic variables can cause statistical models to have challenges in coming up with oversimplified forecasts. Process-based approaches that are physically detailed are computationally cheap, yet require abundant computational resources and appropriate parameterization which can be complex because of uncertainty in ice sheet response and local ocean reactions Medeiros et al., 2021). Furthermore, it can be said that the two approaches can be questioned with regard to the simultaneous integration of many interdependent factors, such as the relationship between atmospheric CO₂ concentration and temperature variations, without necessarily making assumptions that would render predictability flawed.

Creel et al. (2024) also included that these restrictions have led to the creation of more advanced computational algorithms, including machine learning and deep learning, in order to be capable of tackling nonlinearities and high dimensional data. The understanding of weaknesses and strengths of the traditional models provides the basis on which one can compare newer models, such as Long Short-Term Memory (LSTM) neural networks, to increase the accuracy and reliability of sea level predictions (Bharadiya et al., 2023).

Theme 4: Deep Learning in Climate and Environmental Forecasting

Horton et al. (2020) additionally note that more recent advances in computational intelligence introduced machine learning techniques as a powerful tool of climate and environmental prediction. RNNs are particularly suitable to process the sequence data since, unlike alternative types of neural networks, they can be utilized to reveal time-dependent trends and patterns (Camporeale, 2019). The classical RNNs, nevertheless, are typically related to a number of problems such as vanishing gradients that limit their ability to learn long term dependencies in climate information time-series.

Wang et al. (2021) noted that Long Short-Term Memory (LSTM) networks are a certain kind of RNN that can address these limitations by employing memory cells and gating mechanisms to store any information that is important over a long period of time. Together with their capability to obtain complex and nonlinear correlations inherent to climate data, such as interdependencies among sea level, temperature anomalies, and atmospheric CO₂ concentrations, LSTMs become a highly useful model to work with. Indeed, the LSTMs can assign importance to the past data in a dynamic way, hence they can better forecast the future trend compared to the conventional statistical tools.

Dangendorf et al. (2018) note that LSTM models have been successfully applied to other kinds of climate-related forecasting. They have, as an example, been used to predict surface temperature variations, rain patterns, and CO₂ concentration of the atmosphere, where they perform better than linear models and conventional RNNs. LCSTMs can be applied in rain forecasting since it has a potential to recreate seasonal cycles and extreme precipitation which are precision forecasts in controlling water resources. Similarly, LSTMs can predict temperatures and CO₂ since it can capture long-term and short-term variations to aid in climate mitigation and adaptation measures.

According to Hamlington et al. (2020), the successes in the following fields of LSTM models suggest that it can be utilized in the Global Mean Sea Level (GMSL) prediction in which long-term dependencies and nonlinearity interacting are critical factors (Kumar et al., 2023). Using previous climate data, LSTMs have the ability to integrate multiple forecasts, such as GMSL, temperature, and CO₂ to create robust and valid predictions. This will be particularly effective in forecasting sea level rise in the future and the corresponding risk management actions in relation to the coastline.

In summary, deep learning techniques and LSTMs in particular offer a flexible and effective model of climate prediction, which outsmarts the weaknesses of the classical ones and enables the study of the complicated environment on a broader scale.

Theme 5: LSTM Models for GMSL Forecasting – Univariate vs. Multivariate Approaches

Ollila (2023) found that usages of Long Short-Term Memory (LSTM) models have been on the rise when it comes to predicting Global Mean Sea Level (GMSL) due to the ability to capture trends, both long-term and nonlinear, in time-series data. Univariate LSTM models with only historical GMSL have been widely used to make short and medium-

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term predictions. Based on historical data, these models project the future of the sea level that provides an adequate level of accuracy when the changes of GMSL are largely determined by the past (Suradhaniwar et al., 2021). Univariate techniques are simpler in use and less computer time is required hence, good starting point when it comes to predictive modeling.

However, the researchers claim that the rise of sea level seems to be influenced by a set of interrelated climate parameters, such as global temperature imbalances and atmospheric CO₂ levels (Piao et al., 2018). Multivariate LSTM networks operate on these additional predictors and enable a better understanding of the working mechanism of sea level changes. The combination of temperature and CO₂ trends can allow multivariate models to incorporate complex interactions and nonlinear dependencies which univariate models can fail to capture. It also results in improved predictive performance, particularly those made when predictions extend far in time when they are strongly influenced by climate drivers.

Comparative studies Multivariate LSTM models tend to be stronger and more reliable in comparison to univariate models since they have better predictive power as stated by Fernandez-Martinez et al. (2019). As an example, the addition of temperature and CO₂ enables the model to forecast when the sea level increases rapidly because of rapid warming or greenhouse gases (Luaran et al., 2021). Such improvements have implications in policy and adaption planning are critical because exact predictions of sea level rise are vital in the management of coasts, infrastructure planning and disaster preparedness.

In short, multivariate models, which incorporate climate drivers, although more complicated than univariate LSTM models, depict a superior predictive capacity. With multivariate LSTMs, the researchers and policymakers are able to make improved decisions in regard to coastal resilience, mitigation, and long-term climate adjustment work (Chung et al., 2021).

V. CONCLUSION

The authors in this paper state the potential of predicting Global Mean Sea Level (GMSL) using Long Short-Term Memory (LSTM) neural networks through the use of the historical climatic records. The study has demonstrated the advantages of considering a combination of different climate drivers through multivariate model analysis that takes into account both global temperature abnormalities and CO₂ concentrations in the atmosphere through the univariate model analysis that solely depends on GMSL. Historical records indicate that the sea level rise rate is accelerating and this is due to the melting of ice and the expansion of the thermosphere and the relationship between the rise of the sea level and the temperature and CO₂ is non-linear and needs advanced modelling methods.

Univariate lstm models are fairly predictive of the future as they learn the association between historical variations in sea level and thus less prone to the intricate interactions among climate variables. On the contrary, nonlinear interactions can be captured by multivariate LSTM models and improve prediction and offer more plausible long-term forecasts. This comprehensive modeling may be fundamental in the coastal planning, risk assessment and climate adaptation strategy.

Overall, the findings indicate that the combination of historic data sets and the present-day deep learning techniques is significant to enhance forecasting. With the help of multivariate LSTM models, the policy-makers and researchers will have a better chance to forecast the future state of the oceanic levels, direct the mitigation strategy, and organize more productive measures to protect the most dangerous regions along the coastline in case of climate change.

REFERENCES

1. Accarino, G., Chiarelli, M., Fiore, S., Federico, I., Causio, S., Coppini, G. and Aloisio, G., 2021. A multi-model architecture based on Long Short-Term Memory neural networks for multi-step sea level forecasting. *Future Generation Computer Systems*, 124, pp.1-9.
2. Ahmed, M., Song, H., Ali, H., Shuai, C., Abbas, K. and Ahmed, M., 2023. Investigating global surface temperature from the perspectives of environmental, demographic, and economic indicators: current status and future temperature trend. *Environmental Science and Pollution Research*, 30(9), pp.22787-22807.

3. Ayaz, İ., 2024. Forecasting CO₂ Emissions with Machine Learning Methods: Türkiye Example and Future Trends. *Naturengs*, 5(2), pp.82-87.
4. Ayinde, A.S., Yu, H. and Wu, K., 2023. Sea level variability and modeling in the Gulf of Guinea using supervised machine learning. *Scientific Reports*, 13(1), p.21318.
5. Balogun, A.L. and Adebisi, N., 2021. Sea level prediction using ARIMA, SVR and LSTM neural network: assessing the impact of ensemble Ocean-Atmospheric processes on models' accuracy. *Geomatics, Natural Hazards and Risk*, 12(1), pp.653-674.
6. Bharadiya, J.P., Tzenios, N.T. and Reddy, M., 2023. Forecasting of crop yield using remote sensing data, agrarian factors and machine learning approaches. *Journal of Engineering Research and Reports*, 24(12), pp.29-44.
7. Camporeale, E., 2019. The challenge of machine learning in space weather: Nowcasting and forecasting. *Space weather*, 17(8), pp.1166-1207.
8. Cheng, X., 2023. Global Temperature Study based on ARIMA and XGBoost-LSTM Models. *Frontiers*, 4(4).
9. Chin, S. and Lloyd, V., 2024. Predicting climate change using an autoregressive long short-term memory model. *Frontiers in Environmental Science*, 12, p.1301343.
10. Chung, J., Tong, G., Chao, J. and Zhu, W., 2021. Path Analysis of Sea-Level Rise and Its Impact. *Stats* 2022, 5, 12–25 [online]
11. Creel, R.C., Austermann, J., Kopp, R.E., Khan, N.S., Albrecht, T. and Kingslake, J., 2024. Global mean sea level likely higher than present during the holocene. *Nature communications*, 15(1), p.10731.
12. Dangendorf, S., Marcos, M., Wöppelmann, G., Conrad, C., Frederikse, T. and Riva, R., 2018. A reconciled estimate of 20th century global mean sea level rise. *Sea Level Rise*, 16(6).
13. Durhasan, T., Pinar, E., Uluocak, I. and Bilgili, M., 2025. Future forecast of global mean surface temperature using machine learning and conventional time series methods. *Theoretical and Applied Climatology*, 156(1), p.17.
14. Elabd, E., Hamouda, H.M., Ali, M.M. and Fouad, Y., 2025. Climate change prediction in Saudi Arabia using a CNN GRU LSTM hybrid deep learning model in al Qassim region. *Scientific Reports*, 15(1), p.16275.
15. Elneel, L., Zitouni, M.S., Mukhtar, H. and Al-Ahmad, H., 2023, December. Forecasting global mean sea level rise using autoregressive models. In *2023 30th IEEE International Conference on Electronics, Circuits and Systems (ICECS)* (pp. 1-4). IEEE.
16. Elneel, L., Zitouni, M.S., Mukhtar, H. and Al-Ahmad, H., 2024. Examining sea levels forecasting using autoregressive and prophet models. *Scientific Reports*, 14(1), p.14337.
17. Fernández-Martínez, M., Sardans, J., Chevallier, F., Ciais, P., Obersteiner, M., Vicca, S., Canadell, J.G., Bastos, A., Friedlingstein, P., Sitch, S. and Piao, S.L., 2019. Global trends in carbon sinks and their relationships with CO₂ and temperature. *Nature climate change*, 9(1), pp.73-79.
18. Hamdan, A., Al-Salaymeh, A., AlHamad, I.M., Ikemba, S. and Ewim, D.R.E., 2023. Predicting future global temperature and greenhouse gas emissions via LSTM model. *Sustainable Energy Research*, 10(1), p.21.
19. Hamlington, B.D., Piecuch, C.G., Reager, J.T., Chandanpurkar, H., Frederikse, T., Nerem, R.S., Fasullo, J.T. and Cheon, S.H., 2020. Origin of interannual variability in global mean sea level. *Proceedings of the National Academy of Sciences*, 117(25), pp.13983-13990.
20. Hilal, Y.N., Nainggolan, G.D.A., Syahputri, S.H. and Kartiasih, F., 2024. Comparison of ARIMA and LSTM Methods in Predicting Jakarta Sea Level. *Jurnal Ilmu dan Teknologi Kelautan Tropis*, 16(2), pp.163-178.
21. Horton, B.P., Khan, N.S., Cahill, N., Lee, J.S., Shaw, T.A., Garner, A.J., Kemp, A.C., Engelhart, S.E. and Rahmstorf, S., 2020. Estimating global mean sea-level rise and its uncertainties by 2100 and 2300 from an expert survey. *NPJ climate and atmospheric science*, 3(1), p.18.
22. Kamran, M., Tanveer, K., Khalid, N., Khalil, M.N., Ahmad, B., Arooj, A., Majeed, M.K. and Mir, S.Z., 2025. INTEGRATING ADVANCED DEEP LEARNING ALGORITHMS FOR CLIMATE SYSTEMS: ENHANCING WEATHER FORECAST ACCURACY, REAL-TIME CLIMATE MONITORING, AND LONG-TERM CLIMATE PREDICTIONS. *Spectrum of Engineering Sciences*, 3(6), pp.365-403.
23. Kumar, P., Priyanka, P., Dhanya, J., Uday, K.V. and Dutt, V., 2023. Analyzing the performance of univariate and multivariate machine learning models in soil movement prediction: A comparative study. *IEEE Access*, 11, pp.62368-62381.
24. Luaran, N., Alfred, R., Obit, J.H. and On, C.K., 2021. A Review on Deep Learning Approaches to Forecasting the Changes of Sea Level. *Computational Science and Technology: 7th ICCST 2020, Pattaya, Thailand, 29–30 August, 2020*, pp.563-573.

25. Medeiros, M.C., Vasconcelos, G.F., Veiga, Á. and Zilberman, E., 2021. Forecasting inflation in a data-rich environment: the benefits of machine learning methods. *Journal of Business & Economic Statistics*, 39(1), pp.98-119.
26. Nieves, V., Radin, C. and Camps-Valls, G., 2021. Predicting regional coastal sea level changes with machine learning. *Scientific reports*, 11(1), p.7650.
27. Ollila, A., 2023. Natural Climate Drivers Dominate in the Current Warming. *Science of Climate Change*, 3(3), pp.290-326.
28. Piao, S., Liu, Z., Wang, Y., Ciais, P., Yao, Y., Peng, S., Chevallier, F., Friedlingstein, P., Janssens, I.A., Penuelas, J. and Sitch, S., 2018. On the causes of trends in the seasonal amplitude of atmospheric CO₂. *Global change biology*, 24(2), pp.608-616.
29. Ranasinghe, N., 2025. Analyzing and Modelling Historical Global and Regional Temperature Shifts Using Deep Learning Techniques and Greenhouse Gas Emissions Analysis.
30. Reich, P.B., Hobbie, S.E., Lee, T.D., Rich, R., Pastore, M.A. and Worm, K., 2020. Synergistic effects of four climate change drivers on terrestrial carbon cycling. *Nature Geoscience*, 13(12), pp.787-793.
31. Sadhukhan, B., Chakraborty, S. and Mukherjee, S., 2022. Investigating the relationship between earthquake occurrences and climate change using RNN-based deep learning approach. *Arabian Journal of Geosciences*, 15(1), p.31.
32. Song, J., Tong, G., Chao, J., Chung, J., Zhang, M., Lin, W., Zhang, T., Bentler, P.M. and Zhu, W., 2023. Data driven pathway analysis and forecast of global warming and sea level rise. *Scientific Reports*, 13(1), p.5536.
33. Suradhaniwar, S., Kar, S., Durbha, S.S. and Jagarlapudi, A., 2021. Time series forecasting of univariate agrometeorological data: a comparative performance evaluation via one-step and multi-step ahead forecasting strategies. *Sensors*, 21(7), p.2430.
34. Sweeney, C., Bessa, R.J., Browell, J. and Pinson, P., 2020. The future of forecasting for renewable energy. *Wiley Interdisciplinary Reviews: Energy and Environment*, 9(2), p.e365.
35. Taylor, J. and Feng, M., 2022. A deep learning model for forecasting global monthly mean sea surface temperature anomalies. *Frontiers in Climate*, 4, p.932932.
36. Tebaldi, C., Ranasinghe, R., Vourdoukas, M., Rasmussen, D.J., Vega-Westhoff, B., Kirezci, E., Kopp, R.E., Srivier, R. and Mentaschi, L., 2021. Extreme sea levels at different global warming levels. *Nature Climate Change*, 11(9), pp.746-751.
37. Tumse, S. and Alcansoy, U., 2025. Statistical and deep learning approaches in estimating present and future global mean sea level rise. *Natural Hazards*, 121(9), pp.10377-10404.
38. Uluocak, I., 2025. Comparative study of multivariate hybrid neural networks for global sea level prediction through 2050. *Environmental Earth Sciences*, 84(3), p.79.
39. Vignudelli, S., Birol, F., Benveniste, J., Fu, L.L., Picot, N., Raynal, M. and Roinard, H., 2019. Satellite altimetry measurements of sea level in the coastal zone. *Surveys in geophysics*, 40(6), pp.1319-1349.
40. Wang, J., Church, J.A., Zhang, X. and Chen, X., 2021. Reconciling global mean and regional sea level change in projections and observations. *Nature Communications*, 12(1), p.990.
41. Wen, T., Liu, Y., he Bai, Y. and Liu, H., 2023. Modeling and forecasting CO₂ emissions in China and its regions using a novel ARIMA-LSTM model. *Heliyon*, 9(11).



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